Improved Trajectory Planning for On-Road Self-Driving Vehicles via Combined Graph Search, Optimization & Topology Analysis

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Thesis Defense
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Agenda

- Introduction / Related Work / Motivation
- Proposed Planning Framework
- Approach
  - Proposed Method I: Region Segmentation w/ Topology Analysis
  - Proposed Method II: Search-based Planning w/ Edge-augmented Graph
  - Adapted Method I: LQR Path/Trajectory Smoothing
  - Proposed Method III: Sampling-based Maneuver Pattern Analysis
  - Adapted Method II: Focused Trajectory Optimization w/ Iterative-LQR
- Results
- Conclusion/Contribution/Future Work

Introduction

- Self-driving / Autonomous-driving Vehicles

Boss	Cadillac	Google	Uber
			
2007	2011	2013	2016

- Social Benefits

Safety

Two million car crashes per year in the United States [1].

Good Autonomy Software!

Autonomous Driving

Wasted hours in traffic jams.
Wasted parking space to city.

Efficiency

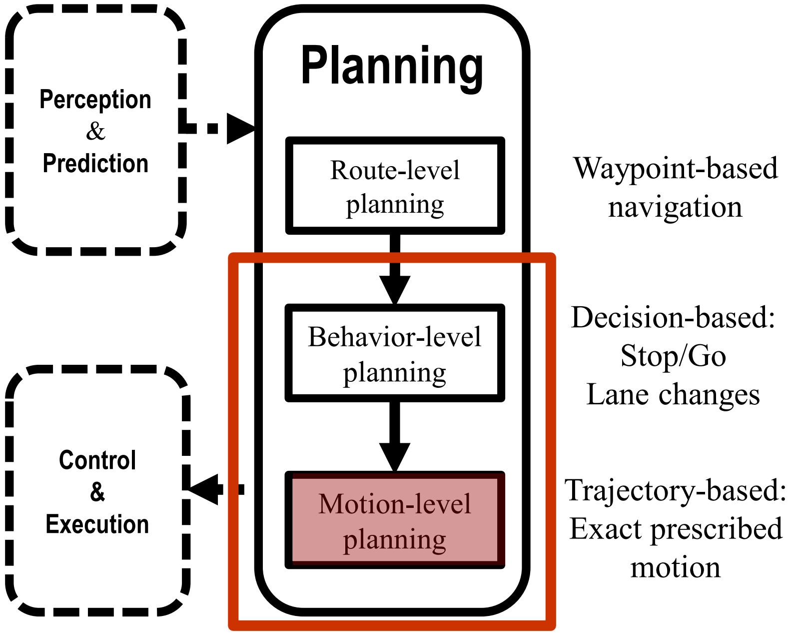
Freedom

Driving is exhausting.
Driving is difficult/impossible for some.

[1] U.S. Department of Transportation. (2014). Traffic Safety Facts: 2013 Data - Alcohol Impaired Driving. *Washington, DC: US Department of Transportation, National Highway Traffic Safety Administration [Online]*. Journal Article.

Introduction

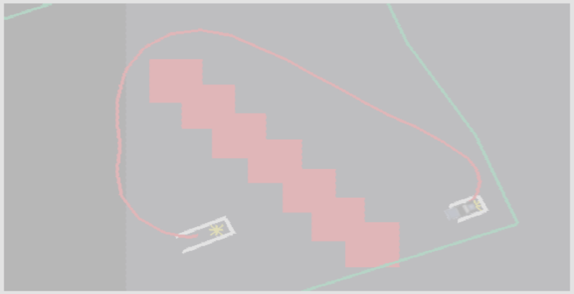
- Thesis Scope



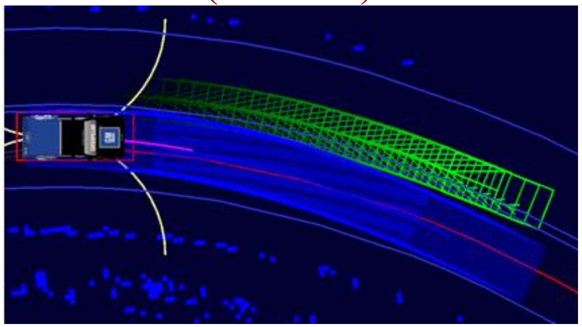
Commonly used architecture (at least conceptually):

1. Urban challenge entries.
2. Main self-driving players.

Less constrained Environment [1]
(Off-road)



More constrained Environment [2]
(On-road)



[1] Likhachev, M., & Ferguson, D. (2009). Planning Long Dynamically Feasible Maneuvers for Autonomous Vehicles. *The International Journal of Robotics Research*, *28*(8), 933–945. Journal Article. http://doi.org/10.1177/0278364909340445
[2] Urmson, C., Bagnell, J., Baker, C., & Hebert, M. (2007). Tartan racing: A multi-modal approach to the darpa urban challenge. Journal Article. Retrieved from http://repository.cmu.edu/robotics/967/

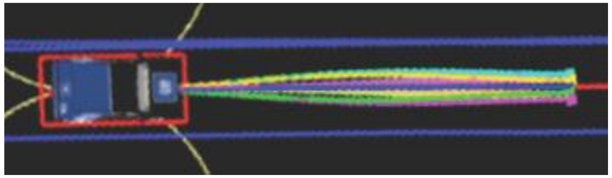
Related Work

- Sampling-based Planners
- Optimization-based Planners
- Hybrid Sampling/Optimization Planners
- Topology-aware Planners

Related Work

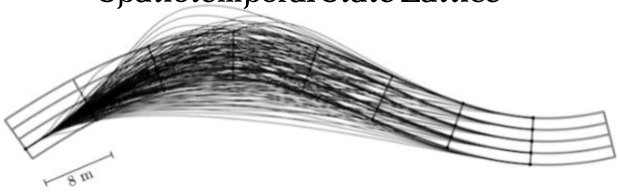
- Sampling-based Planners

Sampled Primitive on CMU's UC Entry



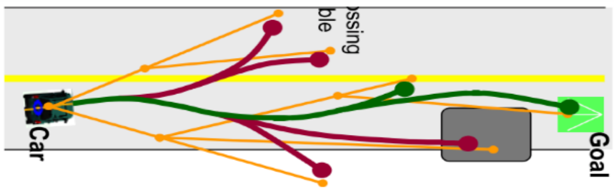
[Urmson et al., 2007]

Spatiotemporal State Lattice



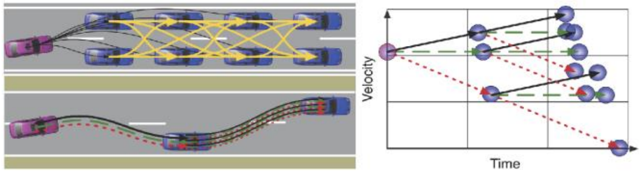
[Ziegler & Stiller, 2009]

Biased RRT on MIT's UC Entry



[Kuwata et al., 2009]

Augmented Spatiotemporal State Lattice



[McNaughton et al., 2011]

Pro

1. Lightweight primitive sampling with model-based evaluation.
2. Deterministic runtime with termination guarantee.
3. Search space is comprehensive with respect to the continuous space of interest.

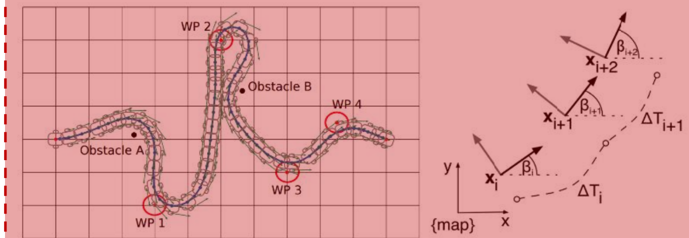
Con

1. Sampling sub-optimality, not converging to local minimum.
2. Search space blow-up due to the curse of dimensionality.

Related Work

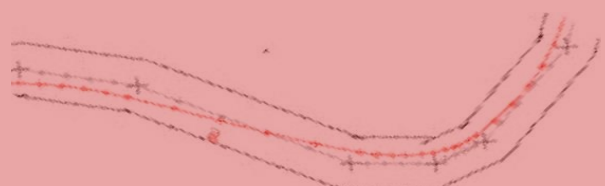
- Optimization-based Planners

Time Elastic Band



[Rösmann et al., 2012]

Gradient-based Cost Minimization

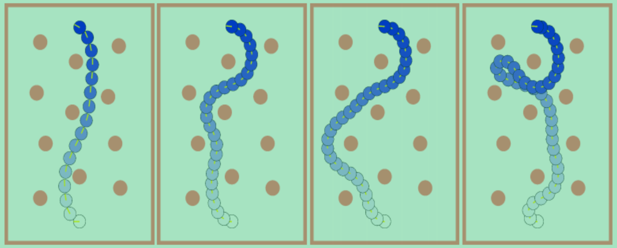


[Thrun et al., 2006]

Direct Method

Indirect Method

Iterative/Extended LQR Trajectory Optimization



[van den Berg, 2016]

Pro

1. Search in the continuous space, alleviate sampling sub-optimality.
2. Efficient if implemented properly, compared to the thousands, even millions of sampled trajectory evaluations.

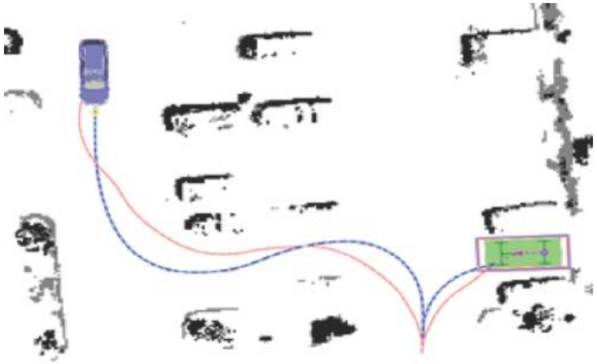
Con

1. Lacks global awareness, can get stuck in the wrong local minimum.
2. Non-deterministic runtime w/o termination guarantee
3. Difficult to parallelize the computation.

Related Work

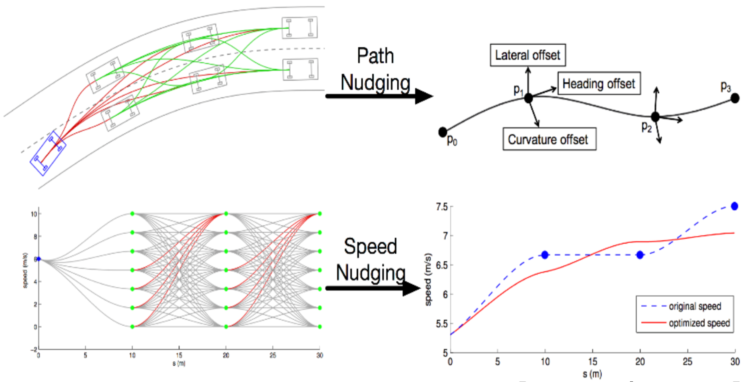
- Hybrid Sampling/Optimization Planners

Hybrid A* + Conjugate Gradient Optimization



[Dolgov et al., 2008]

Lattice Sampling + Simplex Optimization



[Xu et al., 2012]

Pro

1. Achieve local minimum while having global awareness.
2. Moderate computation overhead.

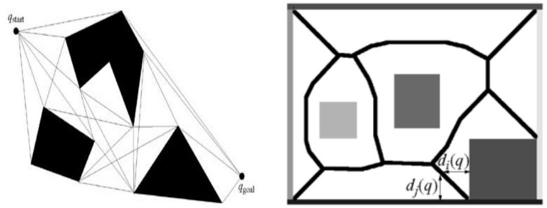
Con

1. Pure path/speed planning, independent spatial/temporal planning.
2. Direct trajectory optimization by manipulating the sampled configuration states. Difficult to guarantee plan feasibility.

Related Work

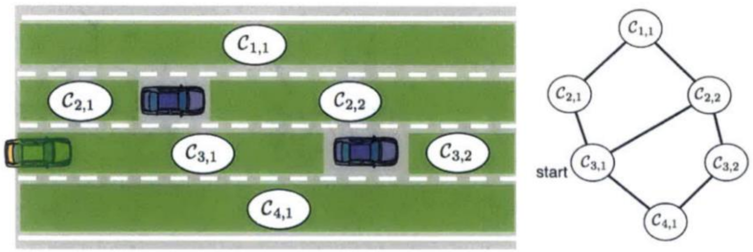
- Topology-aware Motion Planners

Visibility Graph & Voronoi Graph

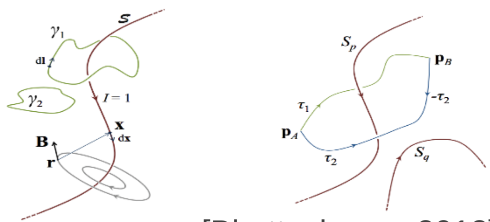


[Schmitzberger, 2002] & [Choset, 2005]

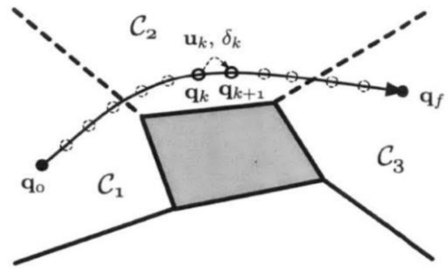
Cell Decomposition + Mixed-Integer-Quadratic Programming



Homology Marker Function



[Bhattacharya, 2012]



[Parker, 2016]

Pro

1. Explicit topological awareness.
2. Focus (narrow down) the search space.

Con

1. Pure spatial topological analysis.
2. Co-terminal requirements for paths under analysis.

Motivation

- Thesis Statement:

By taking advantage of a combined sampling-n-search, optimization and topology analysis approach, we can avoid the pitfalls of standalone methods, and equip self-driving cars with improved high-level reasoning capabilities for on-road trajectory planning.

