European Control Conference 2026 · Tutorial Session

Model Predictive Control for Robot Motion Planning Near Humans

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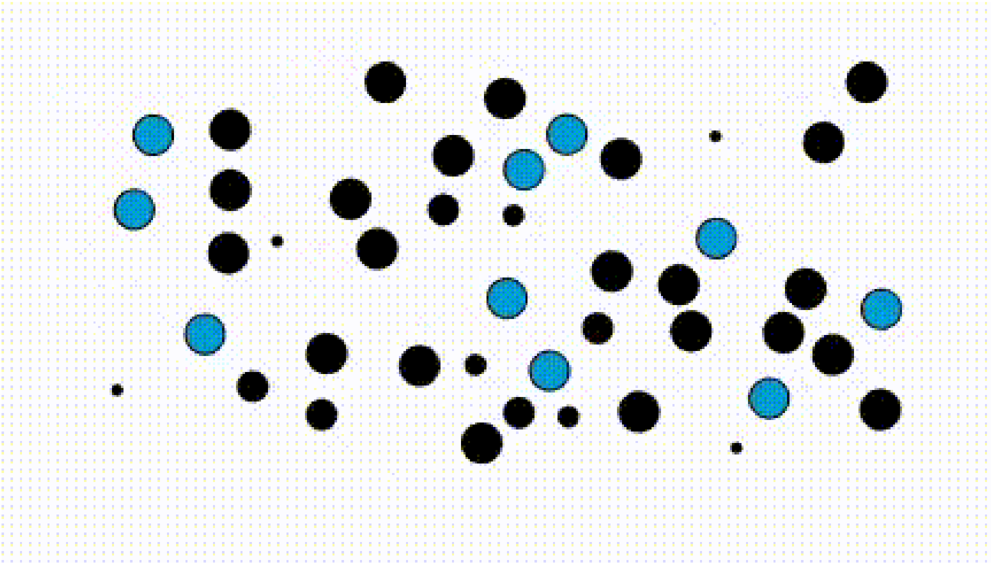


Robots Navigating Among People

- Today, autonomous vehicles share dense urban traffic with people
- **Challenge:** Human behavior is hard to predict, and predictions carry uncertainty
- **Goal:** plan a safe, efficient motion that fully exploits the perception module

Source: https://www.youtube.com/watch?v=pqQSwQLDIK8

Roadmap

From Simple Assumptions to Interaction-Aware Planning

Human motion is hard to predict — we handle the uncertainty directly inside MPC.

MPCC

Plan with simple human assumptions

→

Rules

Encode traffic rules

→

Scenario MPC

Sample futures: stage-wise → trajectories

→

Topology

Keep multiple passing options

→

Games

Interaction-aware → outlook

Model Predictive Contouring Control for Path Planning: Overview

Minimize $\boxed{J(z_k, u_k)}$ subject to the following constraints

Initial condition: $z_0 = z_{\text{init}}$

Dynamics: $z_{k+1} = f(z_k, u_k)$

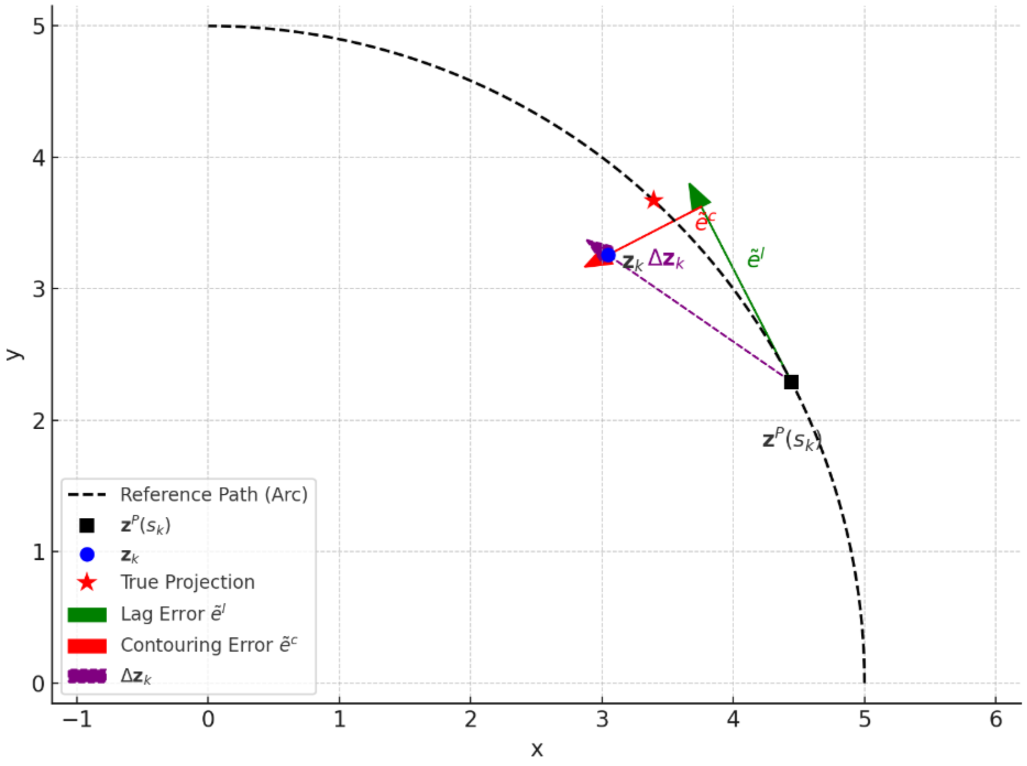
Obstacle avoidance

$$\|z_k^{\text{pos}} - z_{\text{obs}}\|_2 \geq r_{\text{safe}} \quad \forall k$$

Input bounds: $u_{\min} \leq u_k \leq u_{\max}$

State bounds (optional)

Contouring Control: Error Definition



Let the **reference path** be parametrized by arc length s:

$$z^P(s) \;=\; [x^P(s)\; y^P(s)]^T$$

Let the vehicle's actual position at time step k be:

$$z_k = [x_k\; y_k]^T$$

Let the tangent and normal directions at s_k be:

$$\boldsymbol{\tau}(s_k) = \left[\cos\left(\phi_P(s_k)\right) \sin\left(\phi_P(s_k)\right)\right]^T$$

$$\boldsymbol{n}(s_k) = \left[-\sin\left(\phi_P(s_k)\right) \cos\left(\phi_P(s_k)\right)\right]^T$$

$\phi_P(s_k)$ is the **heading** (orientation) of the reference path at s_k:

$$\phi_P(s_k) \;=\; \operatorname{arctan2}\left(\frac{dy^P}{ds}, \frac{dx^P}{ds}\right)\Bigg|_{s_k}$$

Define $\Delta z_k = z_k - z^P(s_k)$

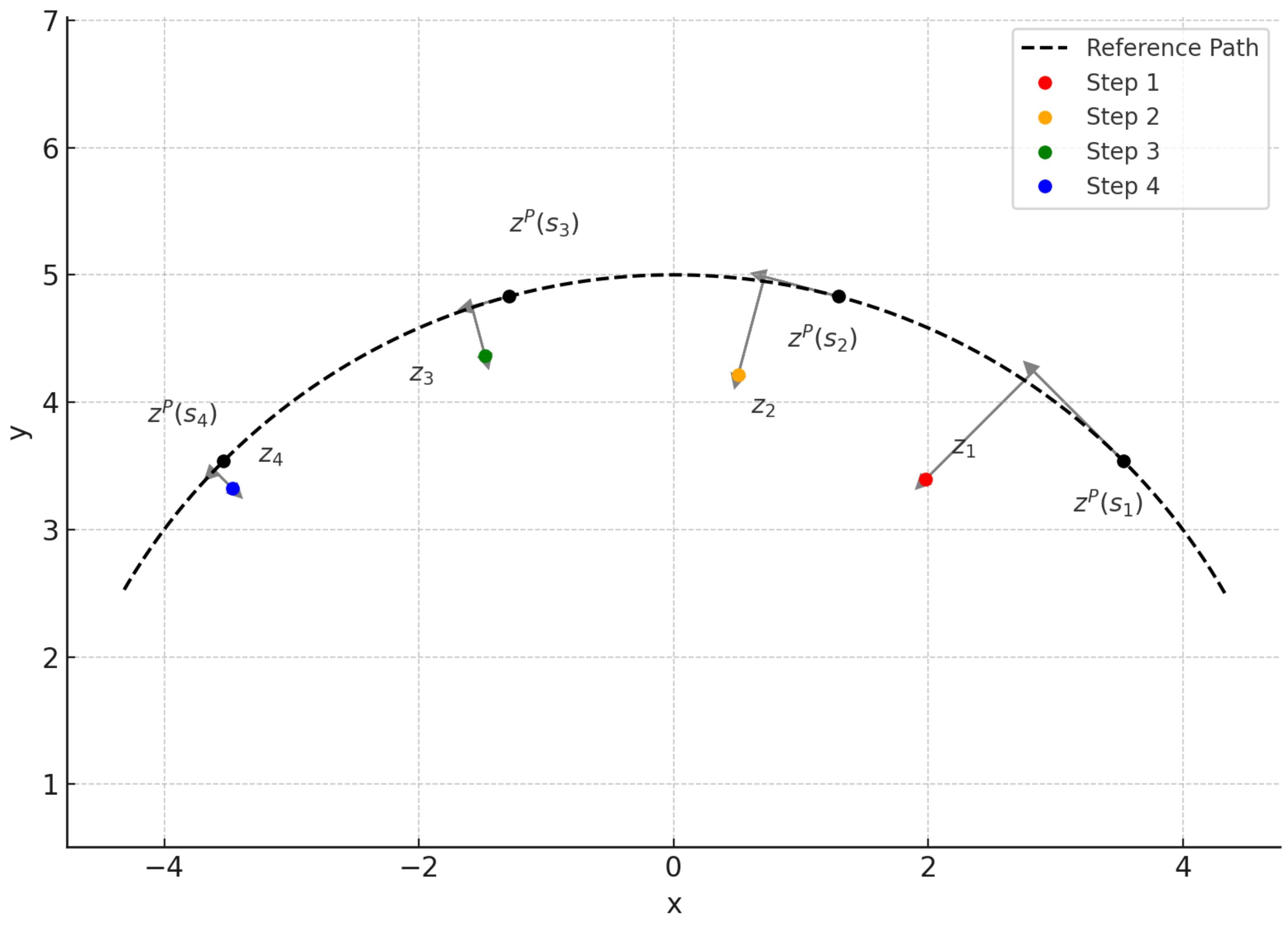
Lag error: Component of the deviation along the path tangent

$$\tilde{e}^l = \boldsymbol{\tau}^\top(s_k) \cdot \Delta\mathbf{z}_k$$

Contouring error: Component off the deviation orthogonal to the path

$$\tilde{e}^c = \mathbf{n}^\top(s_k) \cdot \Delta\mathbf{z}_k$$

Contouring Control: Cost Definition



$$J = \sum_{k=1}^{N} \left(Q_c {\tilde{e}_k^c}^2 + Q_l {\tilde{e}_k^l}^2 + u_k^T R u_k \right)$$

