

SBAMP: SAMPLING BASED ADAPTIVE MOTION PLANNING

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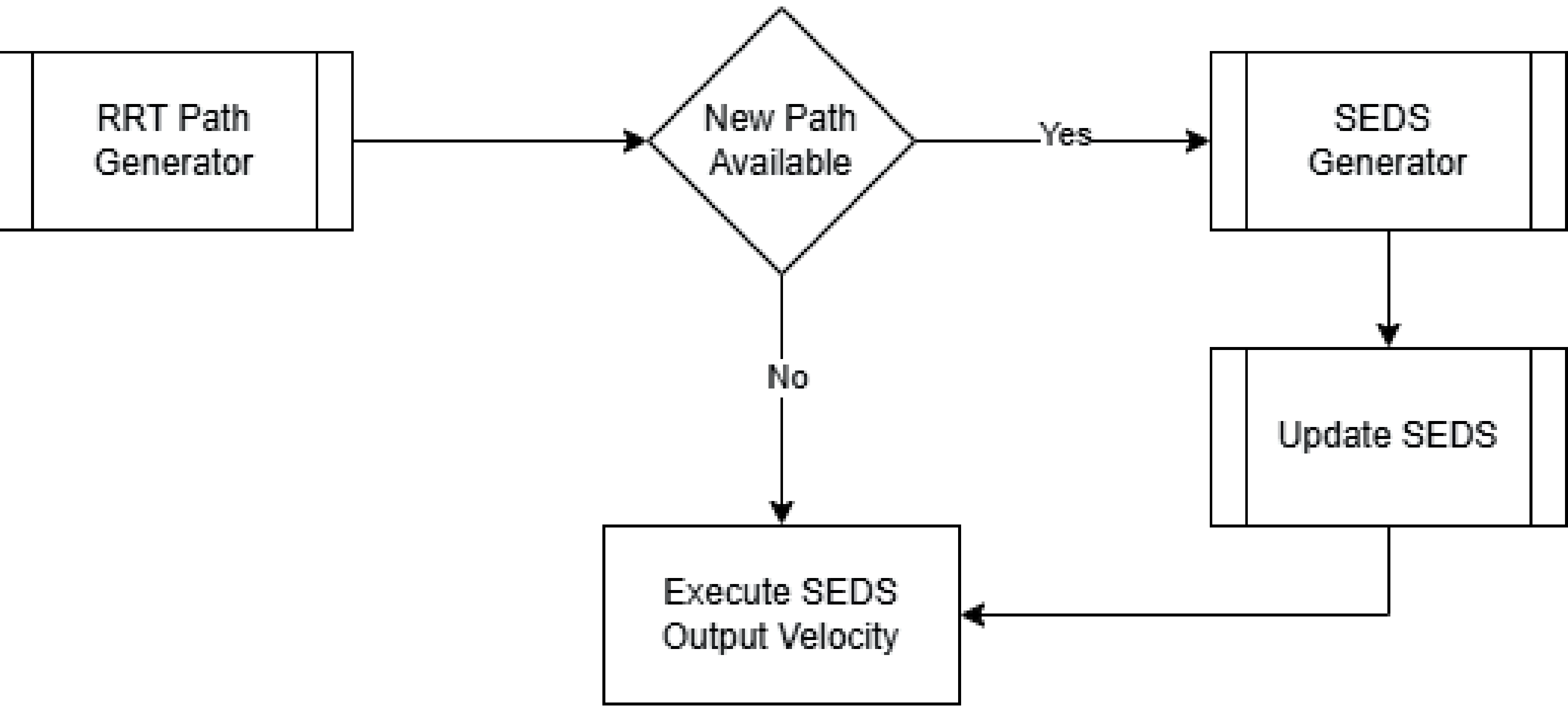
MEAM 6230 Learning & Control for Adaptive & Reactive Robots