Requirement 1: a deliberative trajectory planning system.

Requirement 2: spatiotemporal (trajectory) planning.

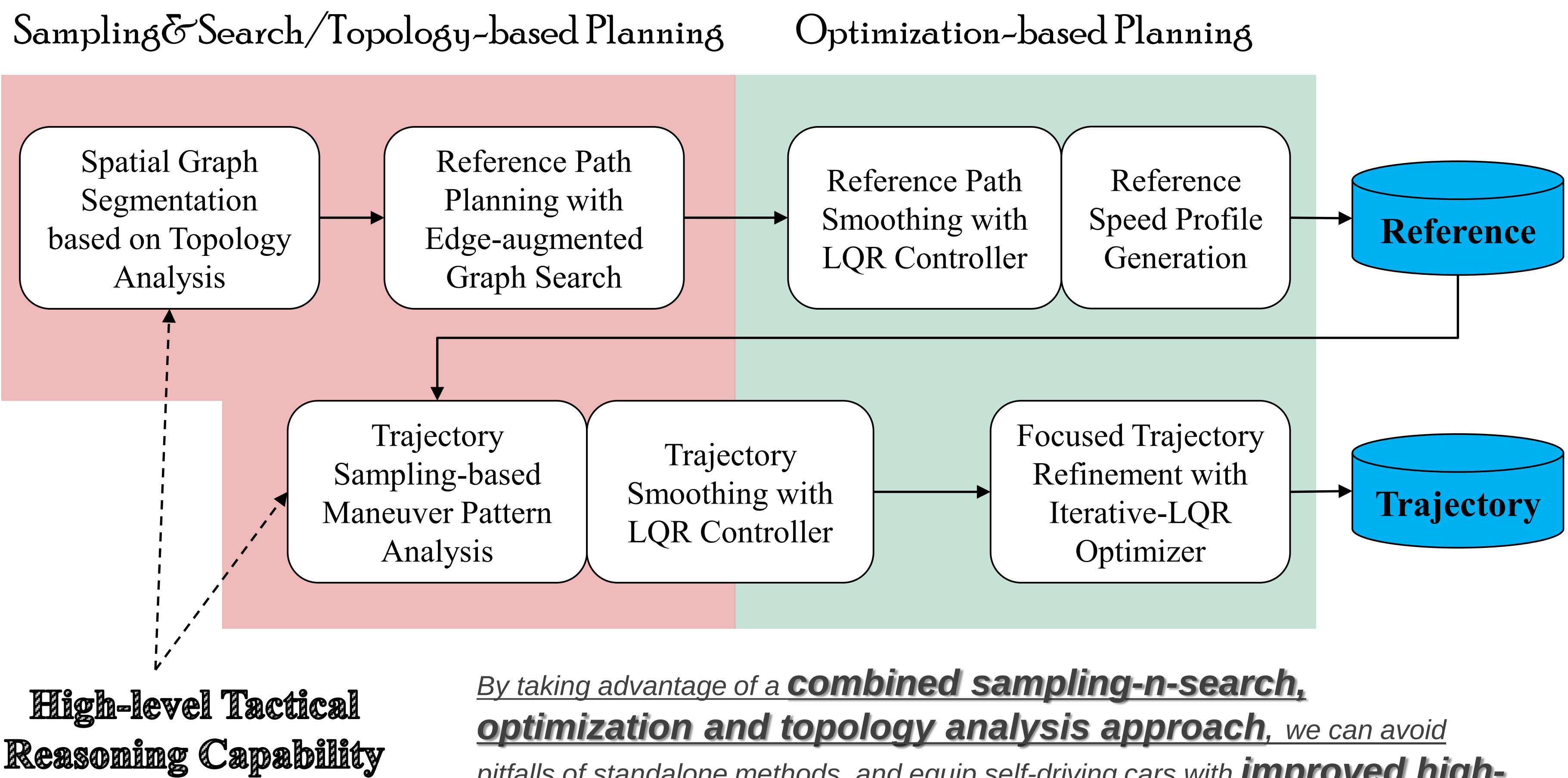
Requirement 3: tactical reasoning capability with topological awareness.

Requirement 4: global awareness with the ability to converge to a local optimum.

Requirement 5: apply to self-driving passenger vehicle on-road driving.

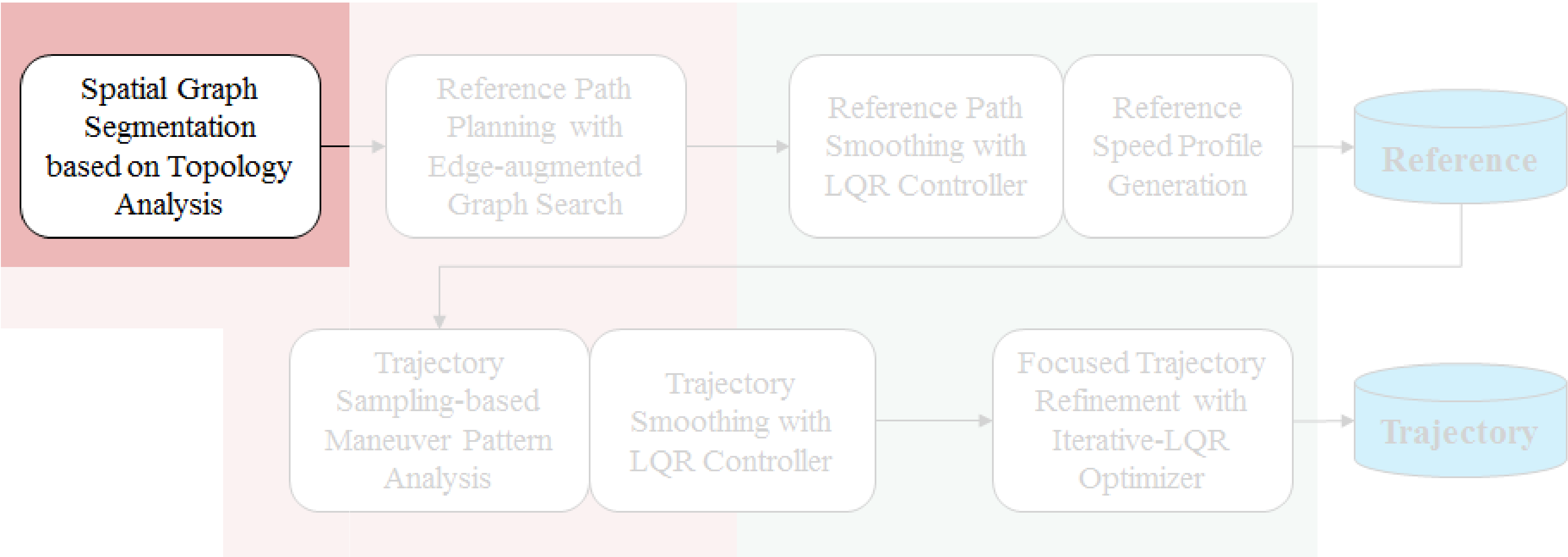
Proposed Planning Framework

- Technical Overview



By taking advantage of a ***combined sampling-n-search, optimization and topology analysis approach****, we can avoid pitfalls of standalone methods, and equip self-driving cars with* ***improved high-level reasoning capabilities*** *for on-road trajectory planning.*

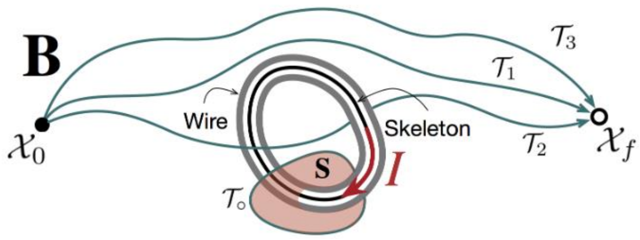
Proposed Method I: Region Segmentation w/ Topology Analysis



Proposed Method I: Region Segmentation w/ Topology Analysis

- Homology Marker Function-based Topological Analysis

Homological Trajectories



Biot-Savart Law:

A steady current flowing through a wire generates a magnetic field **B**.

$$B(r) = \frac{\mu_0 \cdot I}{4\pi} \int_{\mathcal{W}} \frac{dl \times (l - r)}{\|l - r\|^3}$$

Homology Marker Function

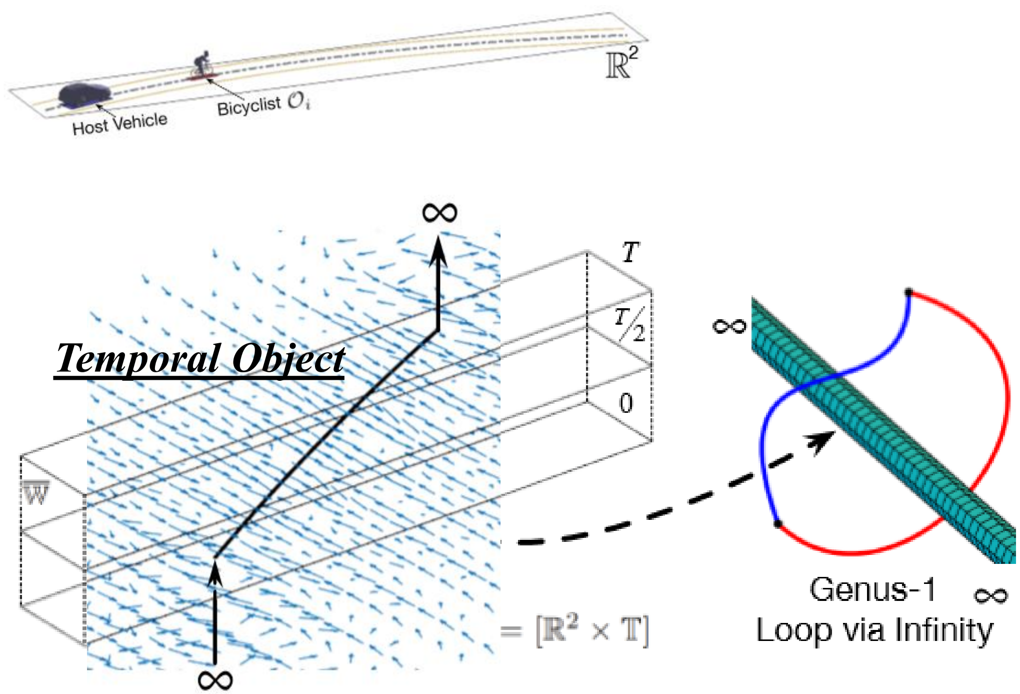
$$\mathcal{H}(\mathcal{T}) = \int_{\mathcal{T}} B \cdot dl$$

$$\mathcal{H}(\mathcal{T}_1) = \mathcal{H}(\mathcal{T}_3) \neq \mathcal{H}(\mathcal{T}_2)$$

$\mathcal{T}_1$ & $\mathcal{T}_3$ are homological.

$\mathcal{T}_1$ & $\mathcal{T}_2$ are NOT homological.

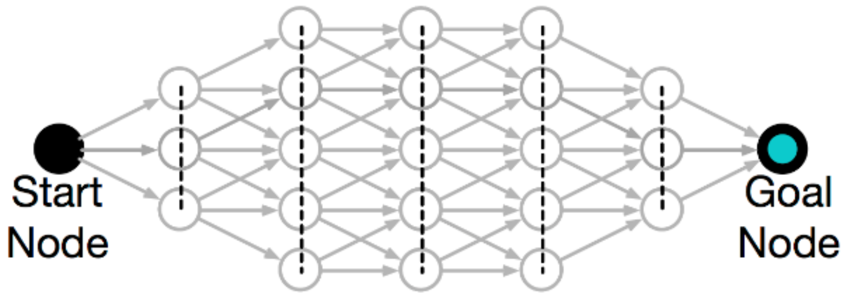
Analysis in Spatiotemporal Configuration Space



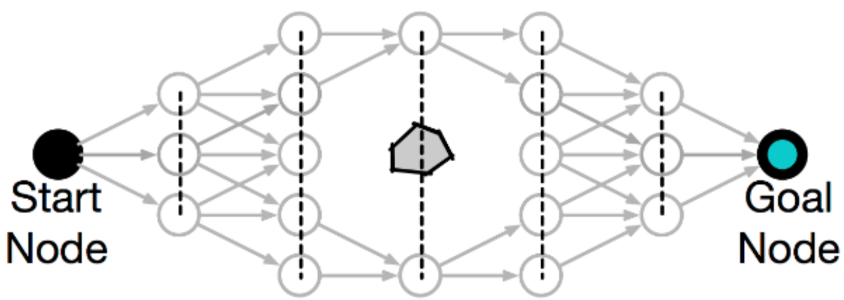
Magnetic field generated to distinguish trajectories.

