Intelligent Intersection Coordination and Trajectory Optimization for Autonomous Vehicles

Yixiao Zhang, Gang Chen and Tingting Zhang

School of Electronics and Information Engineering,
Harbin Institute of Technology, Shenzhen

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OUTLINE:

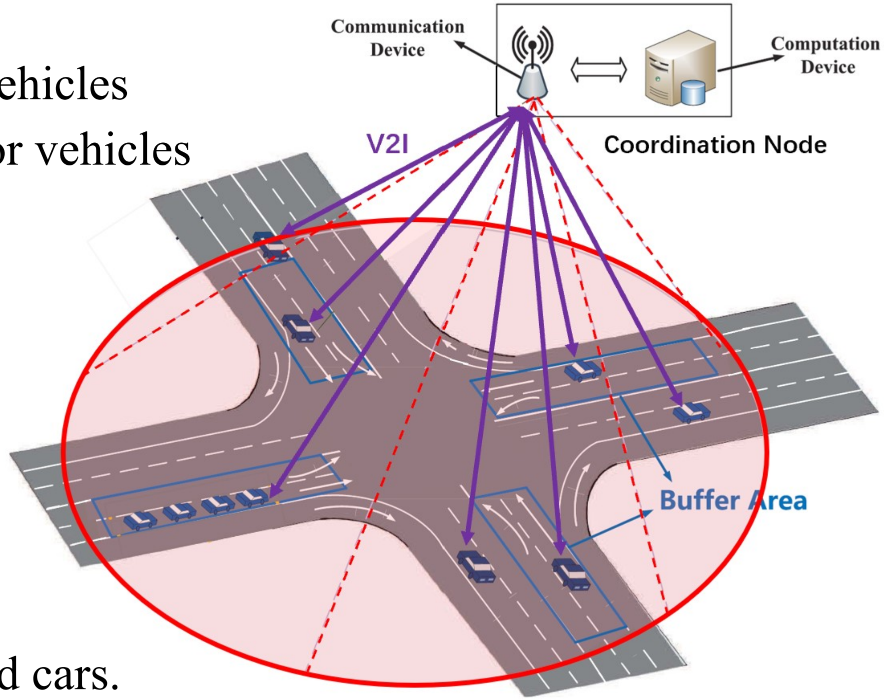
- Introduction
- Model
- High-level Planner (infrastructure-based)
- Low-level Planner (vehicle-based)
- Conclusion

❖ Background

- more and more vehicles are expected to enter the road infrastructure.
- **Intersections**: 40% of traffic accidents, including 20% fatal.
- **Intelligent Intersection Management Systems**:
  - Safety and Efficiency: avoid accidents as well as jams

❖ Infrastructure-based Strategies [1,2]:

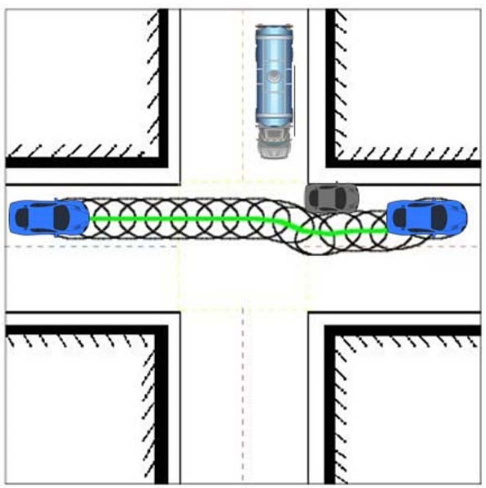
- A coordination node (at RSU):
  - receive the requests sending from vehicles
  - allocate space and time resources for vehicles
- **Merits:**
  - safety among intelligent vehicles
  - fuel efficiency
  - traffic throughput
- **Demerits:**
  lack of flexibility when
  - dealing with unexpected obstacles, such as pedestrians, bicycles, packed cars.
  - communication and perception error



[1] L. Chen and C. Englund, "Cooperative intersection management: A survey," IEEE Transactions on Intelligent Transportation Systems, vol. 17, no. 2, pp. 570–586, 2016.
[2] E. Namazi, J. Li, and C. Lu, "Intelligent intersection management systems considering autonomous vehicles: A systematic literature review," IEEE Access, vol. 7, pp. 91 946–91 965, 2019.