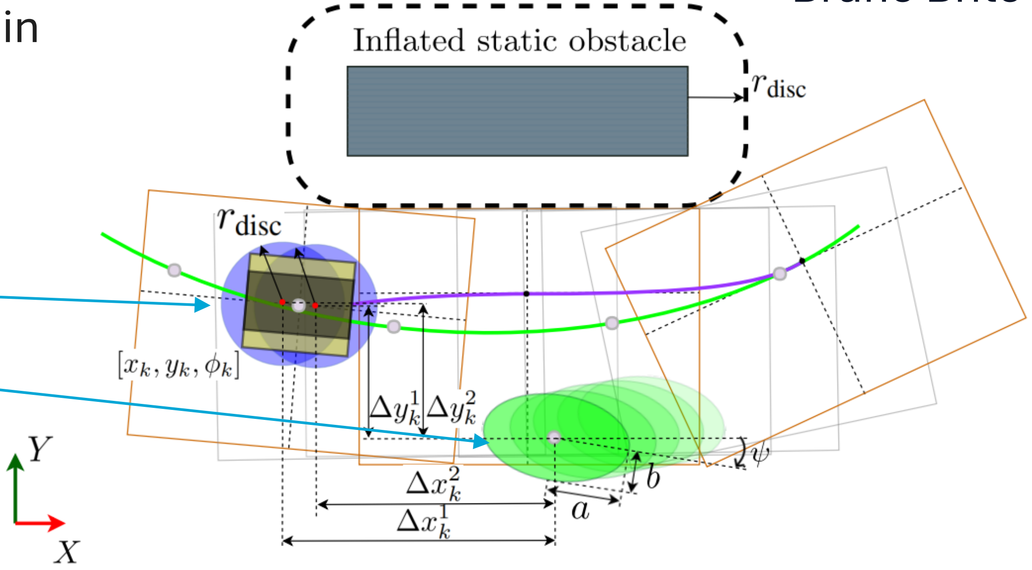
Example of minimization of the errors over 4 consecutive steps

Navigation Envelope

Bruno Brito

Envelope: the free space the planned trajectory must stay within

- To define the envelope, we represent:
    - The robot as **circles**
    - Each pedestrian as an **ellipse**



Assumptions:

- pedestrians move at constant velocity;
- static obstacles inflated by r_{disc};
- collision-free ⇔ disc–ellipse separation

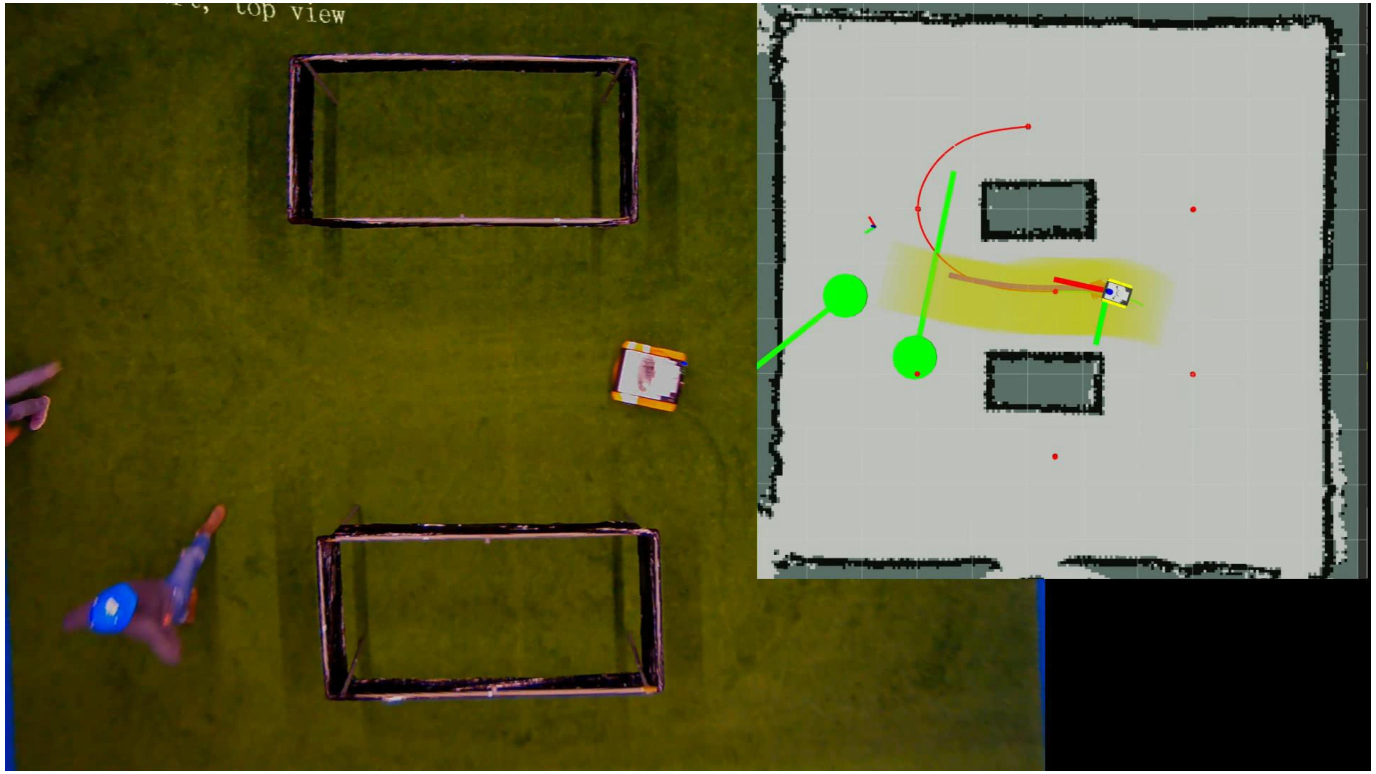
Quantities:

- r_{disc}: disc radius;
- (x, y, ϕ): robot pose;
- a, b: pedestrian ellipse semi-axes;
- ψ: pedestrian heading
-

B. Brito, B. Floor, L. Ferranti, J. Alonso-Mora, “Model Predictive Contouring Control for Collision Avoidance in Unstructured Dynamic Environments,” IEEE RA-L, 2019.

MPCC in Action

Bruno Brito



In our setup

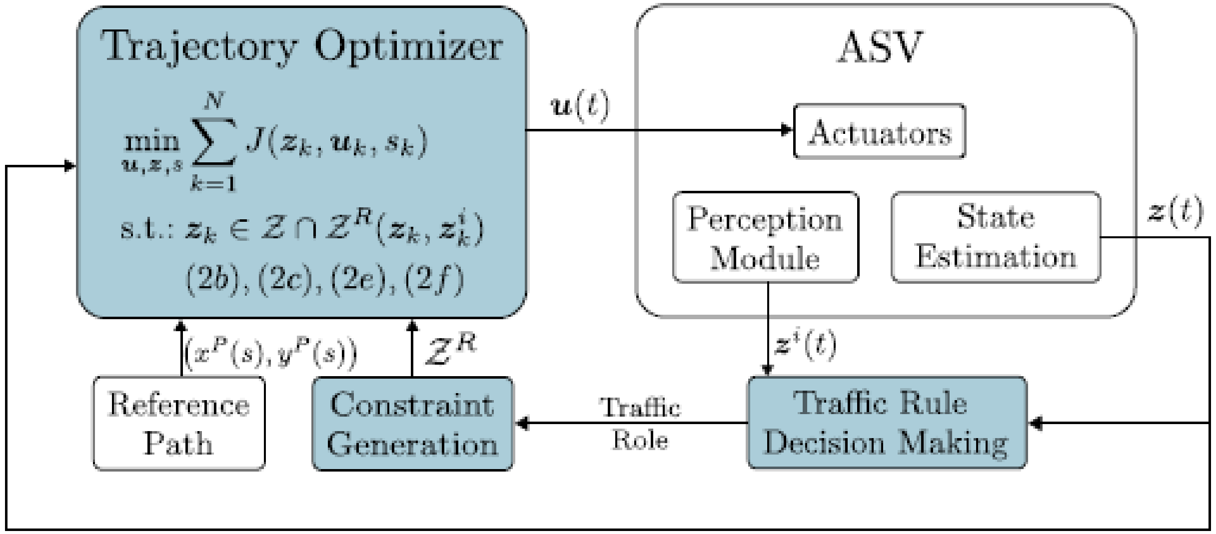
- MPCC runs fully onboard — no external compute
- Pedestrians use a constant-velocity prediction
- Lightweight — scales to several agents in real time

B. Brito, B. Floor, L. Ferranti, J. Alonso-Mora, “Model Predictive Contouring Control for Collision Avoidance in Unstructured Dynamic Environments,” IEEE RA-L, 2019.