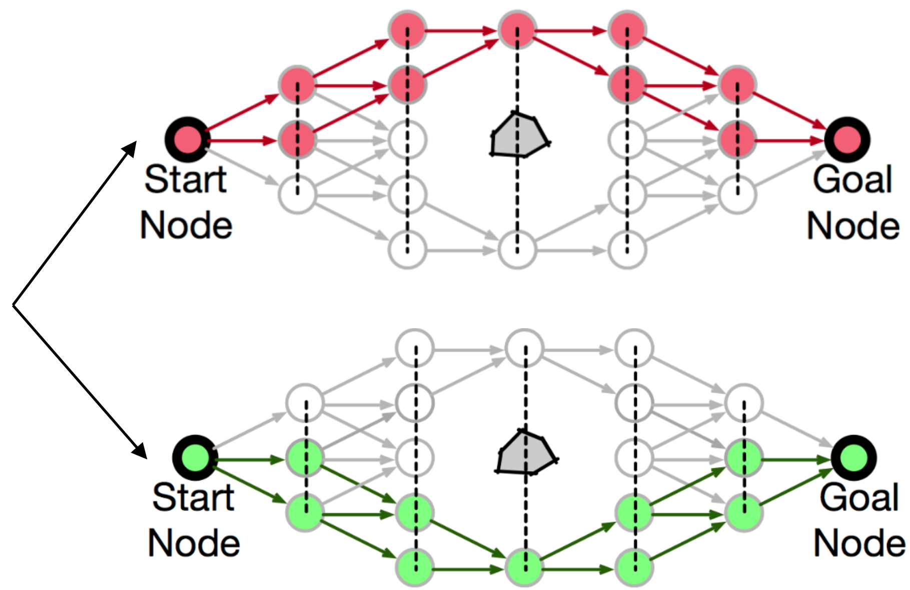
Proposed Method I: Region Segmentation w/ Topology Analysis

- Segment directed acyclic graph (DAG) into several sub-graphs



No obstacle → No segmentation



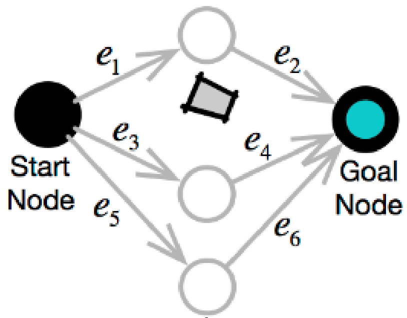


Obstacle → Two Sub-Graphs

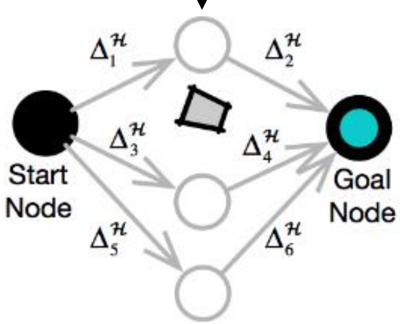
Proposed Method I: Region Segmentation w/ Topology Analysis

- Dynamic Programming-Inspired Backward Topology Induction

Step 1: Construct Topology Graph

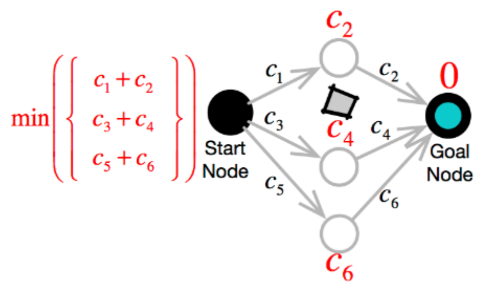


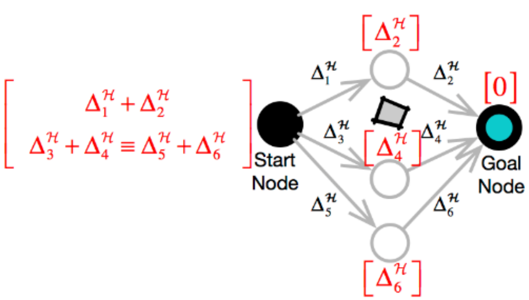
$$\Delta_i^{\mathcal{H}} = \mathcal{H}(e_i) = \int_{e_i} B \cdot dl$$



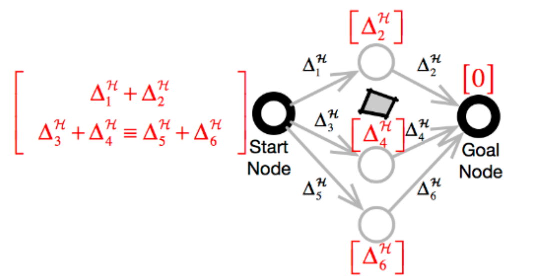
Step 2: Backward Topology Induction

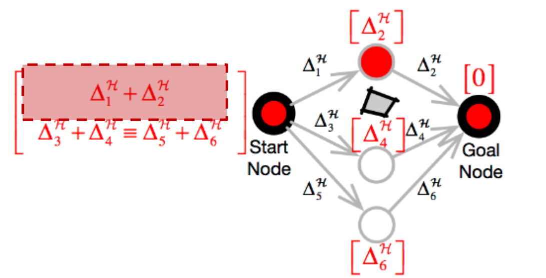
Dynamic Programming

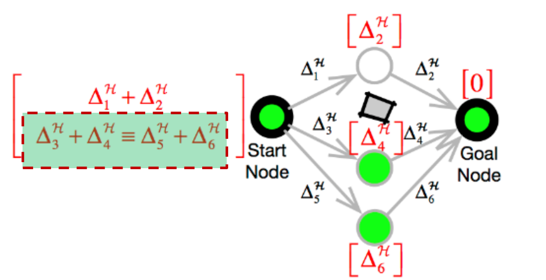




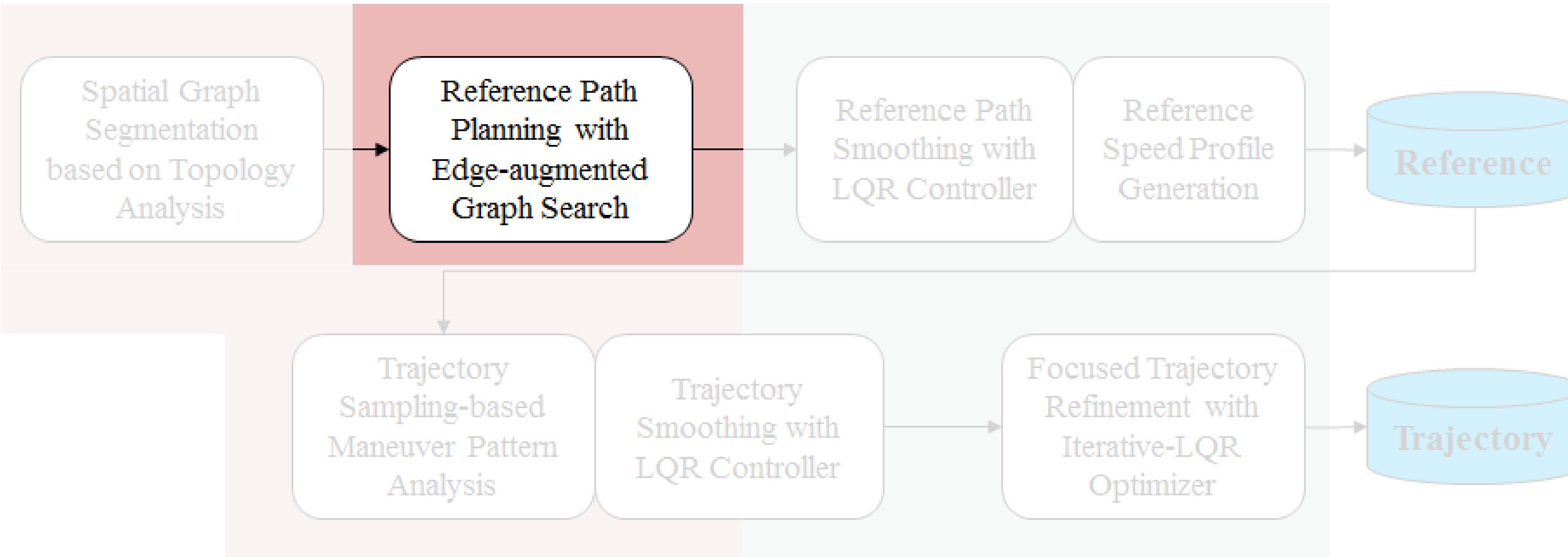
Step 3: Forward Region Marking





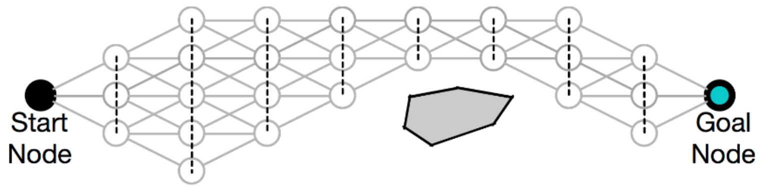


Proposed Method II: Search-based Planning w/ Edge-augmented Graph

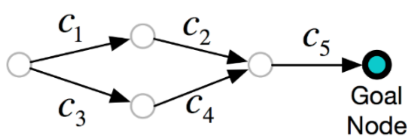


Proposed Method II: Search-based Planning w/ Edge-augmented Graph

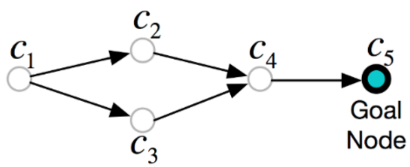
- Motivation: why do we need edge-augmented graph?



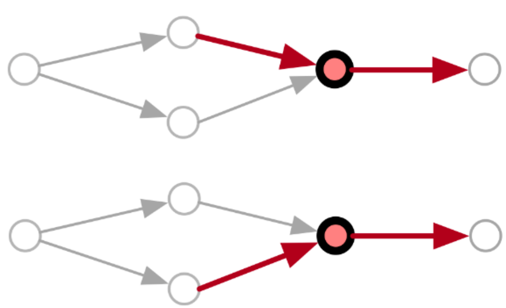
Edge-based Cost:



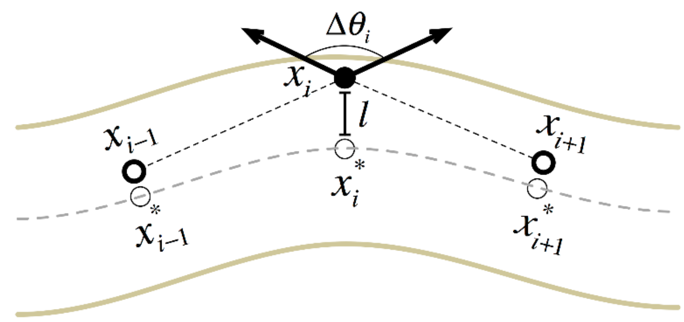
Node-based Cost:



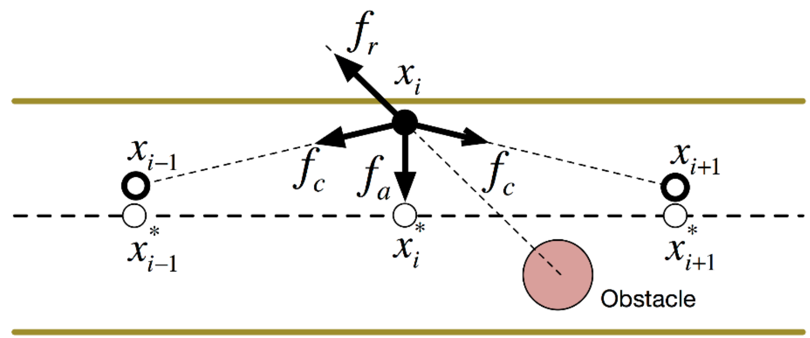
What if the cost is associated with two neighboring edges?