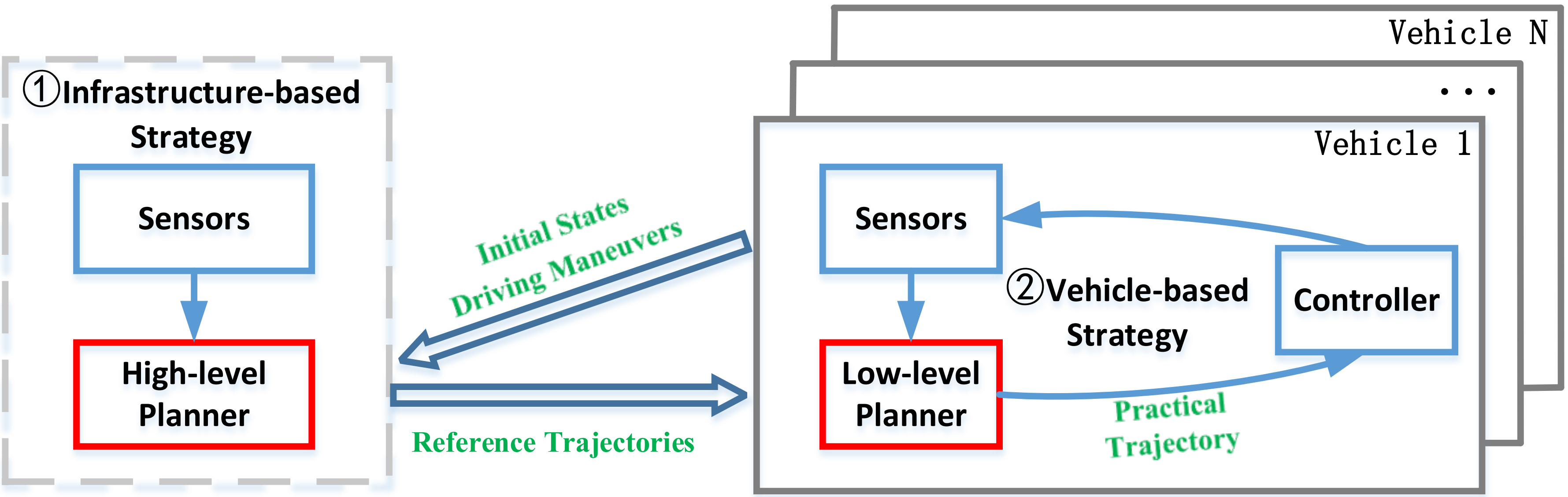
❖ Vehicle-based Strategies [3,4]:

- **Vehicles use their own sensors (cameras, radars and LIDARs) for environment awareness, and then plan trajectories accordingly.**
- **Advantages:** detect possible obstacles, trajectory smoothness
- **Disadvantages:** Deadlocks among vehicles, lacking in traffic throughput



[3] D. González, J. Pérez, V. Milanés and F. Nashashibi, "A Review of Motion Planning Techniques for Automated Vehicles," in IEEE Transactions on Intelligent Transportation Systems, vol. 17, no. 4, pp. 1135-1145, April 2016, doi: 10.1109/TITS.2015.2498841.
[4] L. Claussmann, M. Revilloud, D. Gruyer, and S. Glaser, "A review of motion planning for highway autonomous driving," IEEE Transactions on Intelligent Transportation Systems, vol. 21, no. 5, pp. 1826–1848, 2020.