Collision avoidance using traffic rules

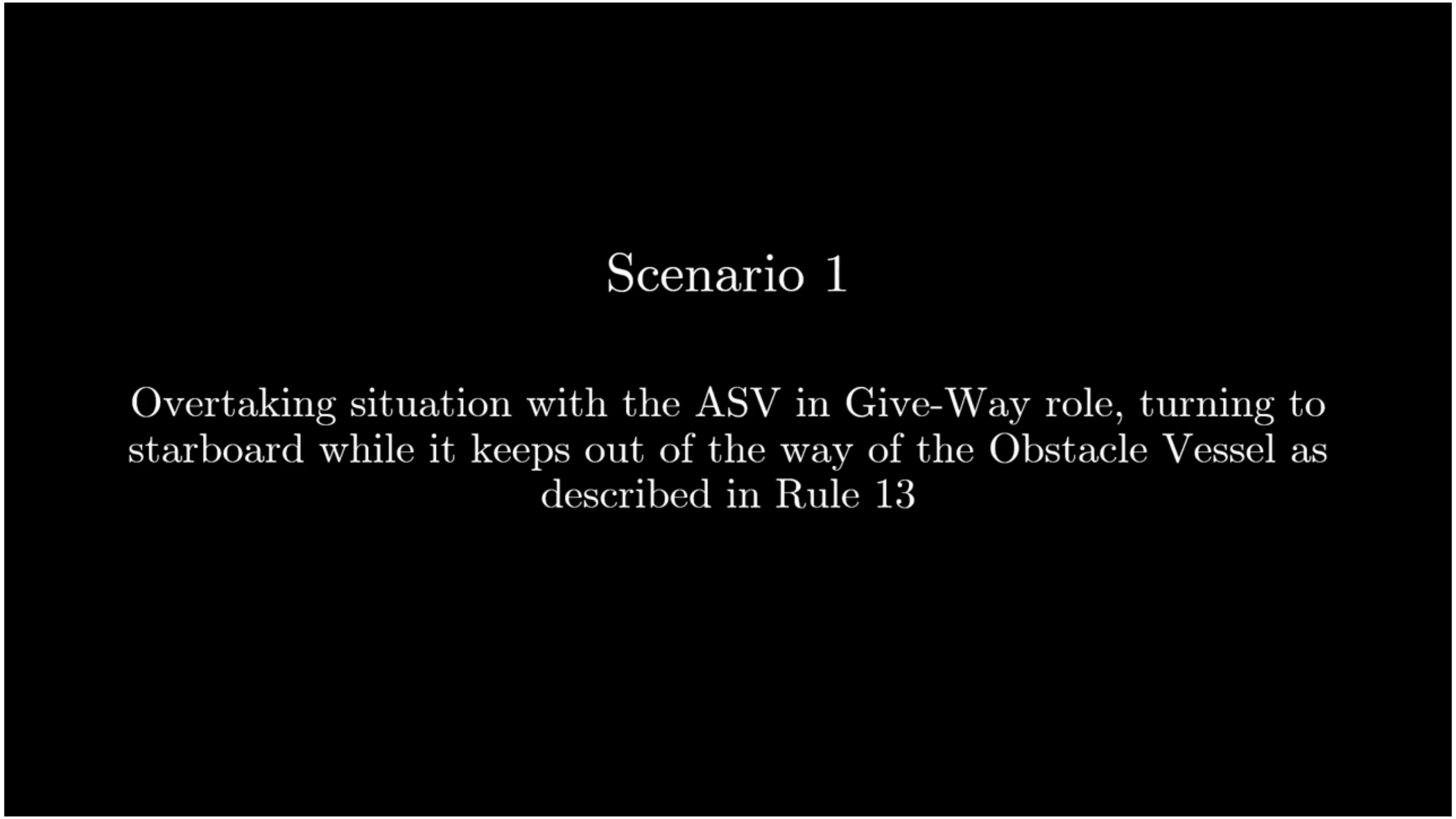
Tasos Tsolakis

- A collision-free path isn't always acceptable — motion must follow the rules
- At sea, COLREGs are strict and codified, yet hard to formalize for planning
- Vessels: an ideal testbed for rule-aware MPC

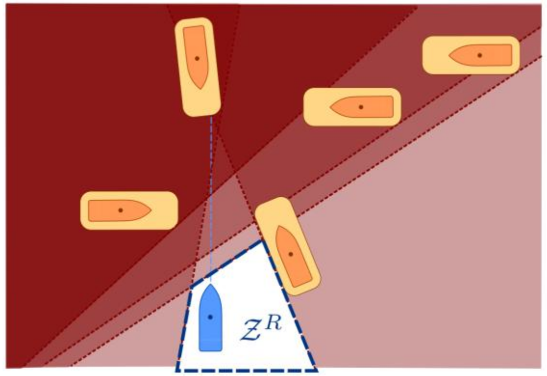


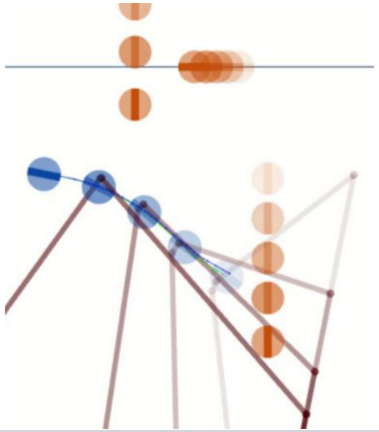
A. Tsolakis, R. R. Negenborn, V. Reppa, L. Ferranti, "Model Predictive Trajectory Optimization and Control for Autonomous Surface Vessels Considering Traffic Rules," IEEE T-ITS, 2024.

Navigation in Mixed Traffic



Tasos Tsolakis

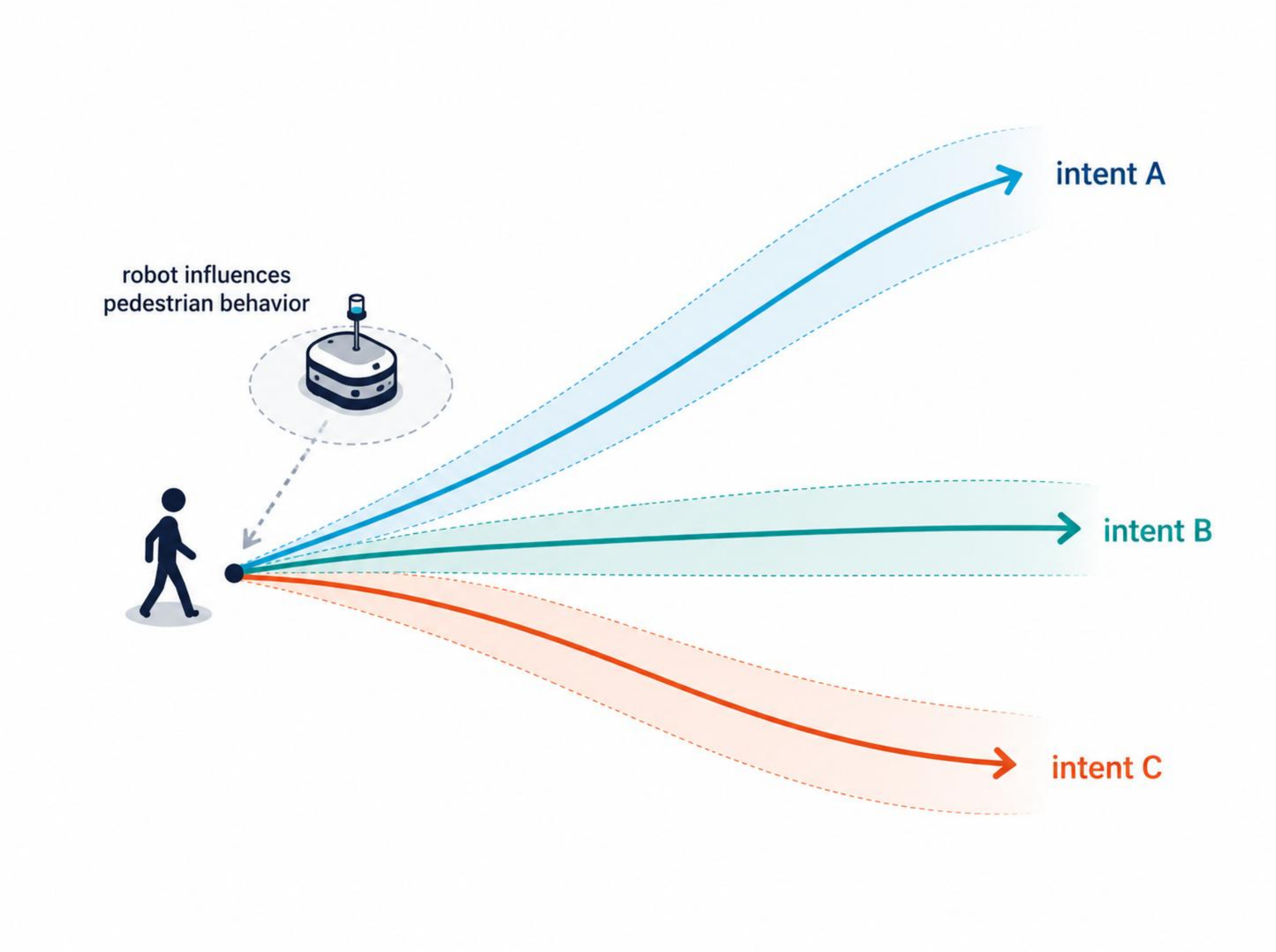




A. Tsolakis, R. R. Negenborn, V. Reppa, L. Ferranti, "Model Predictive Trajectory Optimization and Control for Autonomous Surface Vessels Considering Traffic Rules," IEEE T-ITS, 2024.

Why Human Motion Is Hard to Predict

- Unlike vessels at sea, people follow no codified rulebook
- Human motion is multimodal — several plausible intents at once
- Behavior is reactive: it depends on the robot’s own actions



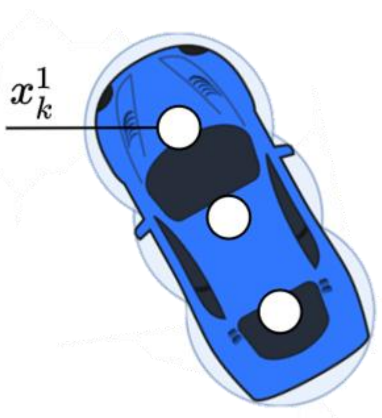
Problem Formulation

Oscar de Groot

Robot

- Nonlinear discretized dynamics

$$x_{k+1} = f(x_k, u_k)$$

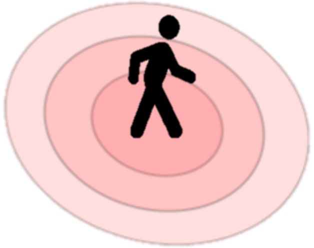


Dynamic Obstacles

- Uncertain position at time step k

$$\delta_k \in \Delta_\mathrm{k}$$

- Δ_k is the probability space



- Uncertainty $\delta_k \sim P_k$
- P_k is the probability density function
  - Non-Gaussian
  - Unbounded
  - Marginal

O. de Groot, L. Ferranti, D. M. Gavrila, J. Alonso-Mora, "Scenario-Based Trajectory Optimization in Uncertain Dynamic Environments," IEEE RA-L, 2021.