Smoothing Cost



Contractive Force in Elastic-Band



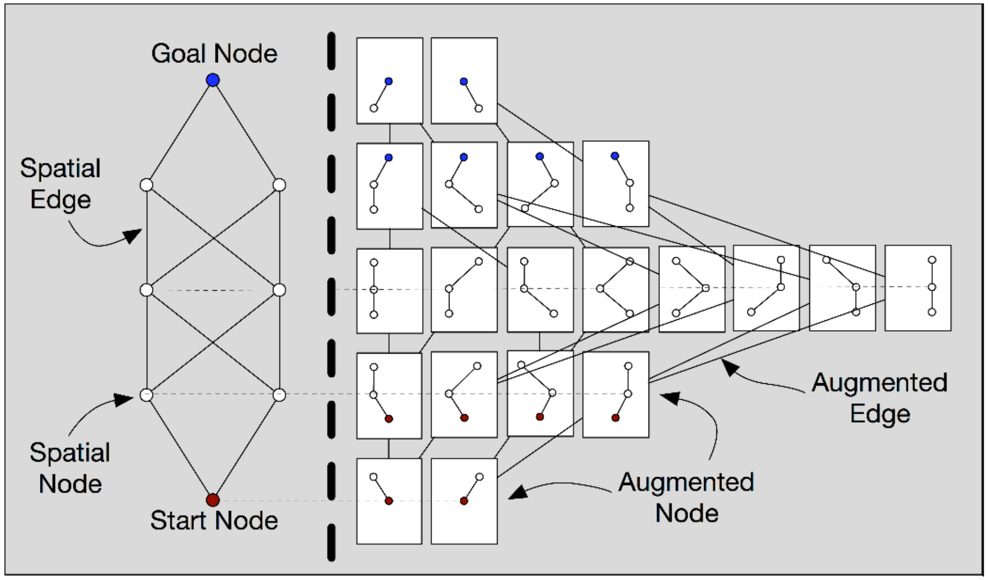
Proposed Method II: Search-based Planning w/ Edge-augmented Graph

- Construct & Search over Edge-augmented Graph

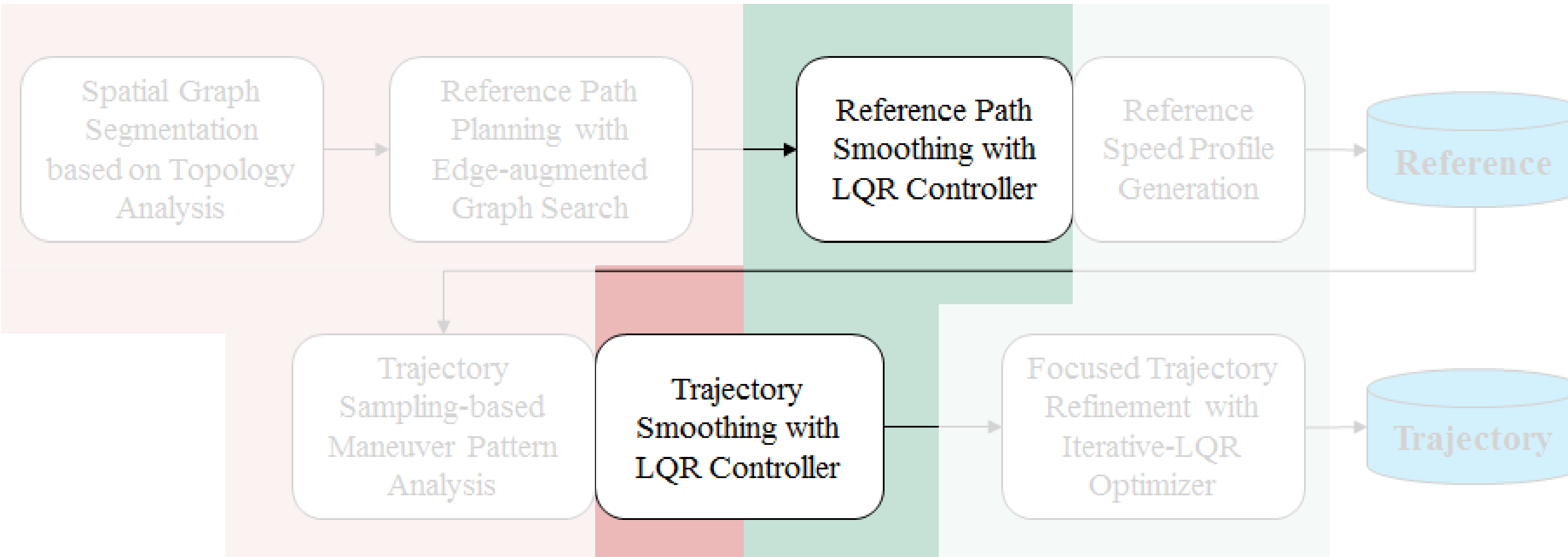
1. Construct regular DAG
2. Evaluate graph node/edge
3. Construct edge-augmented node
4. Evaluate edge-augmented node
5. Build edge-augmented graph

   Edge-augmented graph is still DAG!

6. Search DAG with dynamic programming or topological search.



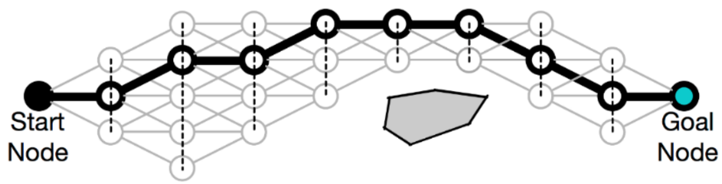
Adapted Method I: LQR-based Path/Trajectory Smoothing



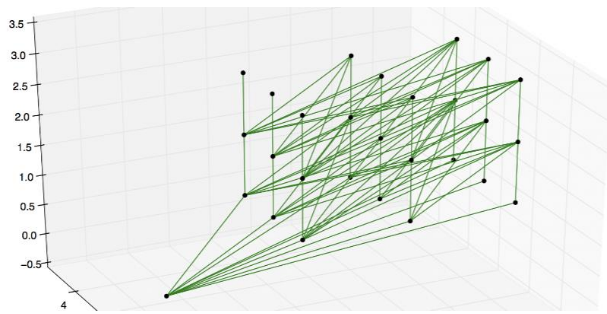
Adapted Method I: LQR-based Path/Trajectory Smoothing

- Motivation: How to convert coarse graph plan to smooth path/trajectory?

Spatial Piecewise-Linear (Path) Plan



Spatiotemporal Piecewise-Linear (Trajectory) Plan



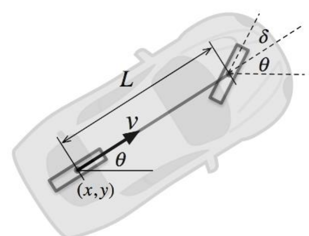
Roughly captures the gist of maneuver.

Not model-feasible, non-smooth.

Solution:

- Treat piecewise linear plan as a coarse reference.
- Use a realistic vehicle model and a trajectory tracking controller to "follow" the reference.
- Keep the trace of the model states as the smoothed trajectory.

<u>What vehicle model to use?</u>



$$\begin{bmatrix}\dot{x}\\ \dot{y}\\ \dot{\theta}\\ \dot{\delta}\\ \dot{v}\end{bmatrix} = \begin{bmatrix}0&0&0&0&cos(\theta)\\0&0&0&0&sin(\theta)\\0&0&0&0&\frac{tan(\delta)}{L}\\0&0&0&0&0\\0&0&0&0&0\end{bmatrix}\begin{bmatrix}x\\ y\\ \theta\\ \delta\\ v\end{bmatrix} + \begin{bmatrix}0&0\\0&0\\0&0\\1&0\\0&1\end{bmatrix}\begin{bmatrix}\gamma\\ a\end{bmatrix}$$

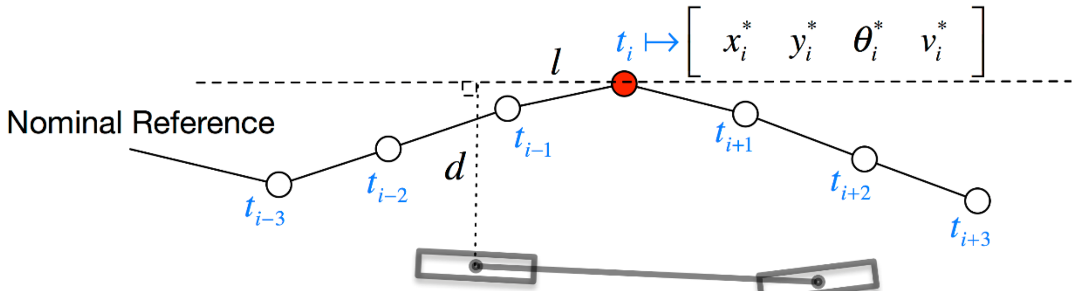
Non-linear, non-holonomic!

<u>What tracking controller to use?</u>

- Geometric tracker, e.g., pure pursuit.
- **Optimal trackers, e.g., LQR-based tracker.**

Adapted Method I: LQR-based Path/Trajectory Smoothing

- Path/Trajectory Smoothing



Lateral Tracking Control

State Transformation:

$$x = \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} = \begin{bmatrix} d \\ \theta^* - \theta \\ \delta \end{bmatrix}$$

Dynamics Linearization:

$$\begin{bmatrix} \dot{x}_1 \\ \dot{x}_2 \\ \dot{x}_3 \end{bmatrix} = \begin{bmatrix} 0 & v & 0 \\ 0 & 0 & -\frac{v}{L} \\ 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix} \dot{\delta}$$

Longitudinal Tracking Control

State Transformation:

$$x = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \begin{bmatrix} l \\ v^* - v \end{bmatrix}$$

Dynamics Linearization:

$$\begin{bmatrix} \dot{x}_1 \\ \dot{x}_2 \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} + \begin{bmatrix} 0 \\ -1 \end{bmatrix} a$$

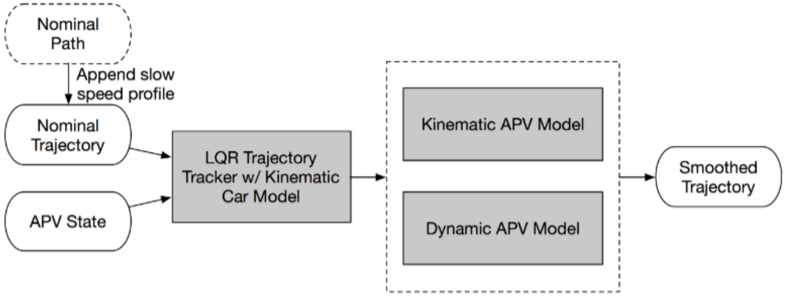
Linear Quadratic Regulator

Minimize: $J = \int_0^\infty (x^T Q x + u^T R u) \cdot dt$

Control: $u = -K \cdot x$

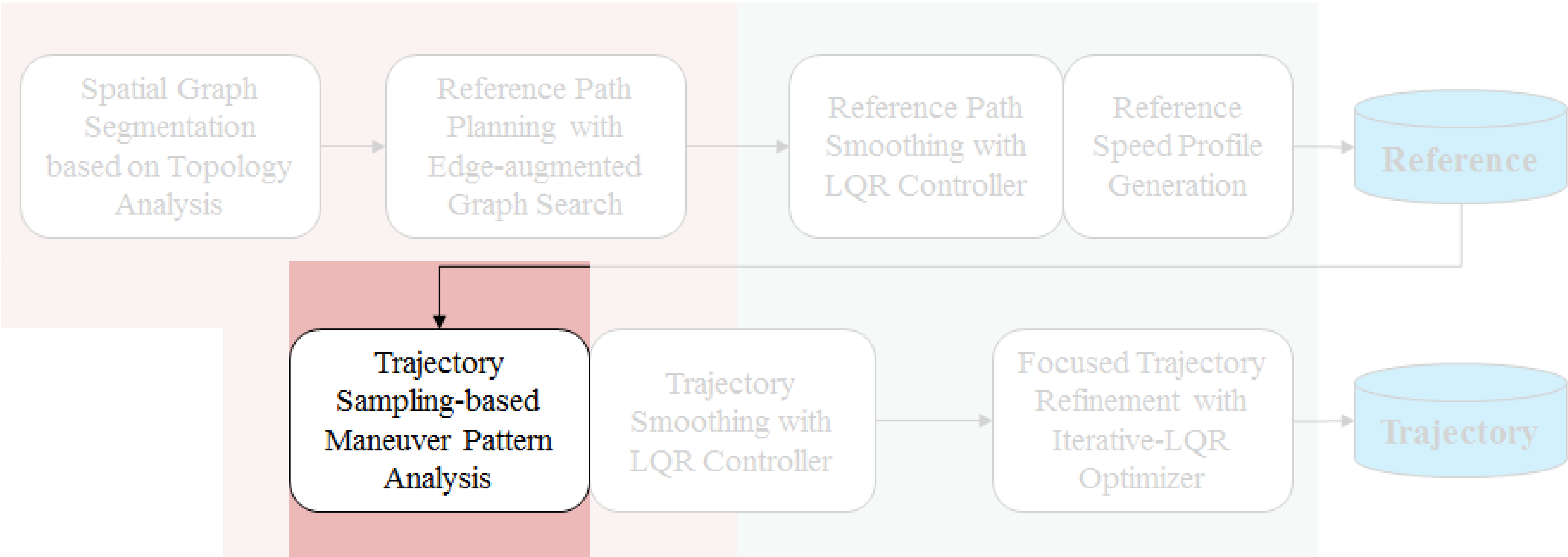
$$K = R^{-1} B^T P$$

$$A^T P + PA - PBR^{-1} B^T P + Q = 0$$



Smoothed model-feasible path/trajectory

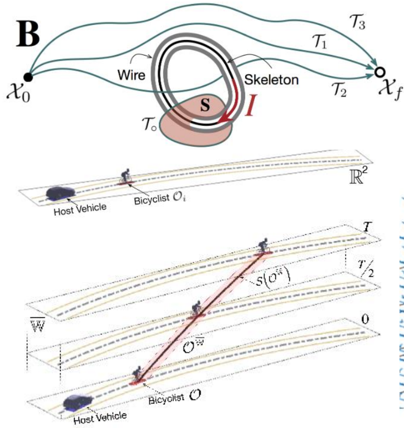
Proposed Method III: Sampling-based Maneuver Pattern Analysis



Proposed Method III: Sampling-based Maneuver Pattern Analysis

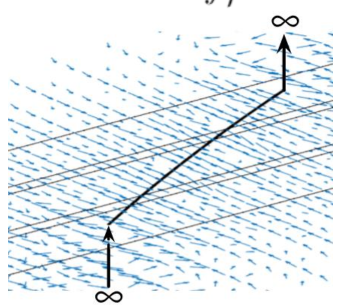
- Motivation: factors other than topology that matter for pattern distinction of spatiotemporal trajectory?