ABSTRACT

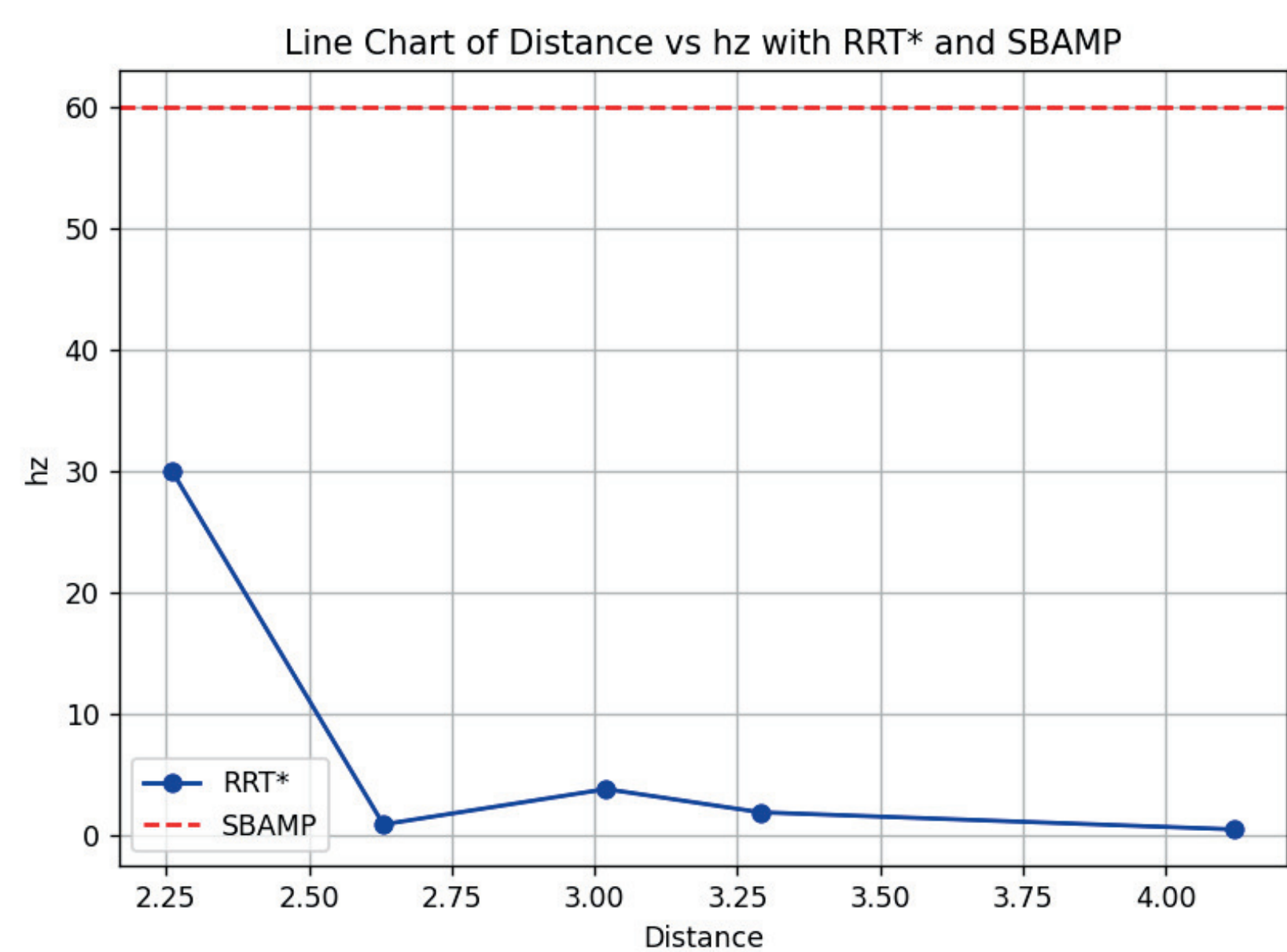
Modern robots need both global planning and real-time adaptability. RRT* efficiently finds collision-free waypoints but can't adjust trajectories on the fly; SEDS-style dynamical systems guarantee stable, adaptive tracking yet demand demonstration data. SBAMP unifies these strengths: it uses RRT* to generate an initial path on the fly, then tracks and locally refines that path via a SEDS-style stable dynamical system without any demonstration data. The resulting framework delivers collision-free global paths with provable stability and continuous refinement in dynamic, unstructured environments.