Problem Formulation

Oscar de Groot

- Chance constrained Model Predictive Control (MPC)

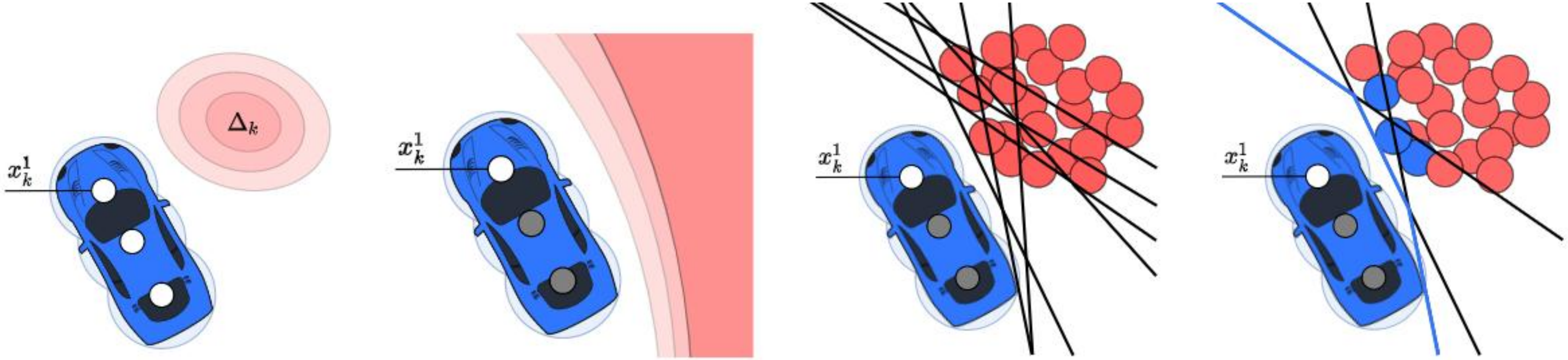
$$
\begin{aligned}
\min_{\boldsymbol{u} \in \mathbb{U}} \quad & \sum_{k=1}^{N} J(\boldsymbol{x}_k, \boldsymbol{u}_k) \\
\text{s.t.} \quad & \boldsymbol{x}_{k+1} = f(\boldsymbol{x}_k, \boldsymbol{u}_k), \;\; \boldsymbol{x} \in \mathbb{X} \\
& \mathbb{P}_k \left[\underbrace{||\boldsymbol{x}_k^d - \boldsymbol{\delta}_k^v||_2 > r}_{\text{Collision Avoidance}}, \forall d, v \right] \geqslant 1 - \underbrace{\epsilon_k}_{\text{Acceptable risk}}, \;\; \forall k
\end{aligned}
$$

- Chance constraint for every stage k

O. de Groot, L. Ferranti, D. M. Gavrila, J. Alonso-Mora, "Scenario-Based Trajectory Optimization in Uncertain Dynamic Environments," IEEE RA-L, 2021.

Scenario-MPCC

Oscar de Groot



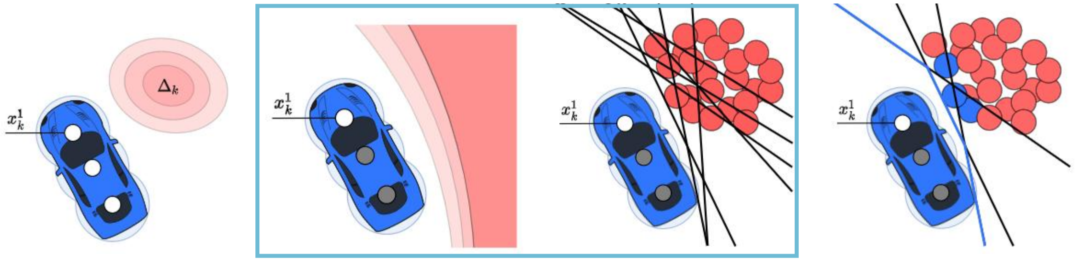
1 Uncertainty **2 Chance constraint** **3 Sample scenarios** **4 Linearized free space**

Scenario – Model Predictive Contouring Control (S-MPCC)

MPCC tracks a reference path; S-MPCC turns the probabilistic **chance constraints** — for unbounded, non-Gaussian uncertainty — into a finite set of sampled deterministic **scenarios**.

O. de Groot, L. Ferranti, D. M. Gavrila, J. Alonso-Mora, "Scenario-Based Trajectory Optimization in Uncertain Dynamic Environments," IEEE RA-L, 2021.

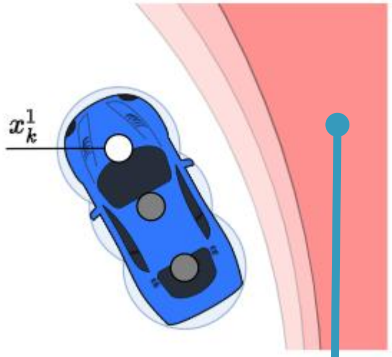
Scenario Optimization



- Chance Constrained Problem (CCP)

$$\begin{aligned} \min_{\boldsymbol{u}\in\mathbb{U}} \quad & J(\boldsymbol{u}) \\ \text{s.t.} \quad & \mathbb{P}\left[g(\boldsymbol{u},\boldsymbol{\delta}) \leqslant 0\right] \geqslant 1-\epsilon, \ \boxed{\boldsymbol{\delta}\in\Delta} \end{aligned}$$

Draw S samples for the probability space



- Scenario Program (SP)

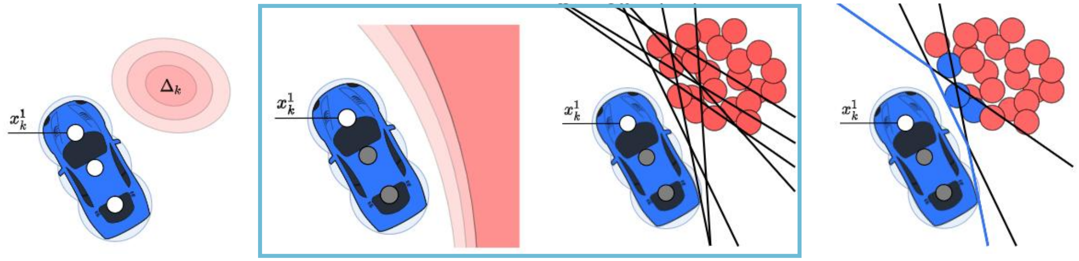
$$\begin{aligned} \min_{\boldsymbol{u}\in\mathbb{U}} \quad & J(\boldsymbol{u}) \\ \text{s.t.} \quad & g(\boldsymbol{u},\boldsymbol{\delta}^i) \leqslant 0, \ \boxed{\boldsymbol{\delta}^i\in\Delta, \ \forall i\in\mathcal{S}} \end{aligned}$$

Scenario optimization embeds the samples directly as constraints and certifies the optimized trajectory itself

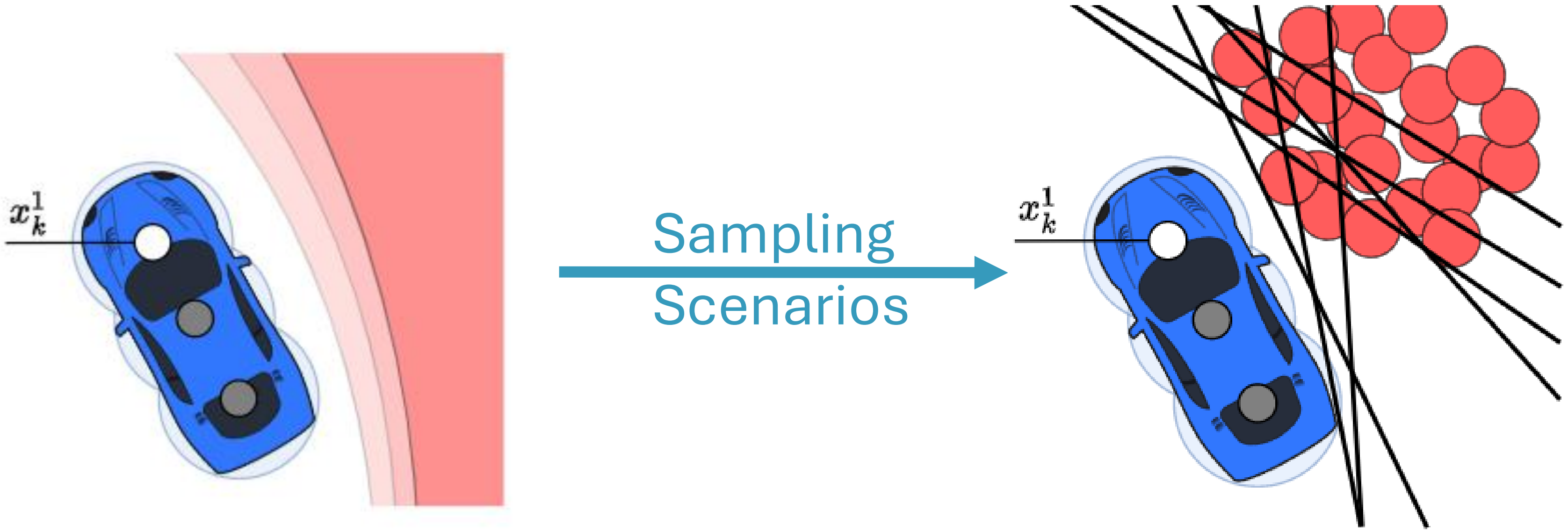
M. C. Campi et al., “A General Scenario Theory for Nonconvex Optimization and Decision Making,” IEEE Trans. Automatic Control, 2018.

O. de Groot, L. Ferranti, D. M. Gavrila, J. Alonso-Mora, "Scenario-Based Trajectory Optimization in Uncertain Dynamic Environments," IEEE RA-L, 2021.