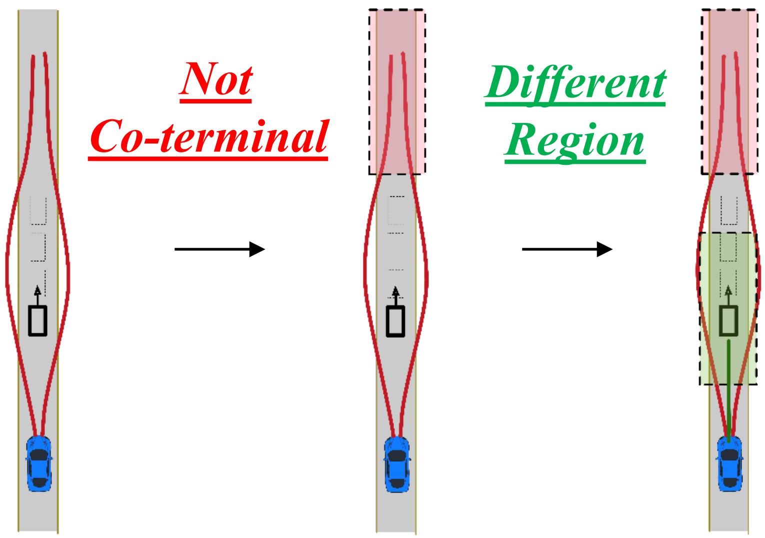
Co-terminal



Homology Marker Function

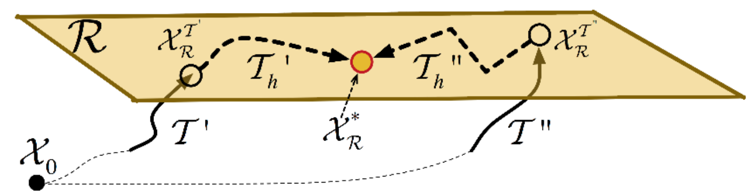
$$\mathcal{H}(\mathcal{T}) = \int_{\mathcal{T}} \mathbf{B} \cdot dl$$





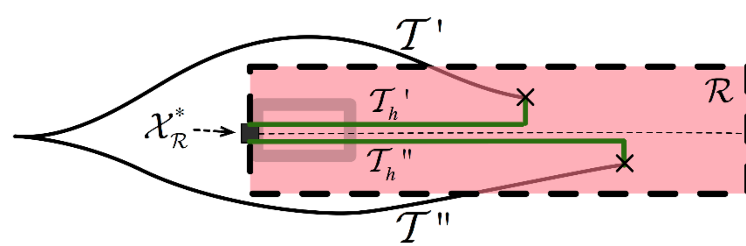
Region-based Distinction

Pseudo-Homology:



$$\mathcal{H}(\mathcal{T}' + \mathcal{T}_h') = \mathcal{H}(\mathcal{T}'' + \mathcal{T}_h'')$$

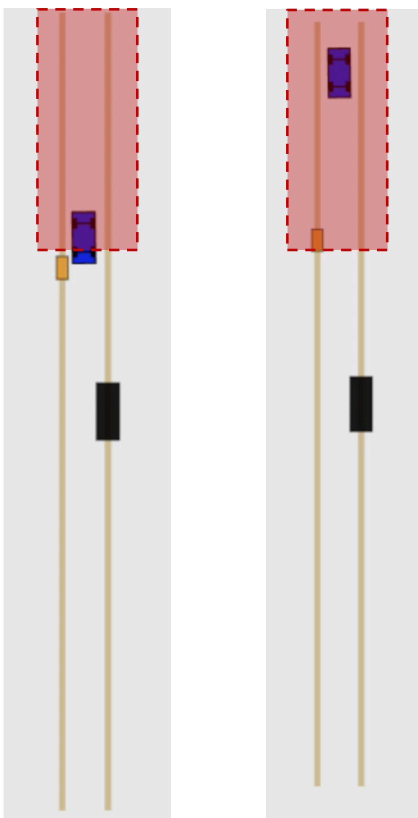
Helper trajectory for corridor-like region:

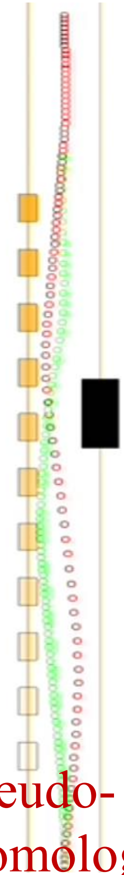


Proposed Method III: Sampling-based Maneuver Pattern Analysis

- Motivation: factors other than topology that matter for pattern distinction of spatiotemporal trajectory?

Conservative **Aggressive**

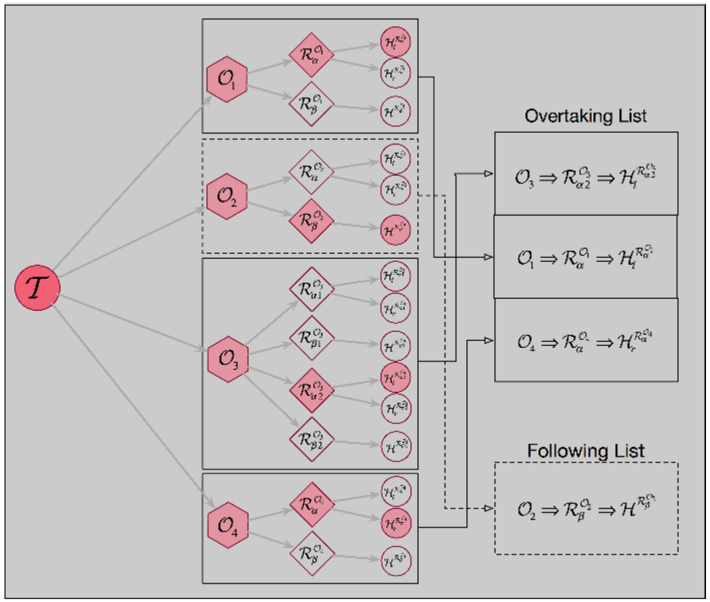




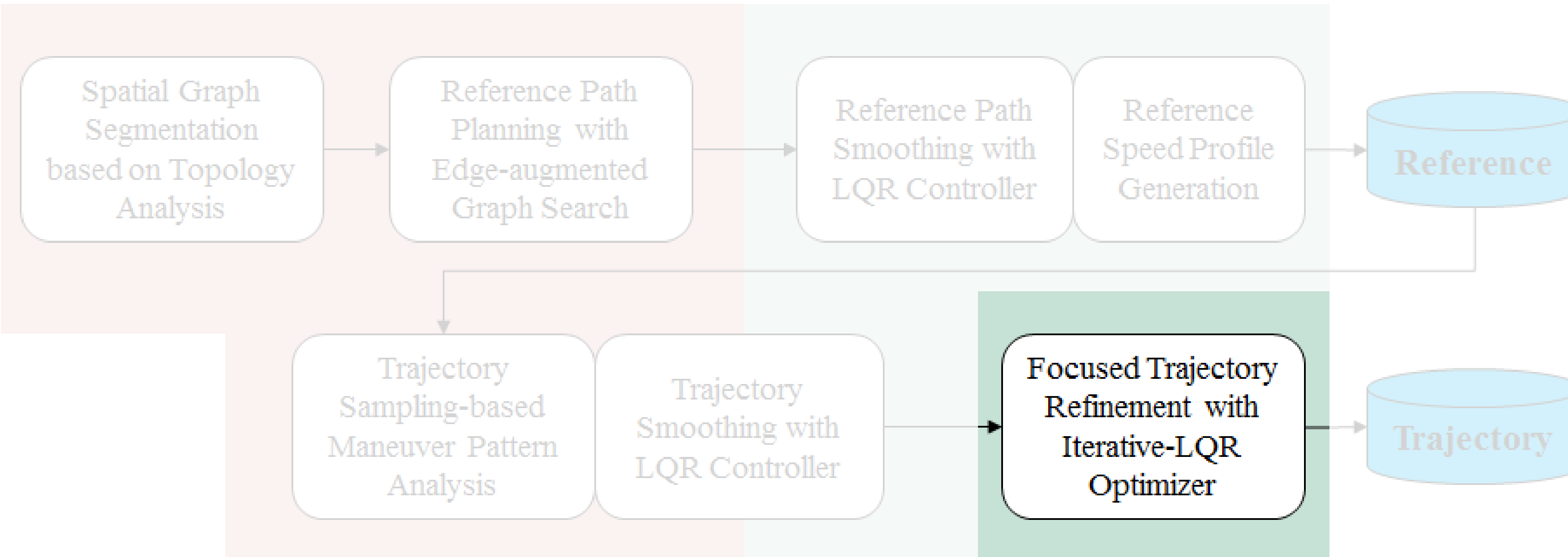
Overtaking Sequence-based Distinction

- Forward simulate APV & objects.
- Keep track of the overtaking timestamp.
- Sort obstacles (identifier) based on the overtaking timestamp.

Maneuver Pattern Distinction Tree

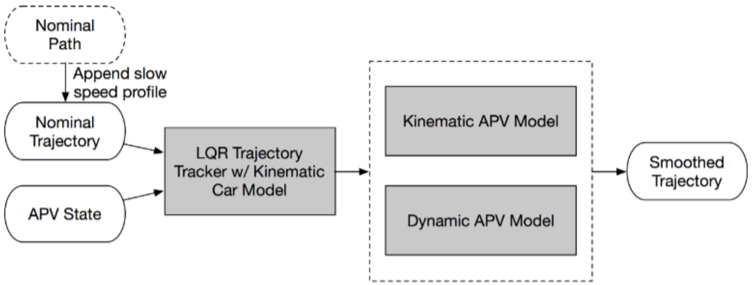


Adapted Method II: Focused Trajectory Optimization w/ Iterative-LQR



Adapted Method II: Focused Trajectory Optimization w/ Iterative-LQR

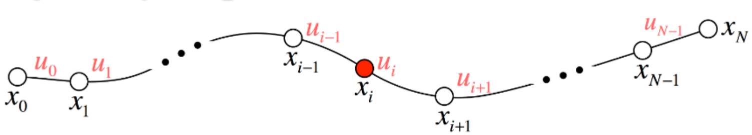
- Iterative LQR Backgrounds



Smoothed model-feasible path/trajectory

- Does not consider any costs other than tracking errors, e.g., obstacles.
- Smoothed trajectory is only model-feasible, but not **execution-feasible**.

Trajectory Representation & Cost

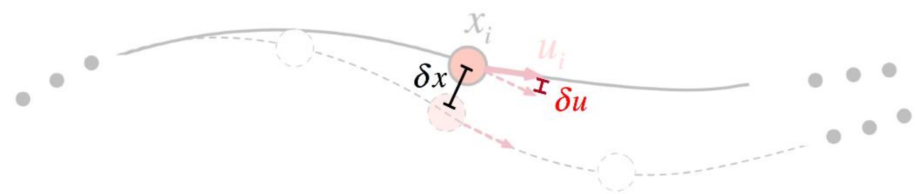


$$x_{i+1} = f_d(x_i, u_i)$$

$$X^{(k)} \doteq \{x_0, x_1, \dots, x_i, \dots, x_{N-1}, x_N\}$$

$$U^{(k)} \doteq \{u_0, u_1, \dots, u_i, \dots, u_{N-1}\}$$

Iterative Linear Quadratic Regulator
(1st order Differential Dynamic Programming)



Perturbation:
δx incurred at (i-1)th timestamp.
δu to be determined at (i)th timestamp.

What is the optimal δu given the δx?

$$\delta u^* = \operatorname*{argmin}_{\delta u} \tilde{Q}(\delta x, \delta u) = k + K \cdot \delta x$$

Singular Value Decomposition

$$Q_{uu} = P \Sigma Q^T$$

$$Q_{uu}^{-1} = Q \Sigma^{-1} P^T$$

$$k = \boxed{-Q_{uu}^{-1}} Q_u$$

$$K = \boxed{-Q_{uu}^{-1}} Q_{ux}$$

$$\Sigma = \begin{bmatrix} \sigma_1 & 0 & 0 \\ 0 & \ddots & \ddots \\ 0 & \ddots & \sigma_n \end{bmatrix} \quad \Sigma^{-1} = \begin{bmatrix} 1/\sigma_1+\lambda & 0 & 0 \\ 0 & \ddots & \ddots \\ 0 & \ddots & 1/\sigma_n+\lambda \end{bmatrix}$$

$+\lambda$

Adapted Method II: Focused Trajectory Optimization w/ Iterative-LQR

- Focused Iterative-LQR & Cost Function

Determine λ

Levenberg-Marquardt Heuristics

iLQR Optimization making progress: $\lambda \downarrow$

iLQR Optimization not making progress: $\lambda \uparrow$

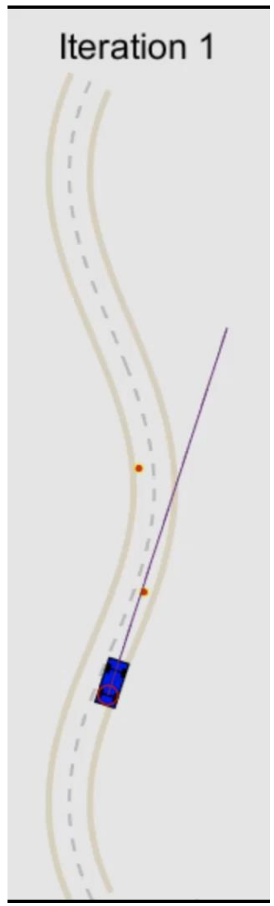
Focused Line-Search Heuristics

Optimization violating maneuver pattern constraint: $\lambda \uparrow$

iLQR Optimization making progress: $\lambda \downarrow$

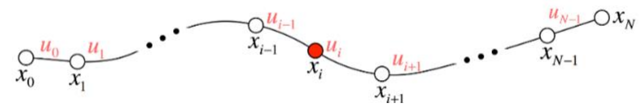
Line-Search Optimization making progress: $\lambda \leftrightarrow$

iLQR Optimization not making progress: $\lambda \uparrow$



Cost Function

Cost penalizes certain undesirable aspect of the plan/trajectory.