❖ Integrated Coordination Framework



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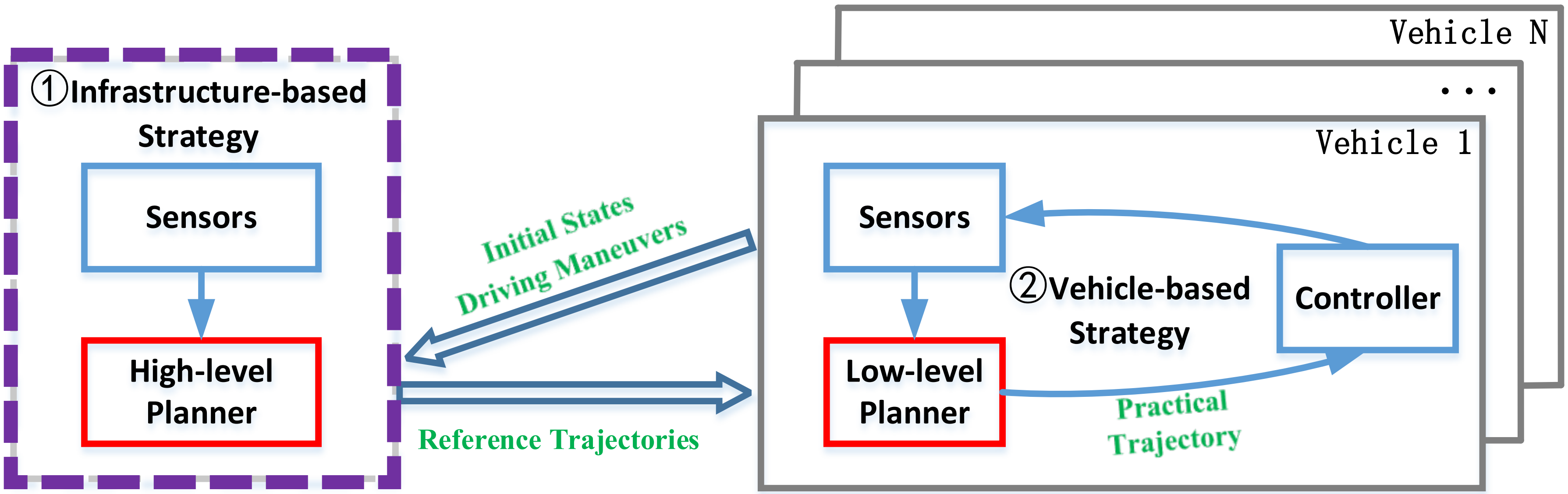
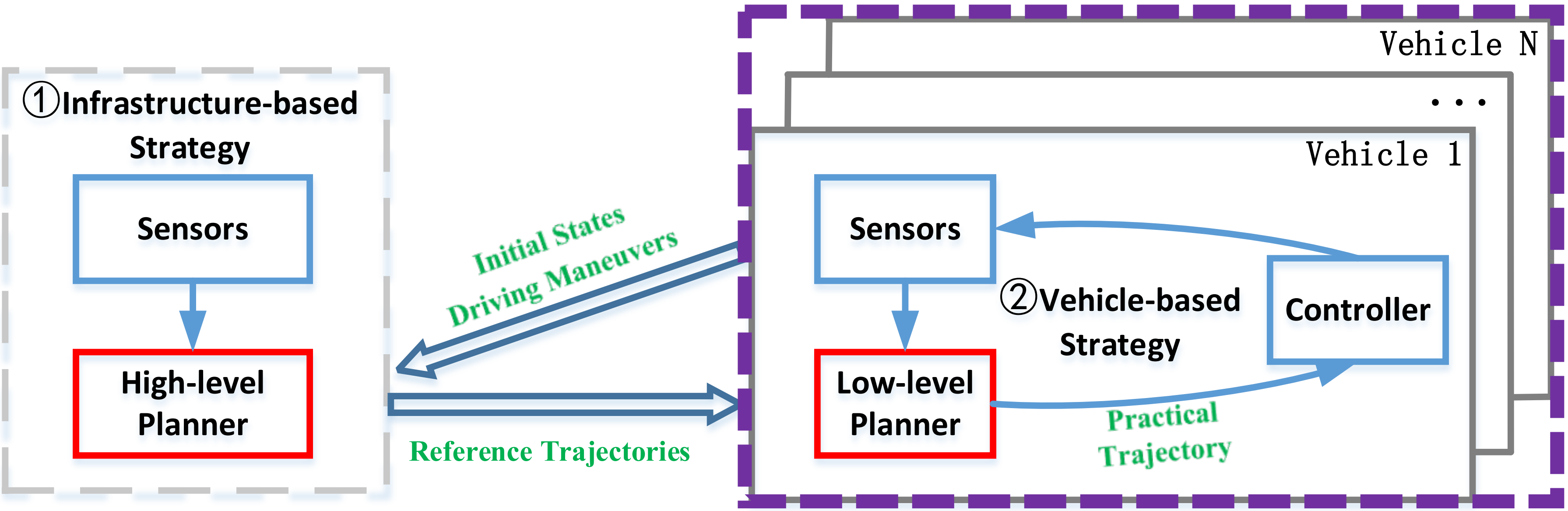