Scenario Optimization

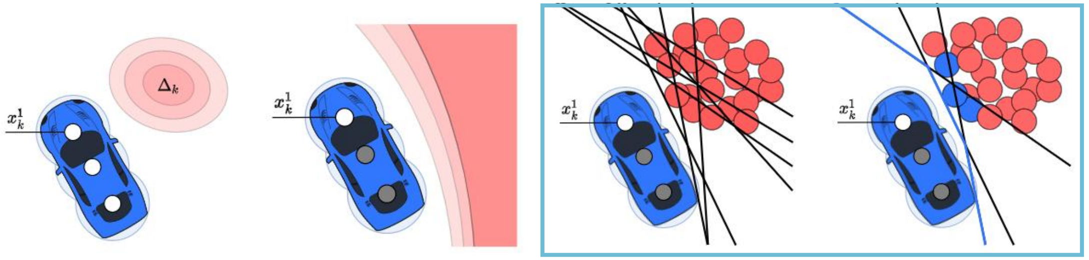


- Generate scenarios from model of P
  - Halfspace for each scenario (we use local linearization)
  - Free-space becomes a convex polygon

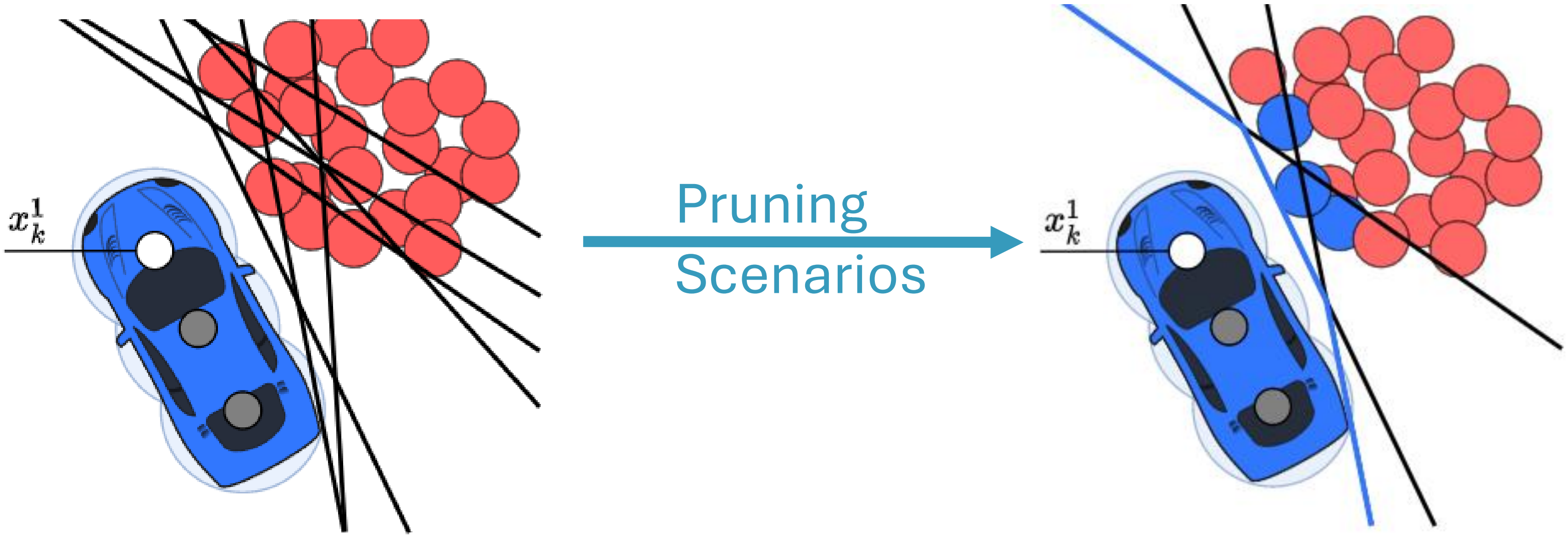


O. de Groot, L. Ferranti, D. M. Gavrila, J. Alonso-Mora, "Scenario-Based Trajectory Optimization in Uncertain Dynamic Environments," IEEE RA-L, 2021.

Pruning Scenarios



- The SP has many redundant constraints we can prune
- Support = the few edge halfspaces that shape the solution

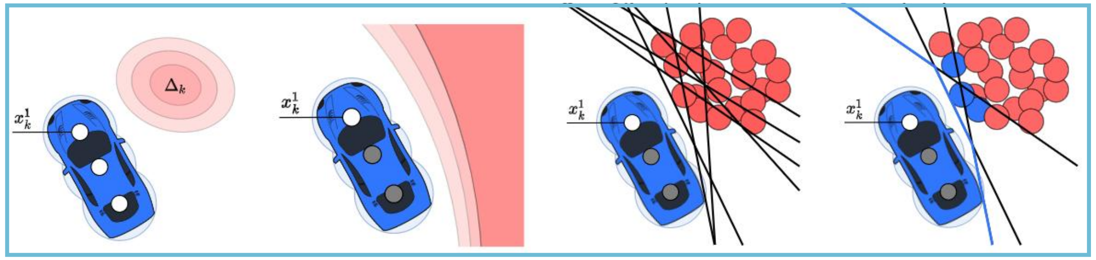


What gets pruned

- Outer, robot-facing samples can bind; center ones are shielded → never active
- Online: search only the nearest samples (a window assumed to hold the support) → intersect
- Pruned = never in the support → same solution & safety bound

O. de Groot, L. Ferranti, D. M. Gavrila, J. Alonso-Mora, "Scenario-Based Trajectory Optimization in Uncertain Dynamic Environments," IEEE RA-L, 2021.

Safety Guarantees



Violation probability is less than $\epsilon(s)$ with probability of at least $1 - \beta$

- β is a confidence parameter that bounds the violation probability
- $\epsilon(s)$ is the acceptable risk

Relation to scenario theory

We use Campi's scenario bound **as-is**, but replace its offline, re-solve-per-sample certification with an **online geometric support estimate** — trading an exact guarantee on the real distribution for a **real-time guarantee on the modeled one.**

O. de Groot, L. Ferranti, D. M. Gavrila, J. Alonso-Mora, "Scenario-Based Trajectory Optimization in Uncertain Dynamic Environments," IEEE RA-L, 2021.

The overall pipeline: offline vs. online

Assumptions: perception supplies the uncertainty model P; per-stage independence.

OFFLINE — once

1. Fix ε, β and the support limit → sample size S
2. Draw S samples in standard-normal space
3. Prune the samples that can never be active

ONLINE — every cycle (~50 ms)

1. Perception → each obstacle's predicted mean μ and spread Σ
2. Map the survivor samples onto that prediction: $\delta = A z + \mu$
3. Keep the ~150 samples closest to the robot; drop far outliers
4. Intersect → free-space polytope → solve MPC → apply first input

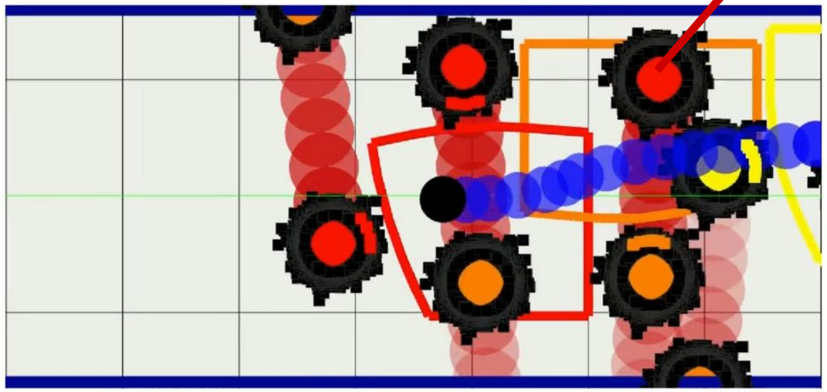
Why it works: $A z + \mu$ only shifts and rescales the cloud of samples — it never turns an inside sample into an edge one. So the edge samples we keep offline stay valid for any obstacle's position and spread, and the risk bound still uses all S samples.

O. de Groot, L. Ferranti, D. M. Gavrila, J. Alonso-Mora, "Scenario-Based Trajectory Optimization in Uncertain Dynamic Environments," IEEE RA-L, 2021.

Scenario-Based MPC

Results

Actual pedestrians in **Red**!



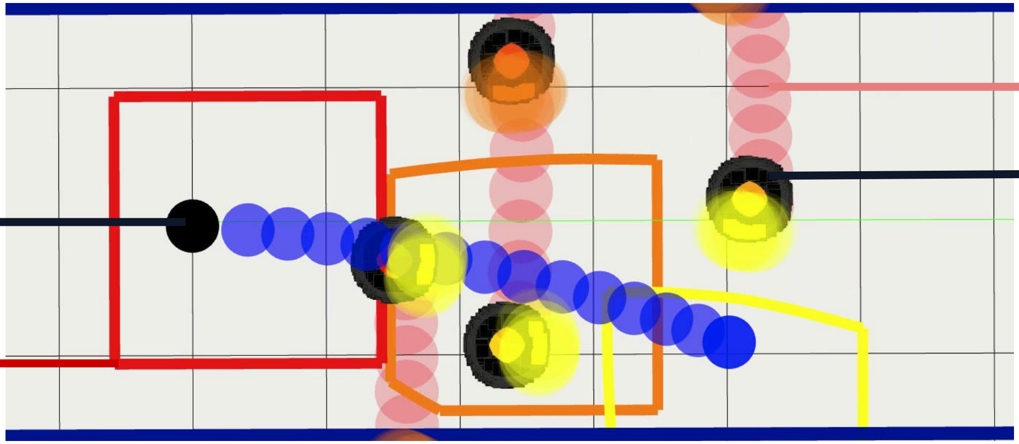
Parameters

Sample size 53,050 — scenarios per stage; ~95% pruned offline

Risk ε = 1.1% — max per-step collision prob. (≈ 3σ)

Confidence β = 10^{-6} — ~1-in-a-million bound failure

More scenarios → safer bound, but more conservative & slower.