Total Cost: $J(X, U) = g_N(x_N) + \sum_{i=0}^{N-1} g(x_i, u_i)$

$$g(x_i, u_i) = \sum_{k=1}^{M} \omega_k \cdot c_k(x_i, u_i)$$

$$g_N(x_N) = \sum_{k=1}^{M} \omega_k \cdot c_k(x_N, 0)$$

Weights **Cost Terms**

	Better be Continuous?
Edge-Augmented Graph Search	✗
Topological Region/Pattern Selection	✗
Iterative-LQR Trajectory Optimization	✓

Adapted Method II: Focused Trajectory Optimization w/ Iterative-LQR

- Cost Function Design

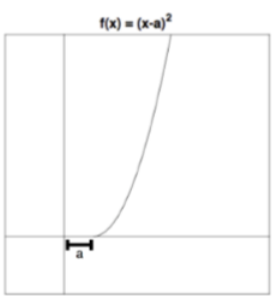
iLQR is underlying Newton's Method:
- Convex Optimization
- 2nd-order Continuous

Key Results in Convex Optimization

2nd –order continuous monotonically non-decreasing convex function	**2nd –order continuous differentiable convex**
$h(y)$	$g(x)$

$f = (h \circ g)(x) = h(g(x))$ **Still Convex!**

Quadratic

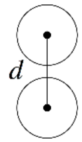


State/Control Variable

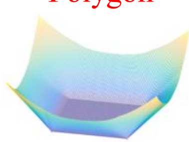
E.g., steering, speed, swirl, acceleration, etc.

Distance Function

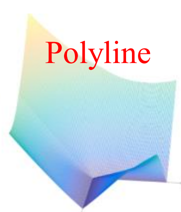
Disk



Polygon



Polyline

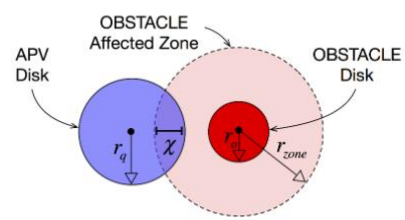


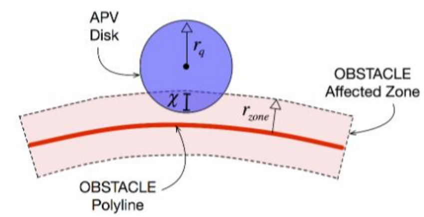
Convex Modulation Function

Convex Feature Function

Non-convex Features

Penetrated Distance:





Distance ↓ **Penetrated Distance** ↑ **Non-Convex!**

Local cost quadratization → Topological Structure

Total Cost Function

Behavioral Feature

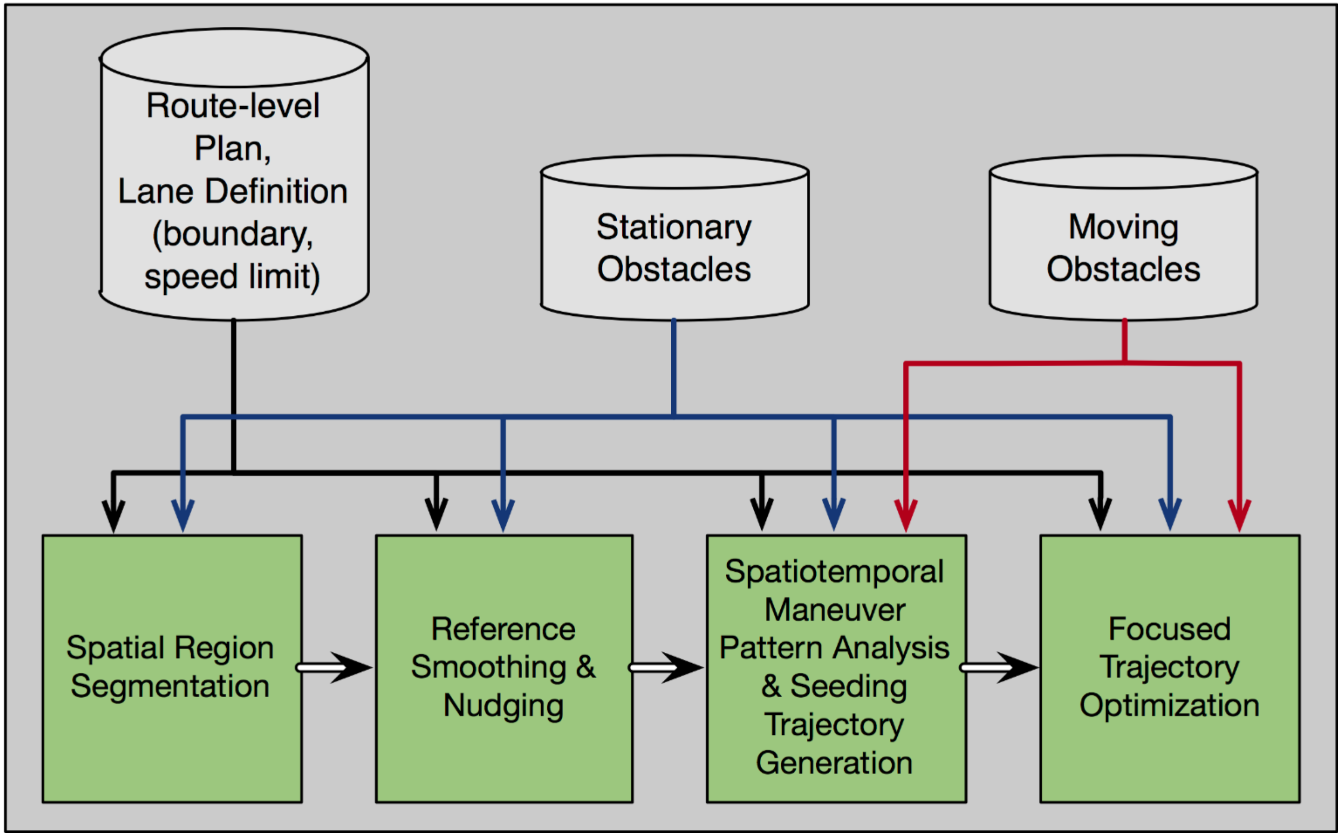
$$g = c^B_{obstacle}(\omega_{obstacle}) + c^B_{ref}(\omega_{ref}) + c^B_{speed}(\omega_{speed}) + c^B_{lat-acc}(\omega_{lat-acc}) + c^B_{swirl}(\omega_{swirl}) + c^B_{lon-acc}(\omega_{acc}, \omega_{dec})$$
$$+ c^C_{obstacle}(\Omega) + c^C_{lane}(\Omega) + c^C_{speed}(\Omega) + c^C_{lat-acc}(\Omega) + c^C_{swirl}(\Omega) + c^C_{lon-acc}(\Omega)$$

Constraint Feature:

Penalty Method → **Constrained Iterative-LQR Optimization** → **Execution Feasible Trajectory**

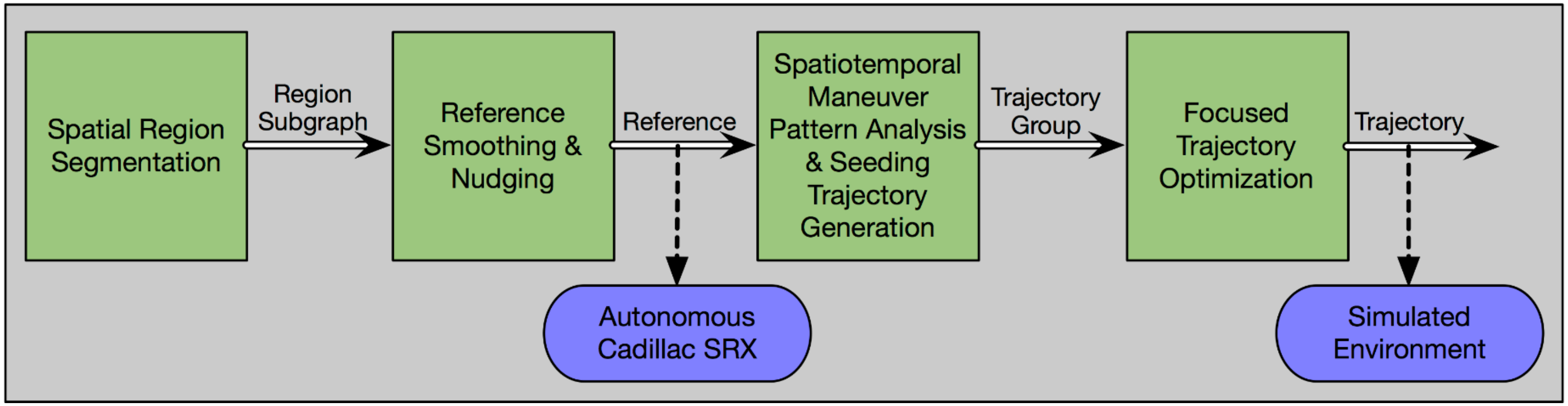
Results

- Planning Framework / Algorithmic Flow

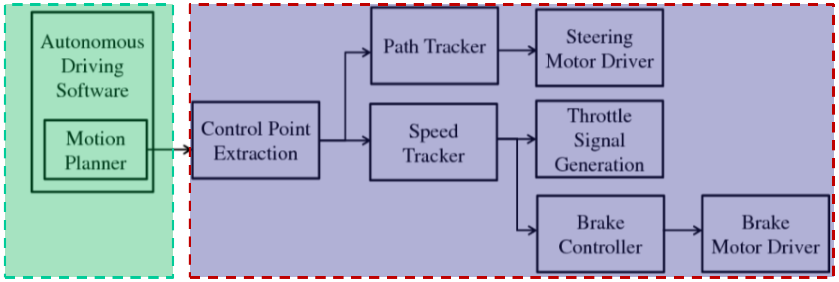


Results

- Experiment Setup



Cadillac Setup



Reference Generation

Tracking Control

Simulation Setup

Scenario:

A particular setup of the environment elements including lanes, obstacles and the APV.

Snapshot:

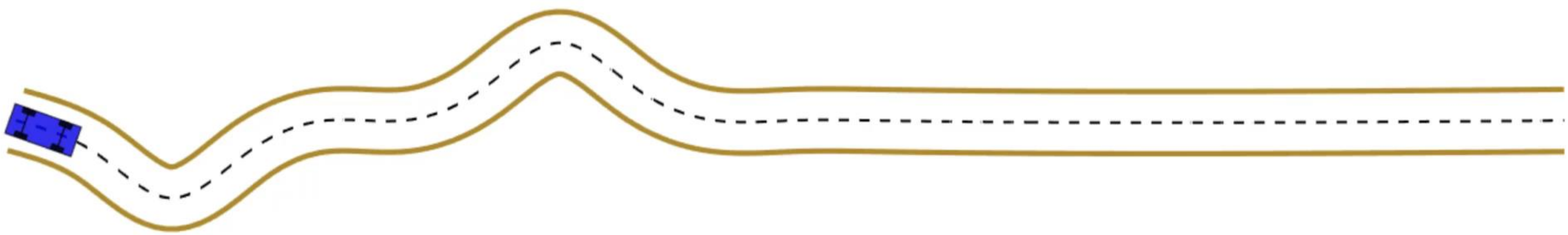
Plots of the environment elements' states and the planning outcome of each planning module at a given time-stamp.

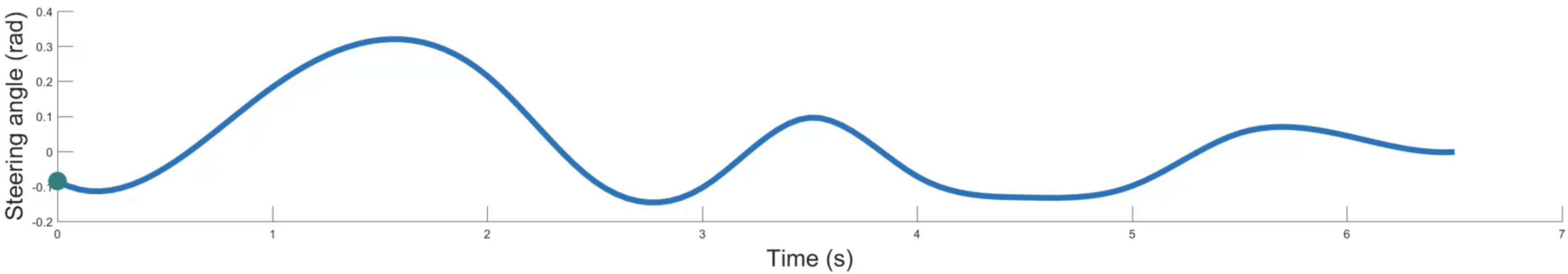
Overlay:

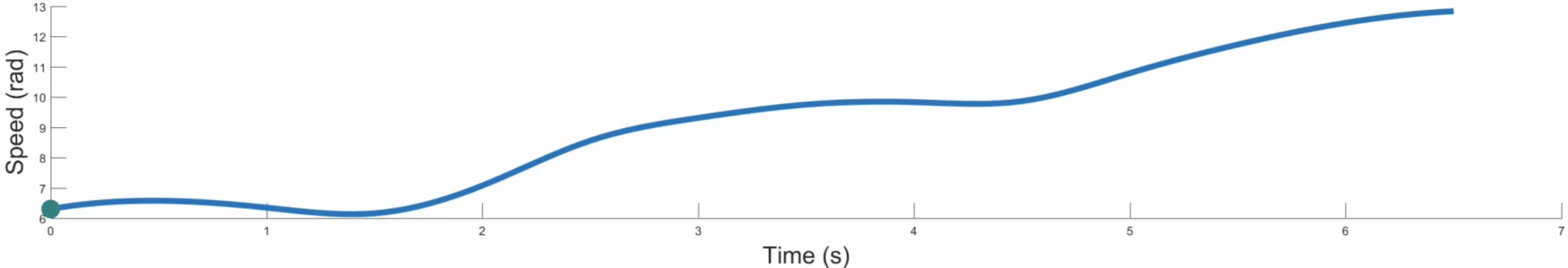
A plot of the overlaid states of the environment elements' states over a time period that the APV demonstrates a maneuver.