BI - LEVEL PLANNING ARCHITECTURE

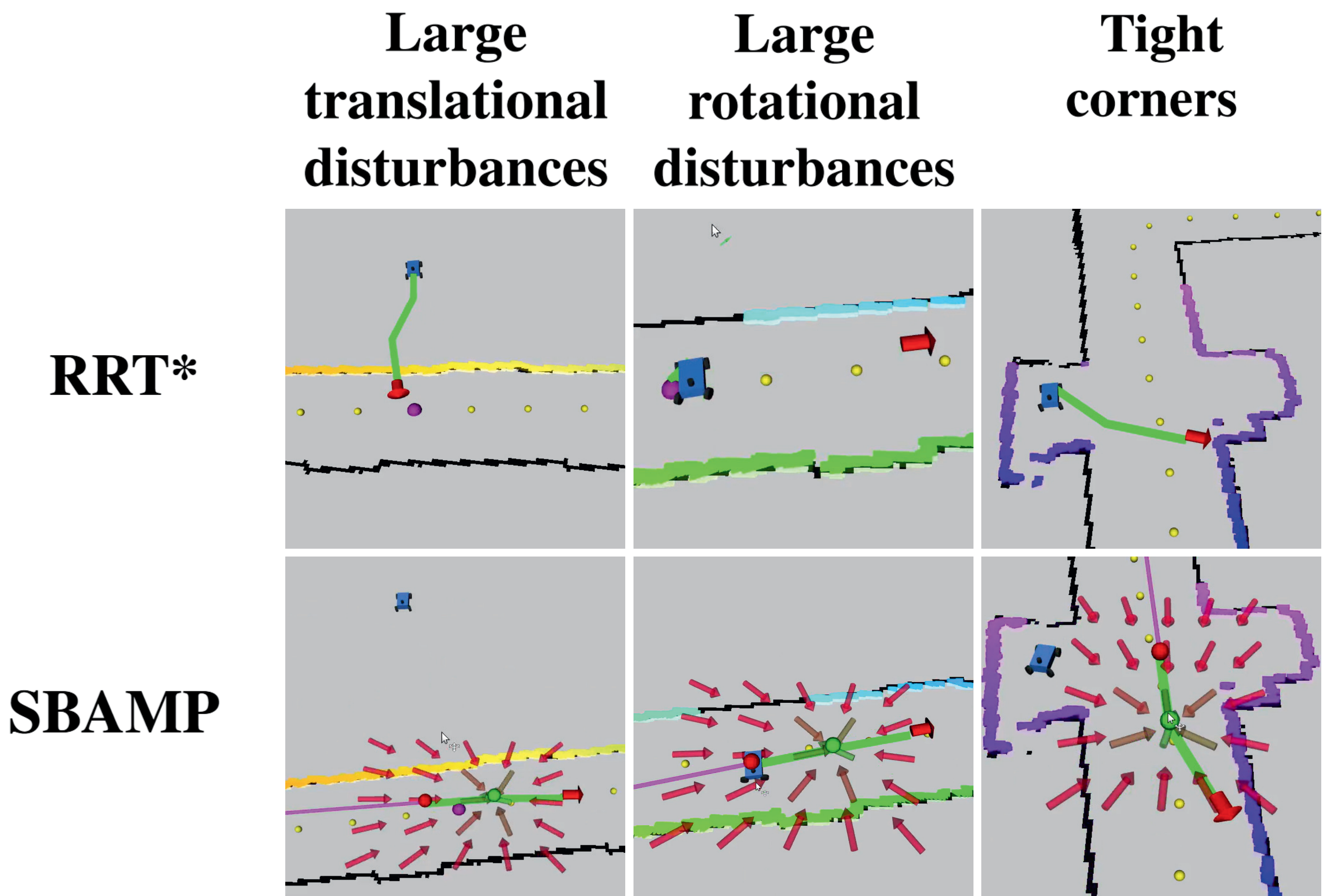


EVALUATION

Recovery Success Rate vs. Perturbation Distance:



Failure Modes of RRT* Resolved by SBAMP:



METHODOLOGY

1. Global Path Planning (RRT*):

- Generate initial obstacle-free path $\tau = \{x_0, x_1, \dots, x_g\}$
- Maintain dynamic tree \mathcal{T} with incremental rewiring.

2. Local Trajectory Adaptation (SEDS)

- 1) At each time step t , we query the dynamical system:

$$\dot{\xi} = f(\xi), \quad f(\xi) = \sum_{k=1}^K \gamma_k(\xi)(A_k \xi + b_k) \quad (1)$$

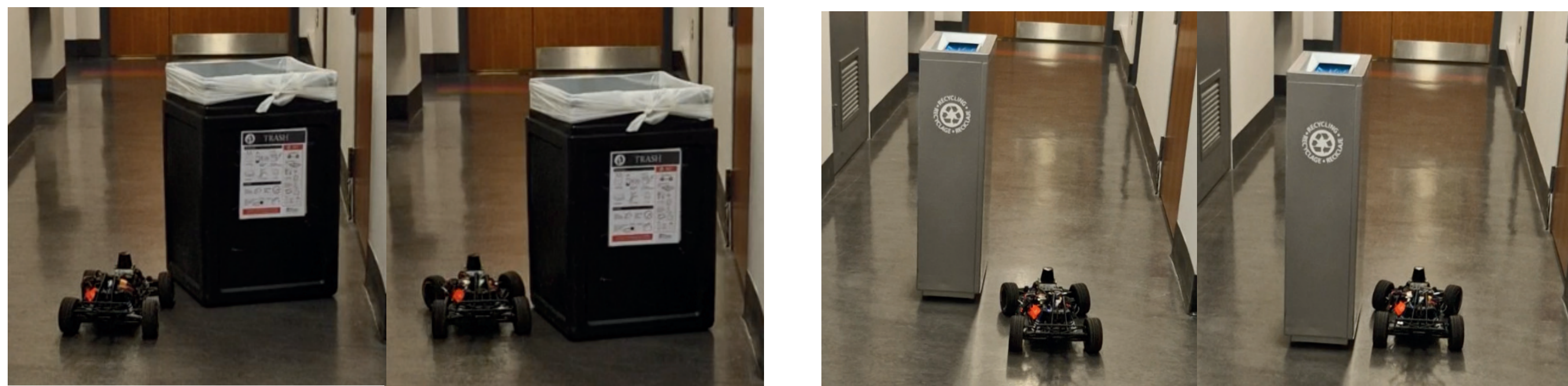
where γ_k are mixing coefficients and A_k Lyapunov-stable matrices.

- 2) Set current waypoint x_i as temporary attractor, switch to x_{i+1} as the RRT* path generates a new waypoint.