- **High-level Planner (on coordination node):**
  - receive *driving maneuvers* and *initial states* from vehicles via V2I communication.
  - generate reference trajectories in Cartesian Coordinates.

❖ Integrated Coordination Framework



- **High-level Planner (on coordination node):**
  - receive *driving maneuvers* and *initial states* from vehicles via V2I communication.
  - generate reference trajectories in Cartesian Coordinates.
- **Low-level Planner (on each vehicle):**
  - replan its practical trajectory based on the reference trajectory in *Frenét Frame*, using on-board observations.

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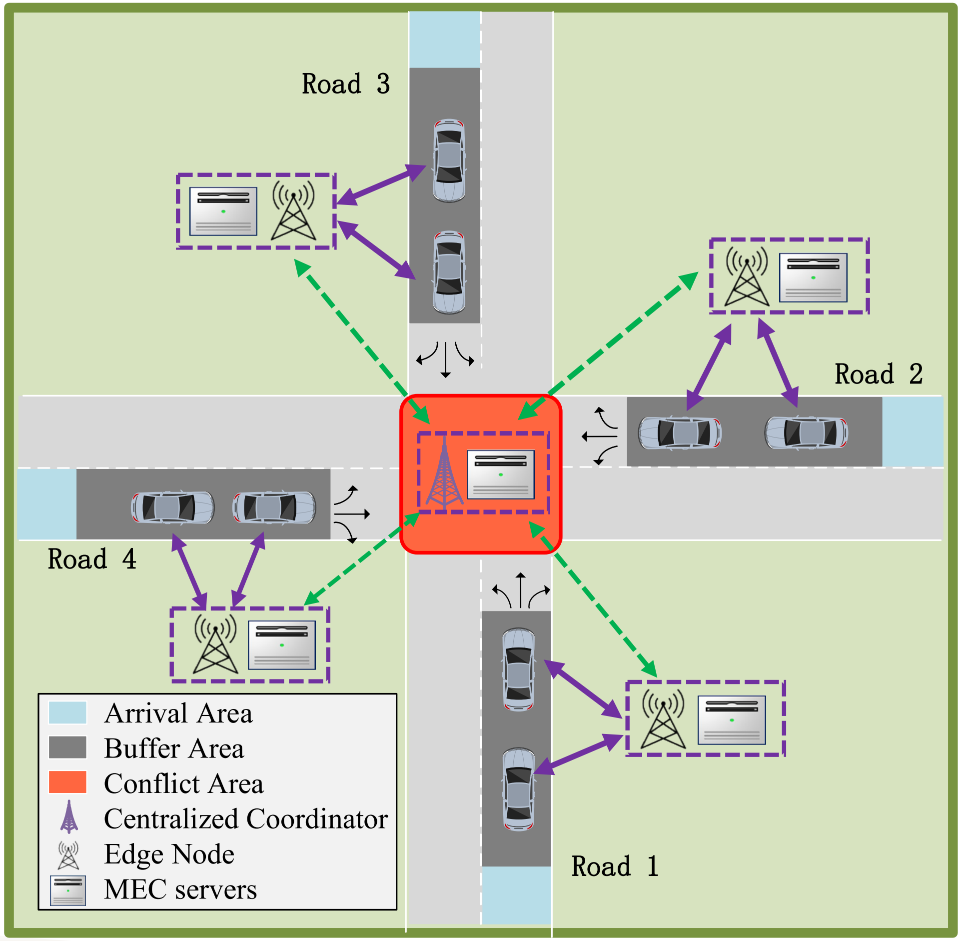
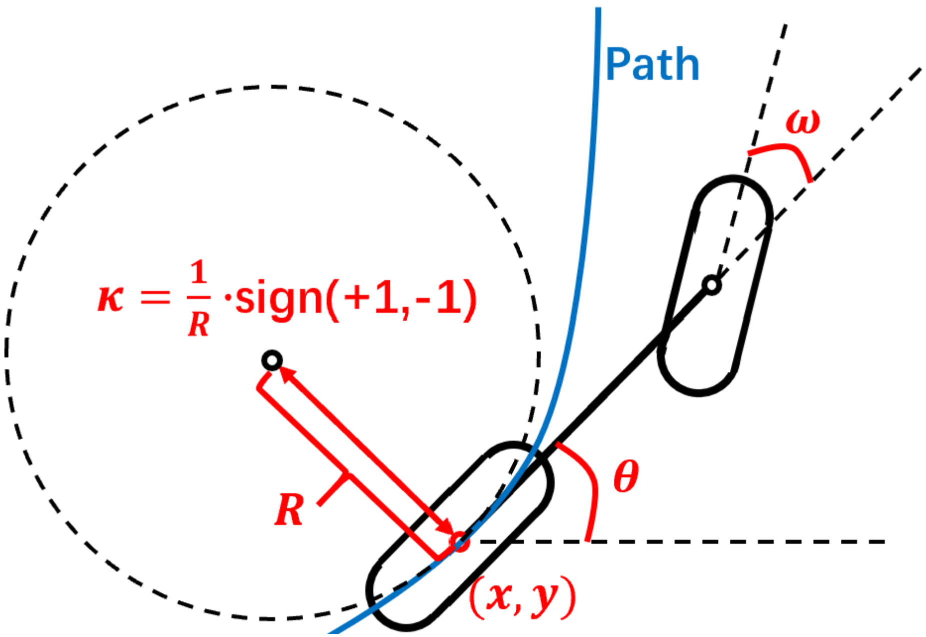
❖ Intersection Model



- **Areas**
  - --- Arrival Area (AA)
  - --- Buffer Area (BA)
  - --- Conflict Area (CA)
- **Computing Units**
  - --- Computing Units on Vehicles
  - --- Centralized Coordinator
  - --- Edge Nodes (Offloading)