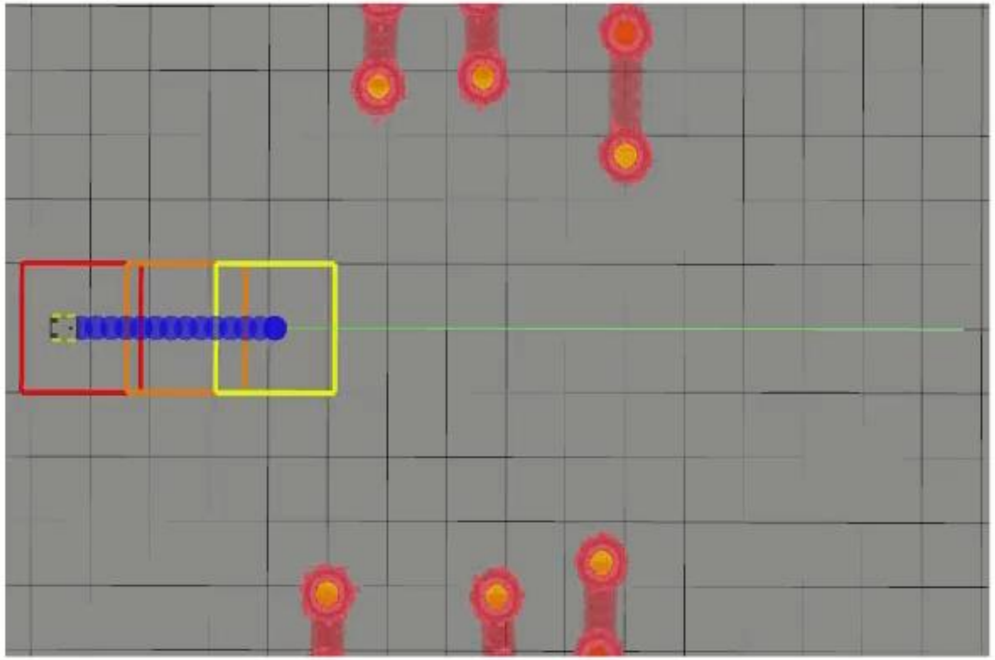
Pedestrian predictions

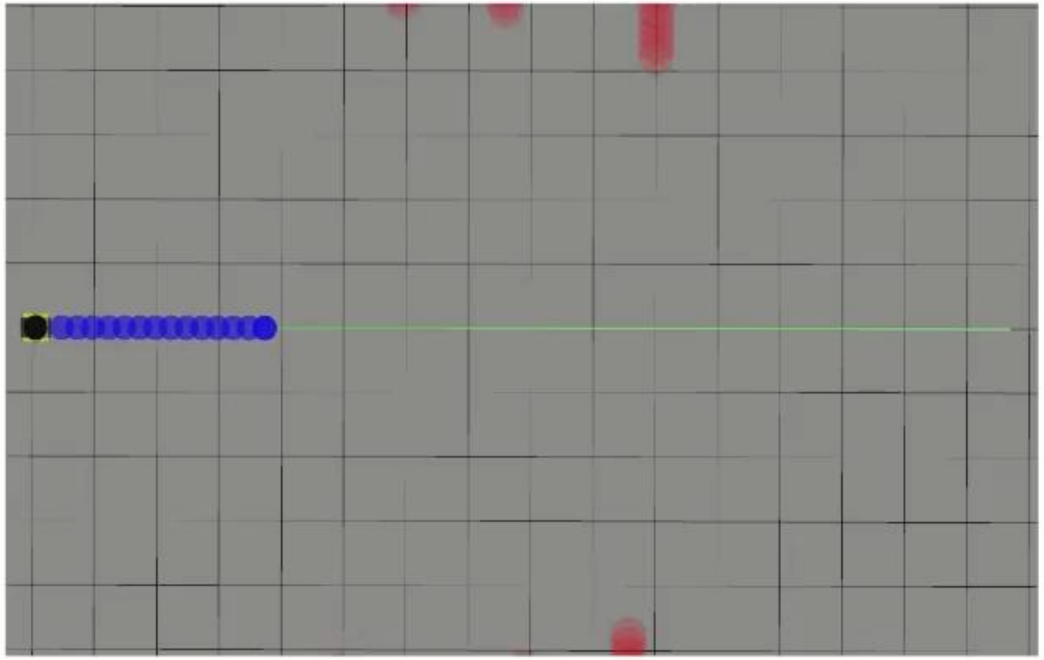
Scenarios

Robot (**Black**)
Trajectory (**Blue**)

Safe regions
Stage 1 (**Red**)
Stage 8 (**Orange**)
Stage 14 (**Yellow**)

Results: Proposed vs. Baseline





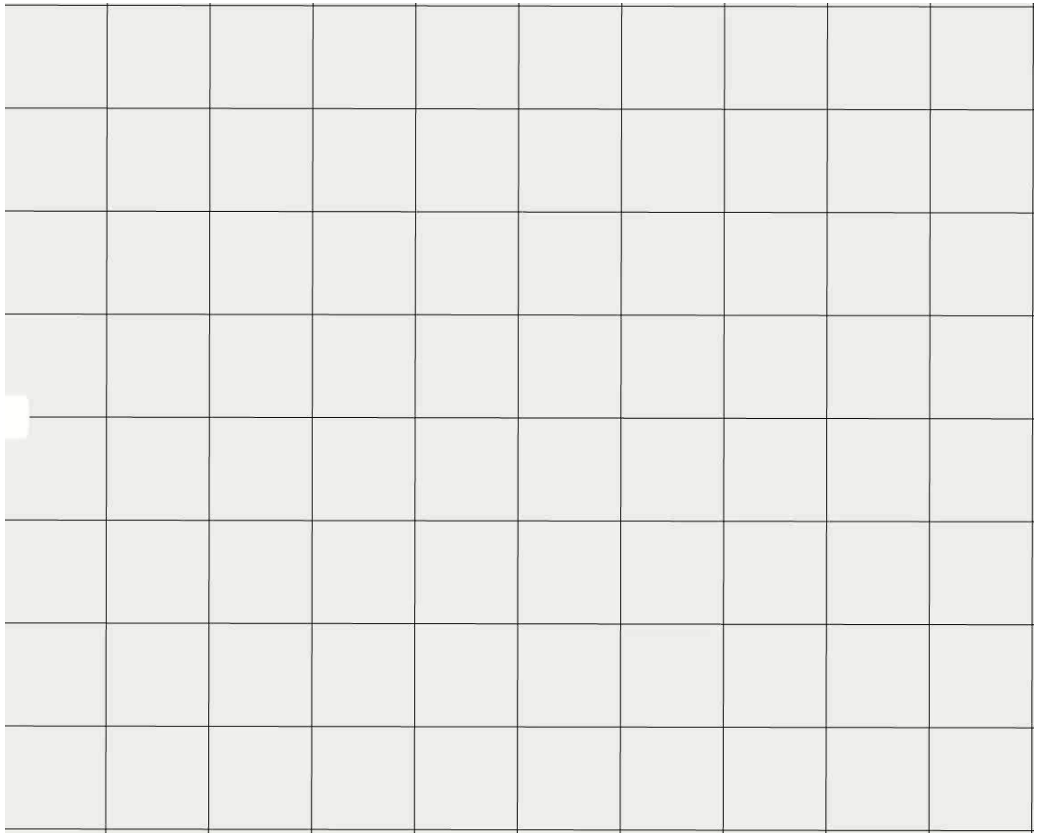
Proposed Approach*

MPC Baseline

Gaussian uncertainty — **S-MPCC stays collision-free and reaches the goal sooner than the MPCC baseline.**

O. de Groot, L. Ferranti, D. M. Gavrila, J. Alonso-Mora, “Scenario-Based Trajectory Optimization in Uncertain Dynamic Environments,” IEEE RA-L, 2021.

Results



Takeaway: handles non-Gaussian (truncated) uncertainty that ellipse / level-set baselines cannot represent.

Results using **Truncated Gaussian uncertainties** for the pedestrian predictions

O. de Groot, L. Ferranti, D. M. Gavrila, J. Alonso-Mora, “Scenario-Based Trajectory Optimization in Uncertain Dynamic Environments,” IEEE RA-L, 2021.

Scenario-Based MPC

Predicted Distributions

One scenario = a full obstacle trajectory (all obstacles jointly) → bounds P(collision over the whole plan) ≤ ε, replacing per-step / per-obstacle marginals.
Unlike S-MPCC: trajectories are sampled online — no standard-normal reuse.

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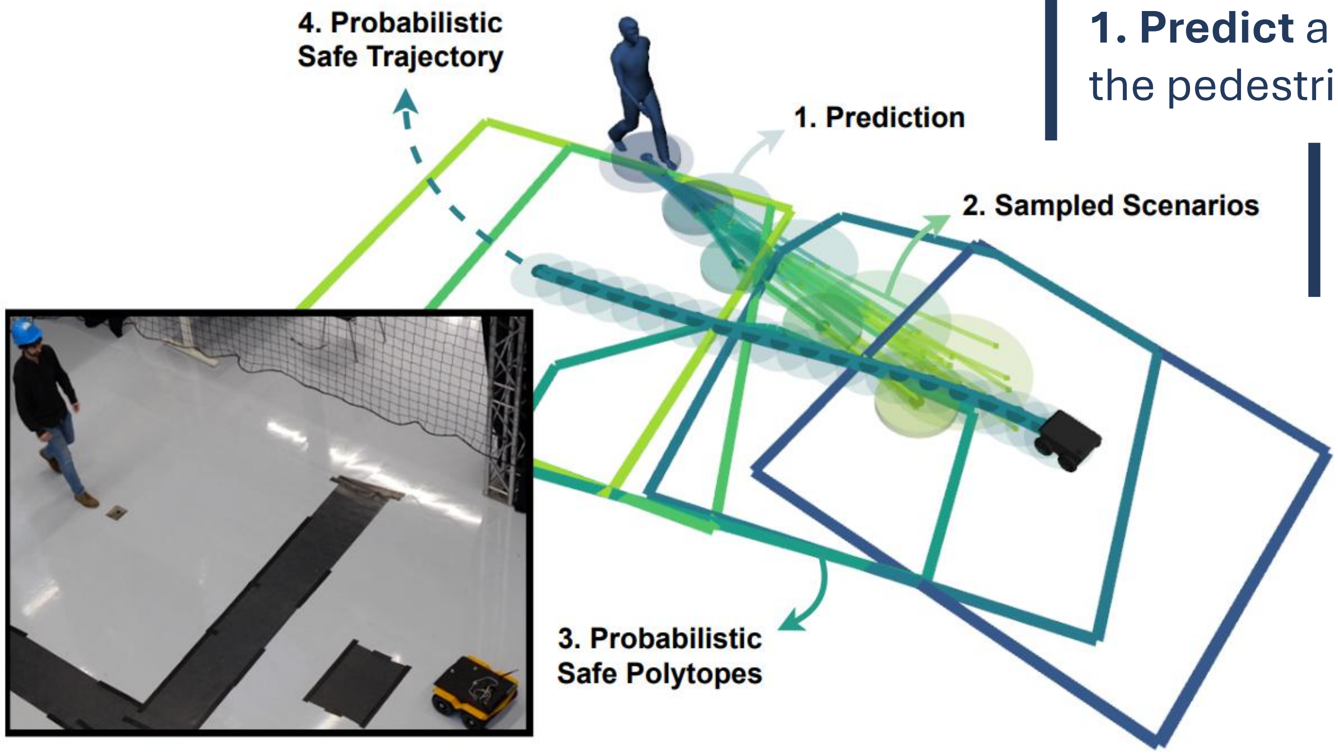