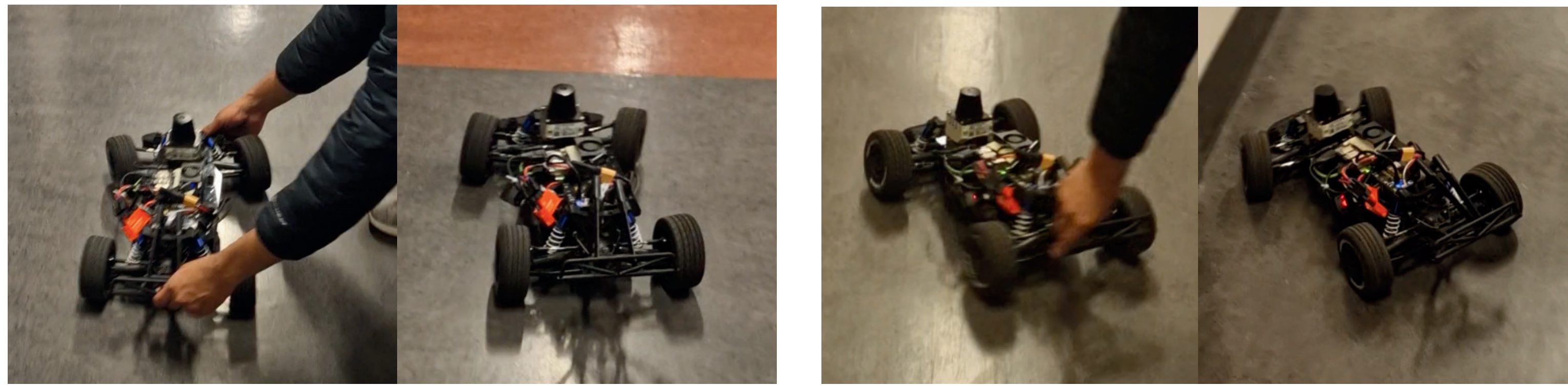
3. Real-Time Integration

- Parallel execution: RRT* updates τ while SEDS tracks current x_i
- Velocity continuity: Preserve $\dot{\xi}_t$ during waypoint transitions

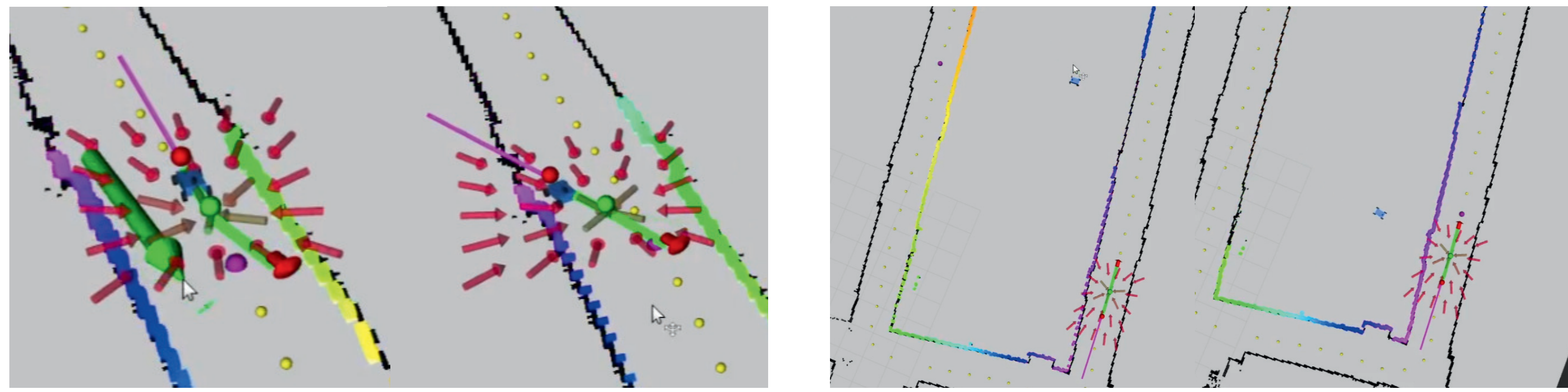
DEMONSTRATIONS



Smooth Obstacle Avoidance Trajectory with SBAMP



Robust Recovery Against Perturbations with SBAMP



Visualization of SBAMP and Large Disturbances Recovery

CONCLUSION

We presented SBAMP, a hybrid planner that integrates RRT* with SEDS for adaptive, real-time motion planning without prior training data. Experiments show improved tracking accuracy and robustness over standard RRT*, demonstrating the effectiveness of combining sampling-based and learning-based approaches for dynamic environments. Future work includes integrating this formulation with receding-horizon methods (e.g. MPC or MPPI) and incorporating modulation-based passive controllers for more stable autonomous navigation.