Results

- Simulation Scenario 1

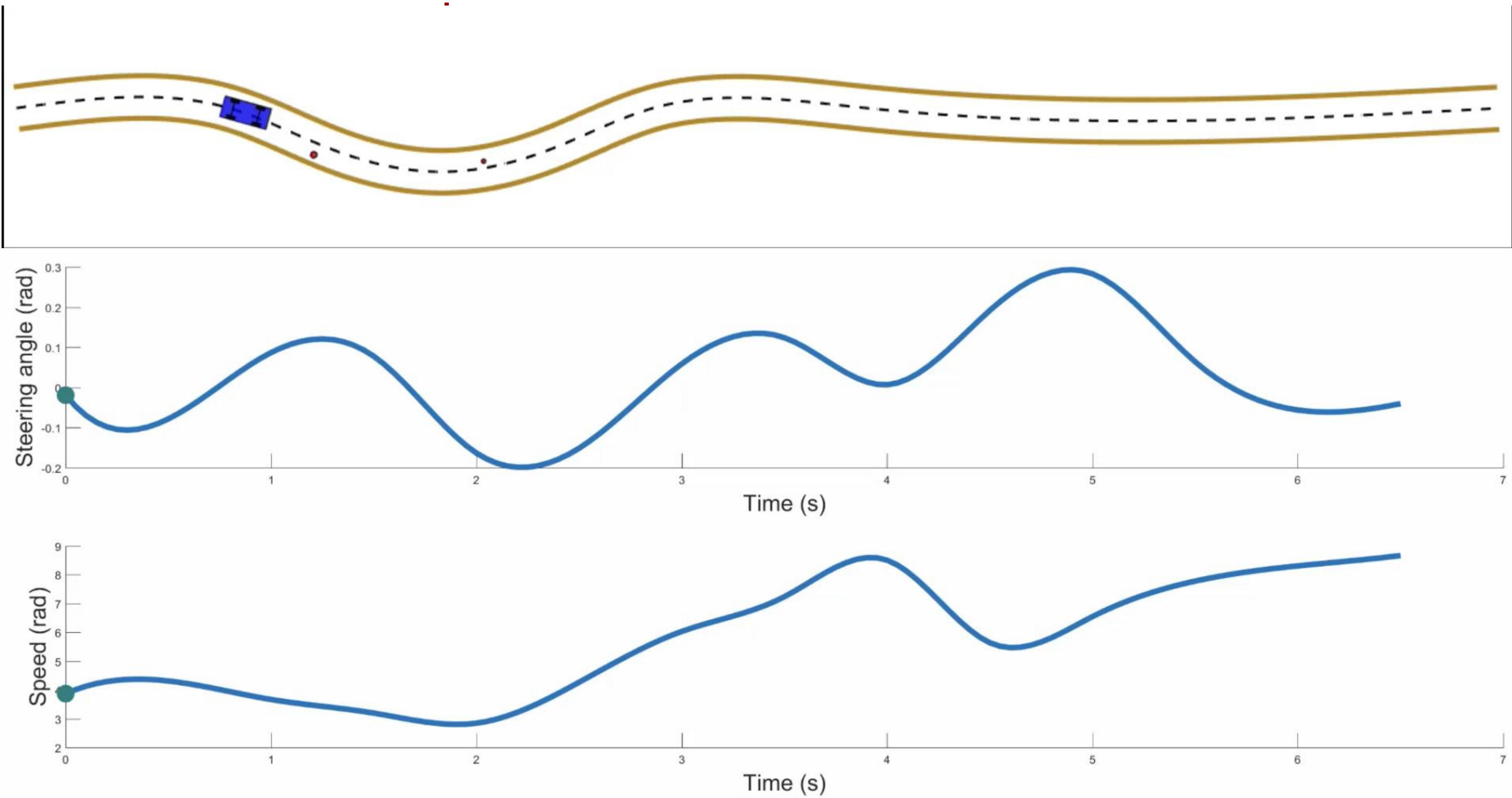






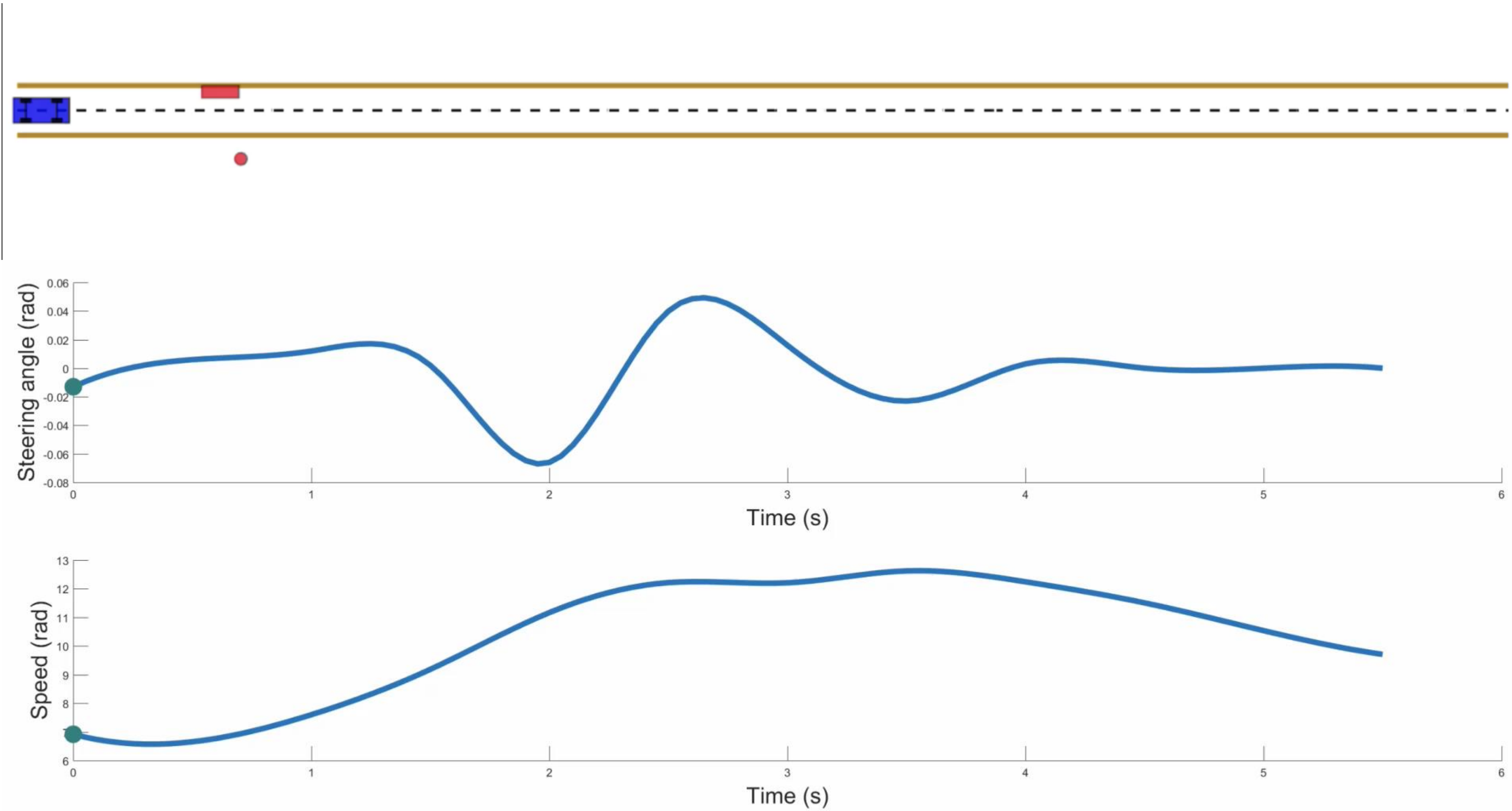
Results

- Simulation Scenario 2



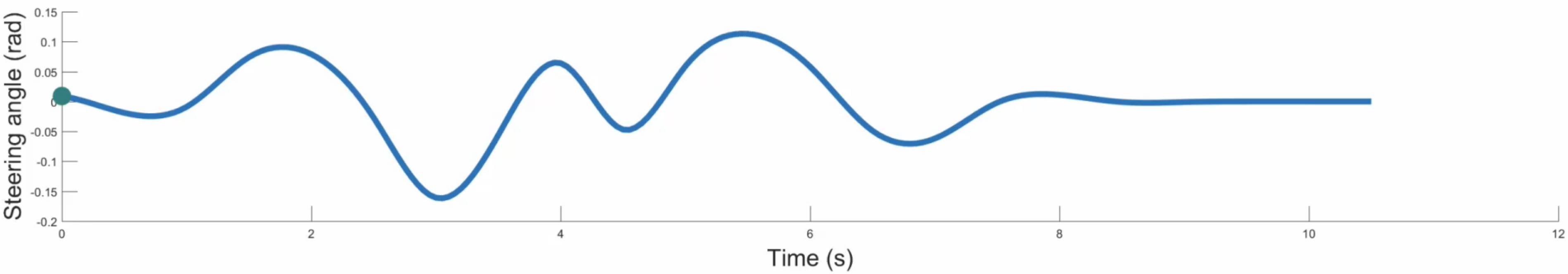
Results

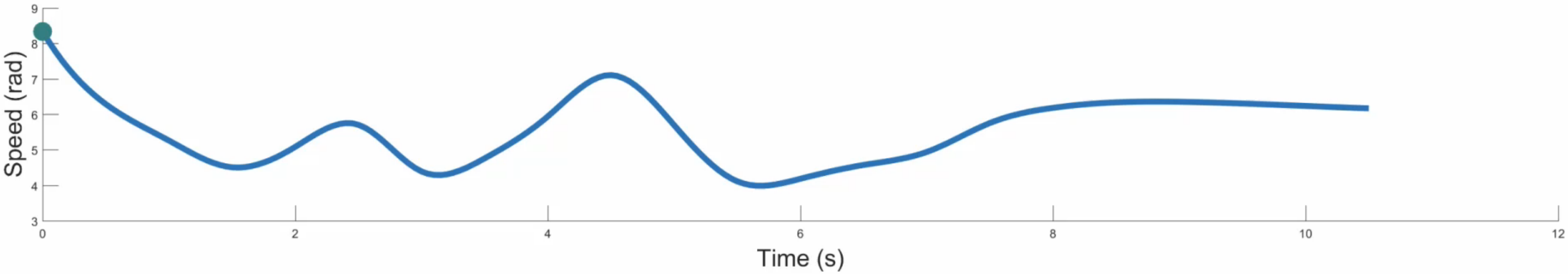
- Simulation Scenario 3



Results

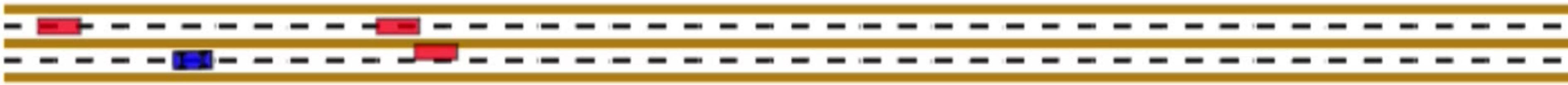
- Simulation Scenario 4

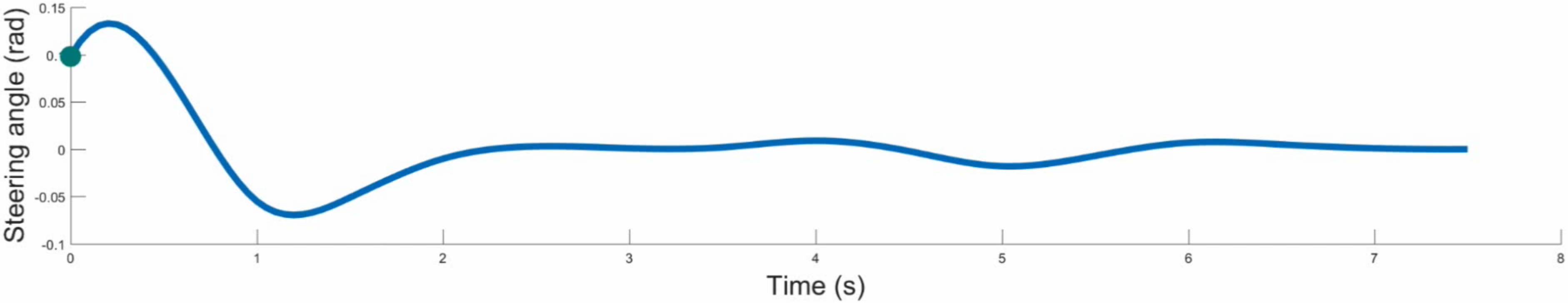


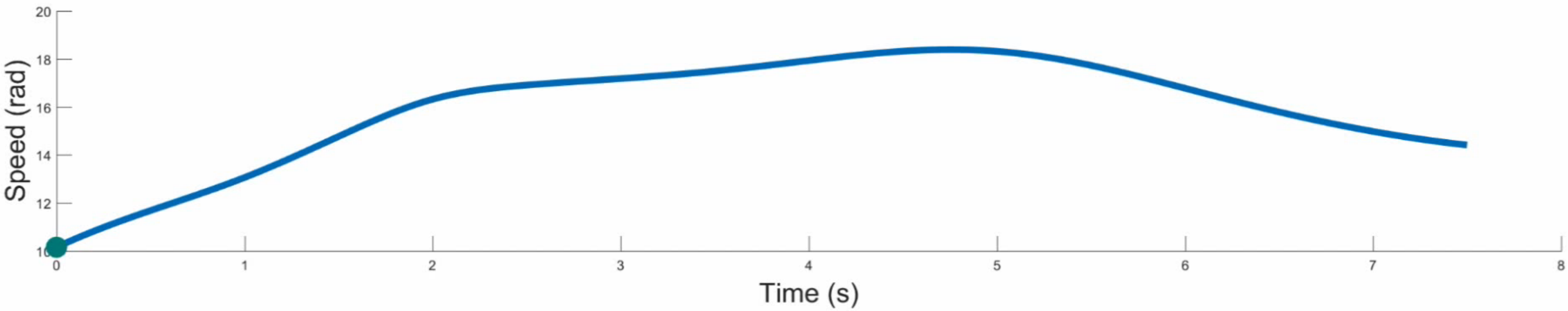


Results

- Simulation Scenario 5

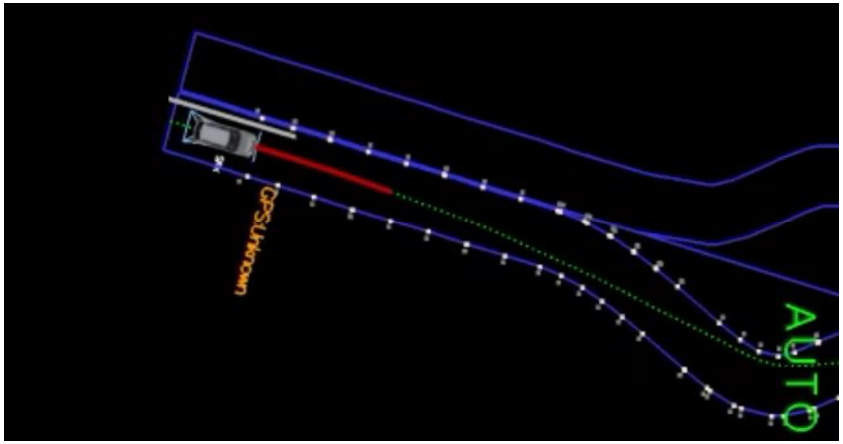


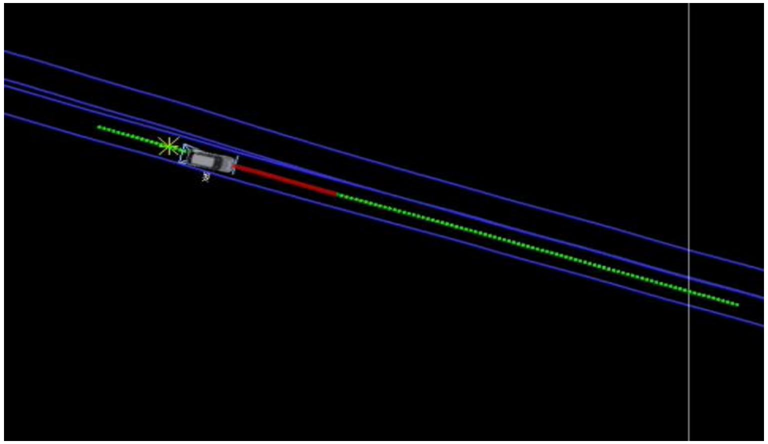


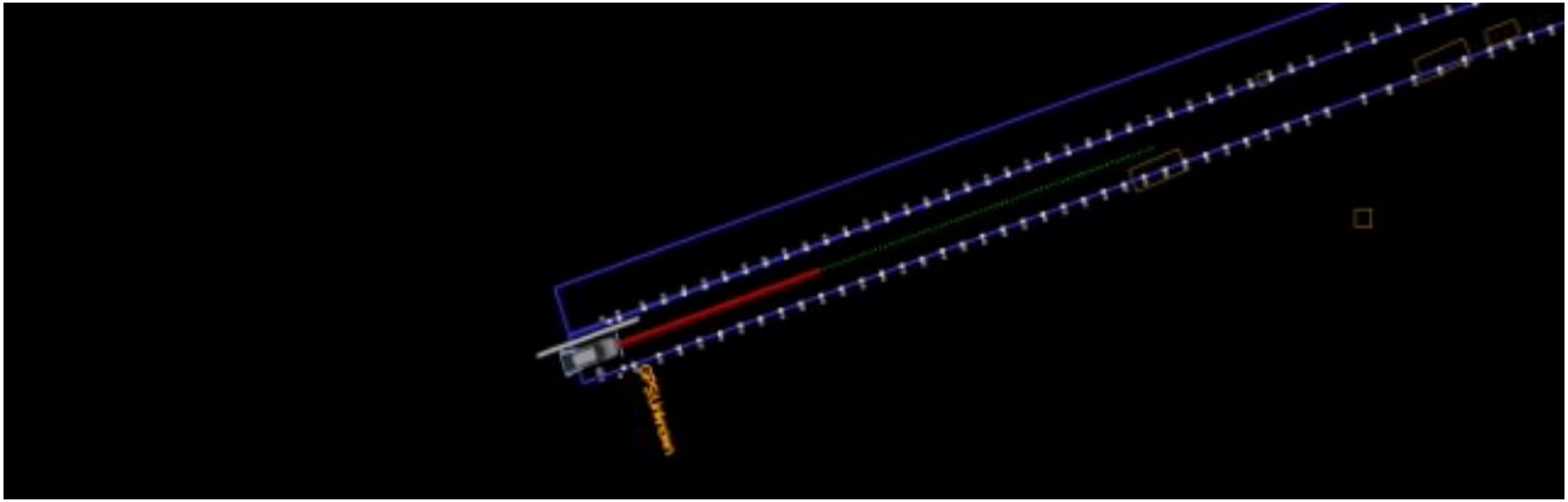


Results

- On-Vehicle (Simulation)







Results

- On-Vehicle (Closed Course)

Results

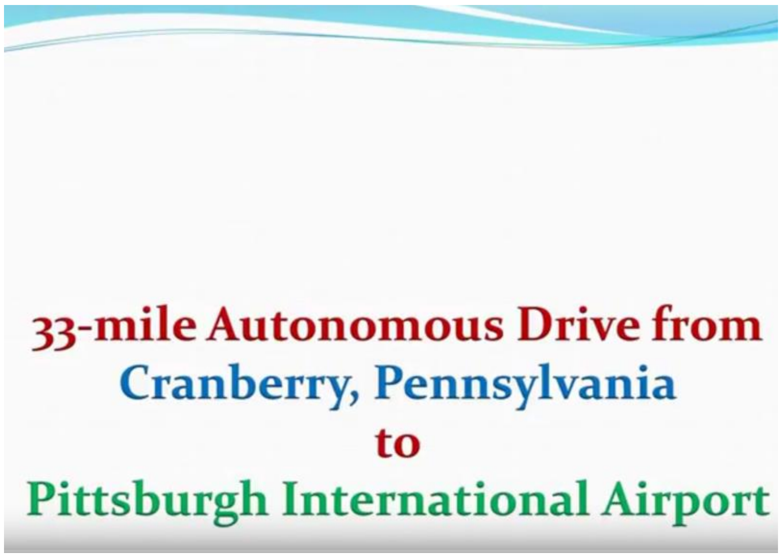
- On-Vehicle (Closed Course)

Results

- On-Vehicle (Schenley Park)

Results

- Past demo video footages.



Link

Link

Conclusions

- Comparison

No #	Methods	$\mathcal{F}_{1a}$	$\mathcal{F}_{1b}$	$\mathcal{F}_{2}$	$\mathcal{F}_{3}$	$\mathcal{F}_{4}$	$\mathcal{F}_{5}$
M1	Boss's Local Planner [Ferguson et al., 2008]	✓	✓	×	✓✗	×	×
M2	Junior's RNDF Follower [Montemerlo et al., 2008]	✓	✓	✓	✓✗	×	×
M3	Nonholonomic Potential field [Huang et al., 2006]	✓	×	×	×	×	×
M4	Biased RRT [Kuwata et al., 2008]	✓	✓	✓	✓	×	×
M5	Spatiotemporal lattice [Ziegler and Stiller, 2009, McNaughton, 2011]	✓	✓	✓	✓	×	×
M6	Timed Elastic Band [Roesmann et al., 2012]	✓	×	✓	✓	×	×
M7	Hybrid-A* + Conjugate Gradient Descent Smoothing [Dolgov et al., 2008]	✓	×	✓	×	×	✓
M8	iLQR/DDP [Li and Todorov, 2004b, van den Berg, 2016, Tassa et al., 2014]	✓	×	✓	✓	×	×
M9	Cell decomposition + Mixed-Integer Programming [Park et al., 2016]	✓	✓✗	✓	×	✓✗	✓
M10	Homotopy marker function + Timed Elastic Band [Rösmann et al., 2015]	✓	×	✓	✓	✓✗	×
P	**Proposed**	✓	✓	✓	✓	✓	✓

Conclusions

- Summary

Requirement 1: a deliberative trajectory planning system.

Reference and Trajectory Planning have long spatial (100m) or temporal horizon (6s).

Requirement 2: spatiotemporal (trajectory) planning.

Maneuver pattern analysis and focused trajectory optimization explicitly plan spatiotemporally.

Requirement 3: tactical reasoning capability with topological awareness.

Region segmentation and maneuver pattern analysis provides tactical reasoning capability.

Requirement 4: global awareness with the ability to converge to a local optimum.

Reference planning and maneuver pattern analysis both perform global sampling.

Requirement 5: apply to self-driving passenger vehicle on-road driving.

Extensively experimented on a real self-driving vehicle.

Conclusions

- Contributions