1. Predict a probability distribution for the pedestrian's future motion

2. Sample possible motions from the distribution **(i.e., scenarios)**

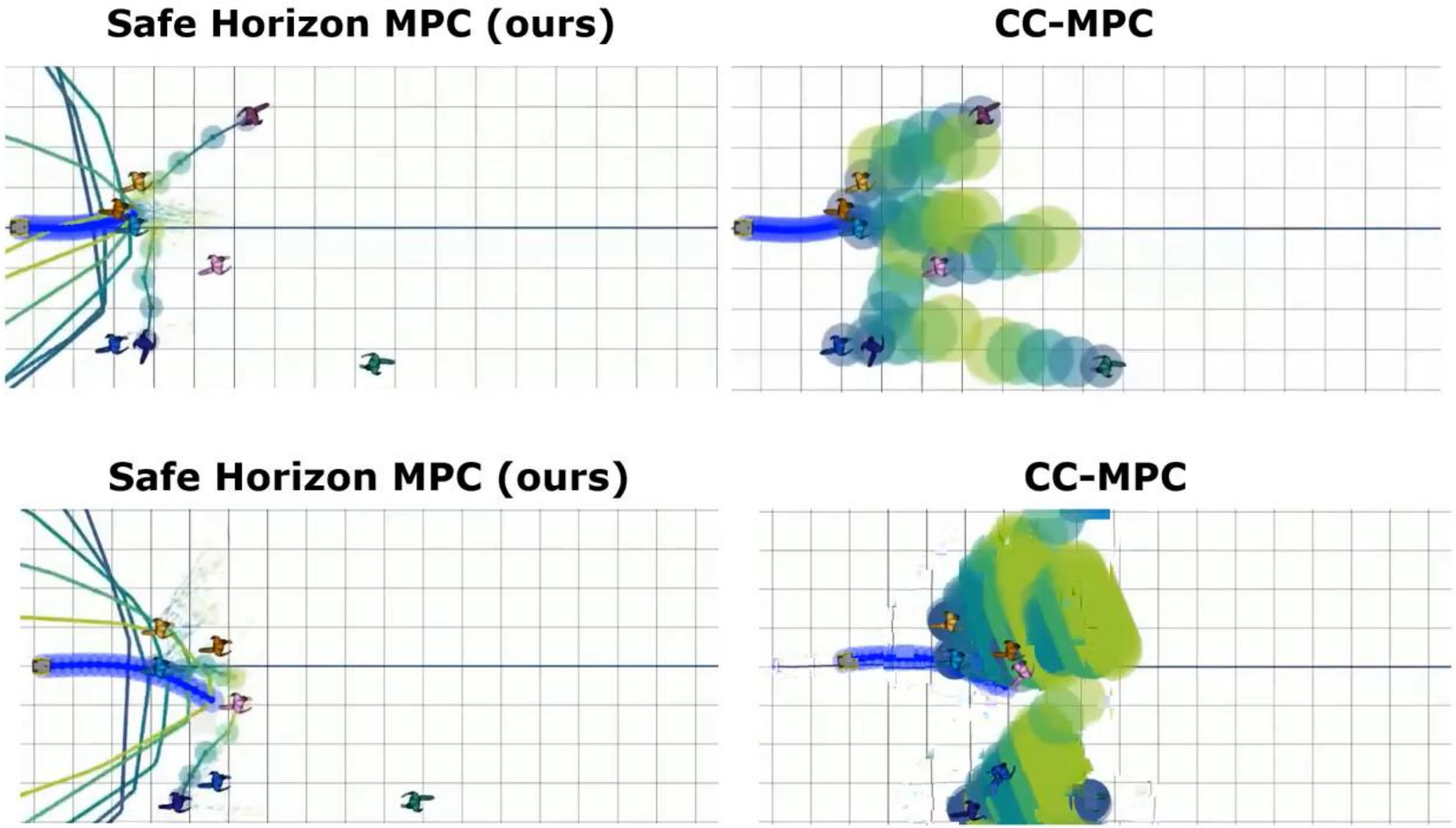
3. Compute safe regions **for each scenario**

4. Optimize to stay in the safe regions to obtain a **probabilistic safe** trajectory

O. de Groot, L. Ferranti, D. M. Gavrila, J. Alonso-Mora, "Scenario-Based Motion Planning with Bounded Probability of Collision," IJRR, 2025.

Beyond Gaussian Uncertainty

Our method vs Chance-Constrained MPC in crowded spaces



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Gaussian uncertainties in the position of the humans

Non-gaussian uncertainties in the position of the humans

O. de Groot, L. Ferranti, D. M. Gavrila, J. Alonso-Mora, "Scenario-Based Motion Planning with Bounded Probability of Collision," IJRR, 2025.

Escaping Local Optima

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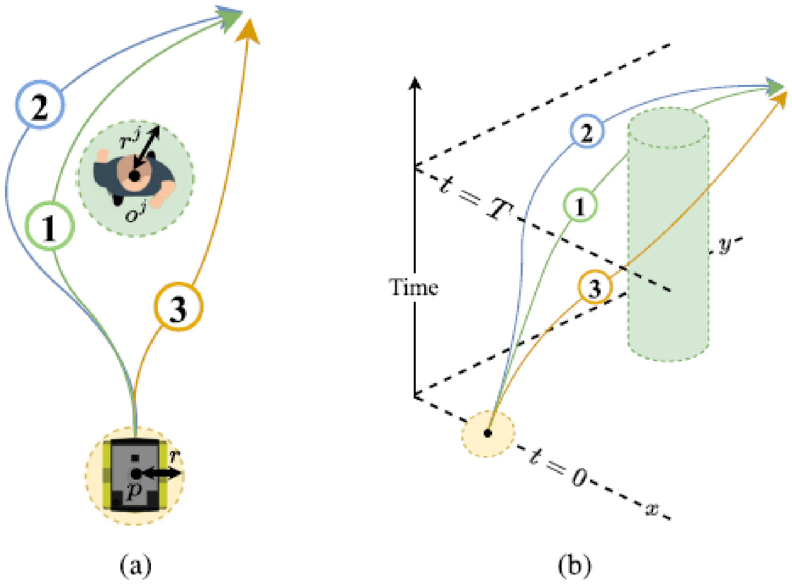
- Scenario MPC returns one locally optimal, safe trajectory
- In dense, dynamic scenes, it can lock onto a poor local optimum — hesitating or freezing
- Passing left vs. right, ahead vs. behind are topologically distinct options (homotopy classes)
- Plan several at once, then commit to the best:
  - robust, non-myopic motion



Optimize Topologies in Parallel, Then Commit

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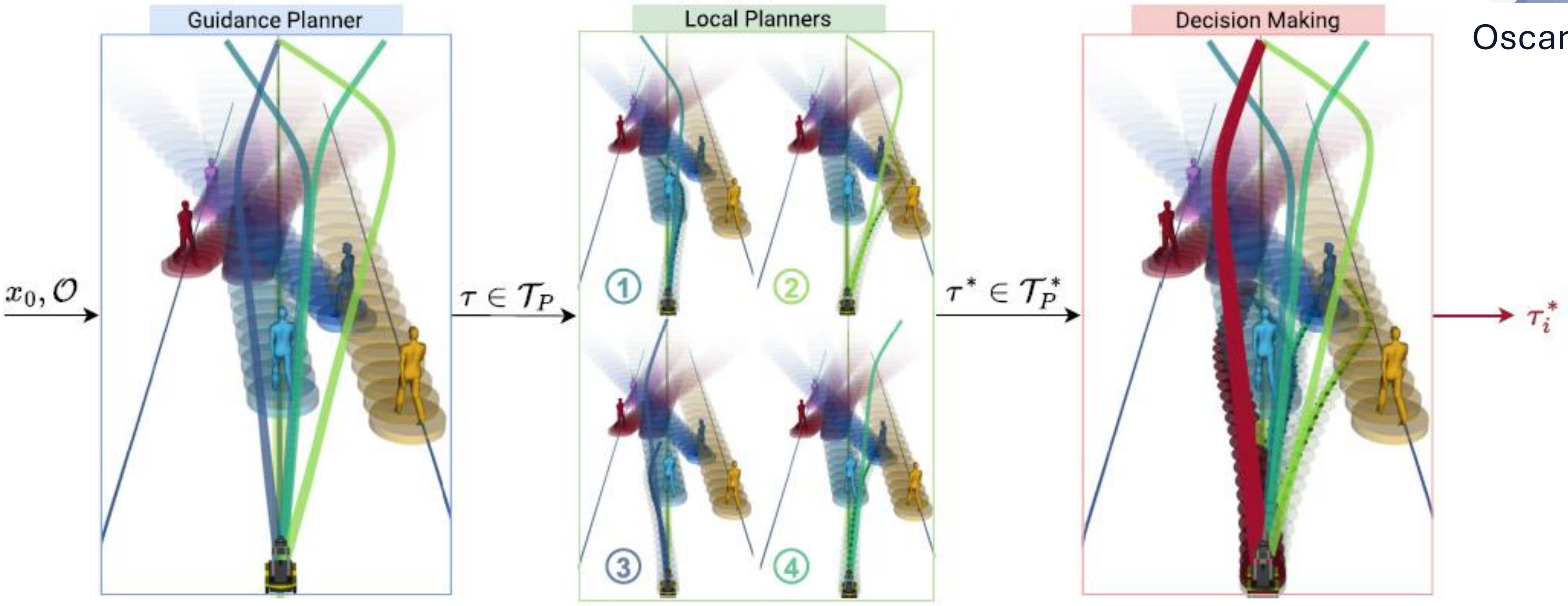

Guidance planner proposes distinct topology classes → local planners optimize each in parallel → commit to the best.

O. de Groot, L. Ferranti, D. M. Gavrila, J. Alonso-Mora, "Topology-Driven Parallel Trajectory Optimization in Dynamic Environments," IEEE T-RO, 2025.

Results: Faster, More Consistent Navigation

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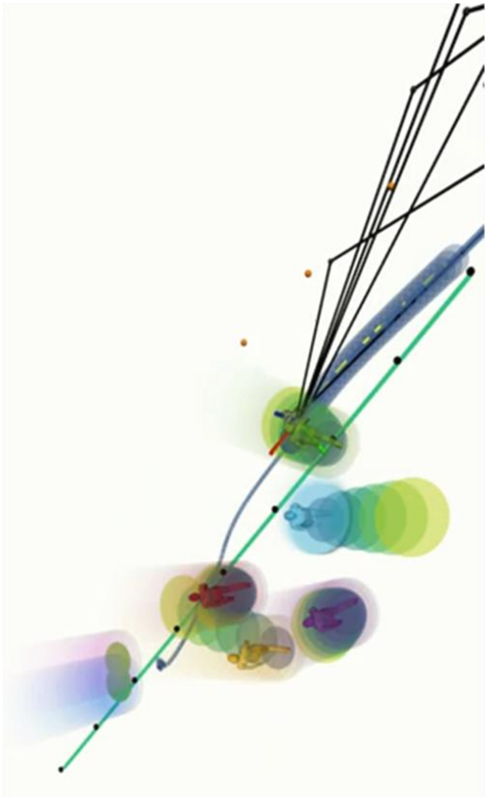
Faster task completion — less than half the variation of the baselines — computation capped at 50 ms (20 Hz).
Demonstrated on a real robot among five pedestrians.

Wraps existing planners out of the box



O. de Groot, L. Ferranti, D. M. Gavrila, J. Alonso-Mora, “Topology-Driven Parallel Trajectory Optimization in Dynamic Environments,” IEEE T-RO, 2025.

Topology Planning in Action

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Video courtesy of the Intelligent Vehicles Group, CoR.

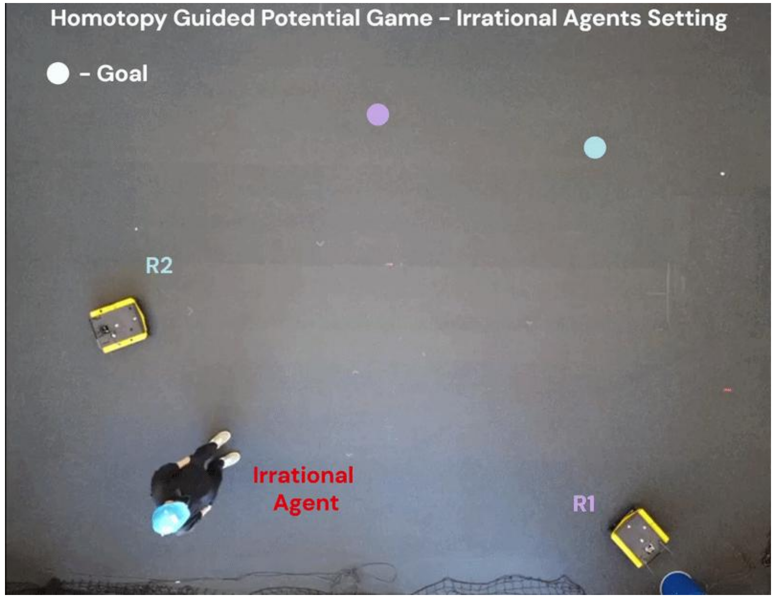
View from the inside

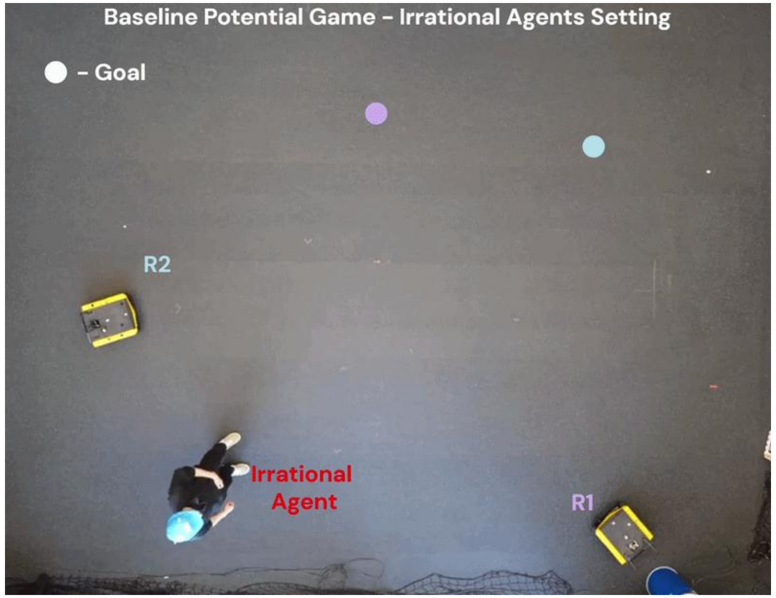
O. de Groot, L. Ferranti, D. M. Gavrila, J. Alonso-Mora, “Topology-Driven Parallel Trajectory Optimization in Dynamic Environments,” IEEE T-RO, 2025.

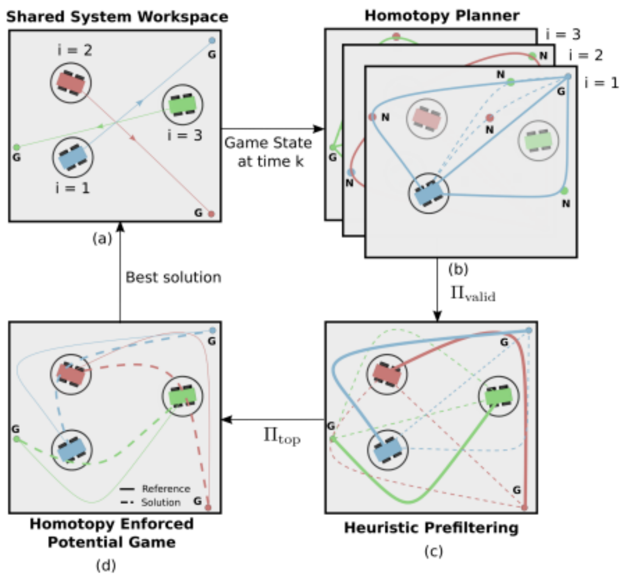
Interaction-Aware Planning: Homotopy-Guided Games

Mohammed Irshadh Imran

- **Recap —** one robot picks distinct ways around obstacles, optimized in parallel so it never gets stuck
- **Why a game —** with several agents, each one's best move depends on what the others do
- **The challenge —** plain game solvers settle into over-cautious, congested outcomes
- **What we do —** give each agent its **homotopies** as its options, then let the game pick the best congestion-free mix → safer, smoother motion







Summary

Takeaways & Key References

- **MPC / MPCC** — a flexible backbone for planning near humans
- **Rule-aware MPCC** — traffic rules (e.g., COLREGs) as constraints for lawful motion
- **Scenario MPC** — bounded collision probability under human uncertainty
- **Topology-driven planning** — distinct passing options via parallel optimization
- **Interaction-aware planning** — games + learning model how agents influence each other
- **Next — make human interaction realistic & tractable:**
  - learn human intent from data; use bounded-rational models
  - stay real-time: top-K strategy pruning + receding-horizon MPC
  - validate with human-in-the-loop trials

Key References

1. B. Brito et al., "Model Predictive Contouring Control for Collision Avoidance in Unstructured Dynamic Environments," IEEE RA-L, 2019.
2. O. de Groot et al., "Scenario-Based Motion Planning with Bounded Probability of Collision," IJRR, 2025.
3. O. de Groot et al., "Scenario-Based Trajectory Optimization in Uncertain Dynamic Environments," IEEE RA-L, 2021.
4. O. de Groot et al., "Topology-Driven Parallel Trajectory Optimization in Dynamic Environments," IEEE T-RO, 2025.
5. M. I. I. S. Imran et al., "Homotopy-Guided Potential Games for Congestion-Aware Navigation," IEEE RA-L, 2026.
6. A. Tsolakis et al., "COLREGs-aware Trajectory Optimization for Autonomous Surface Vessels," IFAC-PapersOnLine, 2022.

Code & Resources

- **mpc_planner** — modular MPC planner (ROS/C++)

  github.com/tud-amr/mpc_planner

- **scenario_module** — scenario / SH-MPC constraints (non-Gaussian)

  https://github.com/tud-amr/mpc_planner/releases/tag/v1.1.0
  https://github.com/oscardegroot/scenario_module

- **guidance_planner** — topology-driven global planner

  https://github.com/tud-amr/guidance_planner

Papers & Setup

Papers

- SH-MPC, joint collision prob.: de Groot et al., IJRR 2025 — arXiv:2307.01070
- Topology-Driven MPC: de Groot et al., IEEE T-RO 2024

Setup

- Needs an MPC solver: Acados or Forces Pro
- ROS / C++ · guidance_planner is Apache 2.0

13th IFAC Symposium on Fault Detection, Supervision and Safety for Technical Processes

IFAC SAFEPROCESS 2027

INTERNATIONAL FEDERATION OF AUTOMATIC CONTROL

29 June - 2 July, Delft, The Netherlands

Main Topics

- AI-enhanced methods in the SAFEPROCESS scope
- Data-driven diagnosis methods
- Model-based fault diagnosis
- Health aware control
- Predictive and preventive maintenance
- Safety and security by design
- Cybersecurity for cyberphysical systems
- Fault-tolerant and resilient control
- Condition and health monitoring
- Prognostics
- Anomaly detection
- Reliability, availability, maintainability and safety
- Sector applications of the topics above

Important Dates

- Submission:
  - Invited session, Panel discussion &Tutorial proposals **30/09/2026**
  - All regular/invited session papers **31/10/2026**
  - Abstracts for dissemination papers **31/01/2027**
- Notification of acceptance 28/02/2027
- Final paper submission 01/04/2027
- Early registration 01/04/2027
- Late registration 01/06/2027