  1. A Hybrid Trajectory Planning Framework
  2. Search over Edge-augmented Graph for Reference Path Planning
  3. Topological Backward Propagation Algorithm for Region (Sub-Graph) Segmentation
  4. Sampling-based Maneuver Pattern Analysis/Seeding Trajectory Generation for On-Road Self-Driving
  5. Adapted Linear Quadratic Regulator (LQR) and Iterative-LQR for Trajectory Smoothing/Optimization
  6. Identification of Useful Cost Function Generation Principles

Future Work

- TBC: the fusion of sampling-based and optimization-based method.
- TBC: The inclusion in topological analysis in a trajectory planning system.
- Automated parameter tuning through machine learning techniques.
- Unstructured learning of driving skill, a.k.a, neural network, etc.
- Misc:
  - More complex/realistic vehicle model.
  - Planning with better shape representations.
  - Faster collision checking (distance function evaluation).
  - Faster homology information calculation.

Publications

- Gu, T., et al. (2016). Automated Motion-based Tactical Maneuver Discovery, Reasoning and Trajectory Planning for Autonomous Driving (IROS), 2016
- Gu, T., et al. (2016). Runtime-Bounded Tunable Motion Planning for Autonomous Driving (IV), 2016
- Gu, T., et al. (2016). Human-like Planning of Swerve Maneuvers for Autonomous Vehicles (IV), 2016
- Gu, T. and J. Dolan (2015). A Lightweight Simulator for Autonomous Driving Motion Planning Development. the Fourth International Conference on Intelligent Systems and Applications (INTELLI), 2015.
- Gu, T., et al. (2015). Tunable and Stable Real-Time Trajectory Planning for Urban Autonomous Driving. International Conference on Intelligent Robots and Systems (IROS), 2015. ***Best student paper finalist***
- Wei, J., et al. (2014). A behavioral planning framework for autonomous driving. Intelligent Vehicles Symposium (IV), 2014, IEEE.
- Gu, T., et al. (2014). On-Road Trajectory Planning for General Autonomous Driving with Enhanced Tunability. Intelligent Autonomous Systems (IAS-13), 2014, Springer International Publishing Switzerland.
- Gu, T. and J. Dolan (2014). Toward human-like motion planning in urban environments. Intelligent Vehicles Symposium (IV), 2014, IEEE.
- Gu, T., et al. (2013). Focused trajectory planning for autonomous on-road driving. Intelligent Vehicles Symposium (IV), 2013, IEEE.
- Gu, T. and J. Dolan (2012). On-road motion planning for autonomous vehicles. International Conference on Intelligent Robotics and Applications (ICIRA), 2012, Springer.

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