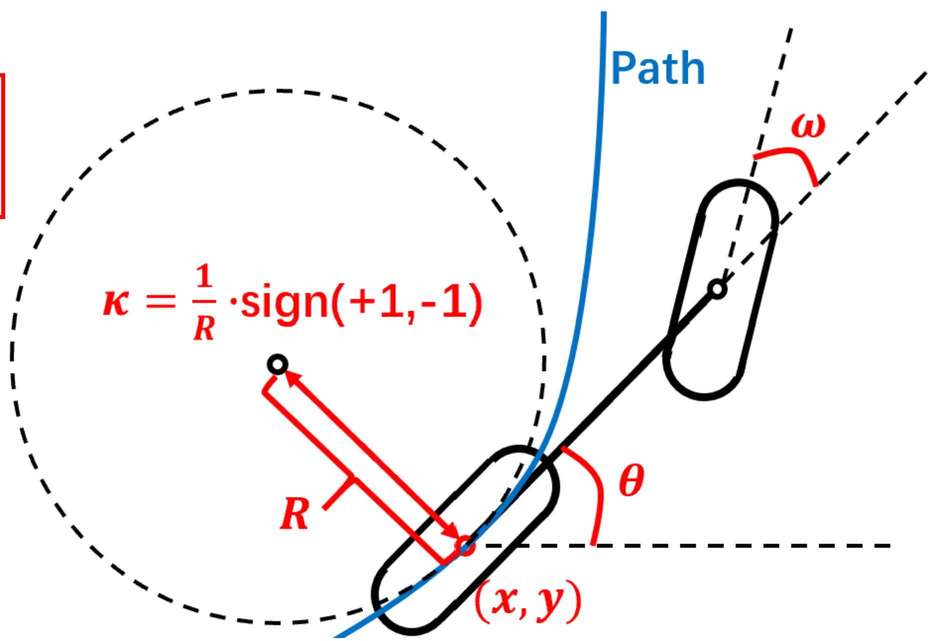
❖ Kinematic Bicycle Model

- **State parameters:** $[x, y, \theta, v]$
- **Inputs:** $[\kappa, a]$



❖ Kinematic Bicycle Model

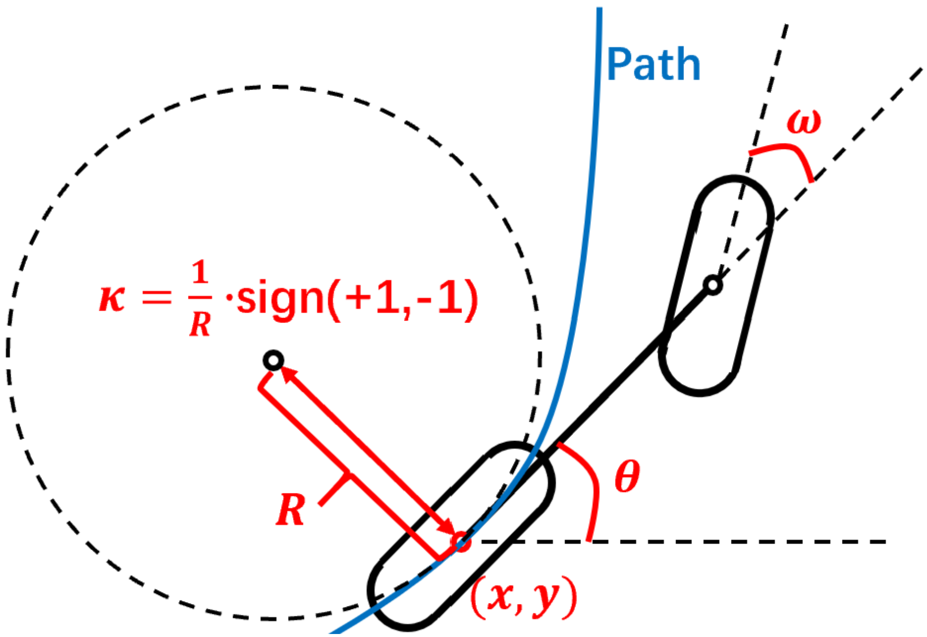
- **State parameters:** $[x, y, \theta, v]$
- **Inputs:** $[\boxed{\kappa}, a]$ $\boxed{\kappa = \dfrac{\tan(\omega)}{L}}$



❖ Kinematic Bicycle Model

- **State parameters:** $[x, y, \theta, v]$
- **Inputs:** $[\kappa, a]$
- **Kinetic Equation:**

$$\begin{bmatrix} \dot{x} \\ \dot{y} \\ \dot{\theta} \\ \dot{v} \end{bmatrix} = v \cdot \begin{bmatrix} \cos(\theta) \\ \sin(\theta) \\ \kappa \\ 0 \end{bmatrix} + a \cdot \begin{bmatrix} 0 \\ 0 \\ 0 \\ 1 \end{bmatrix}$$



❖ Trajectory Functions

- **Cartesian Coordinates:**

$$\begin{cases} \text{Path:} & \begin{cases} x = f(s) \\ y = g(s) \end{cases} \\ \text{Speed Profile:} & s = u(t) \end{cases}$$

Trajectory Functions

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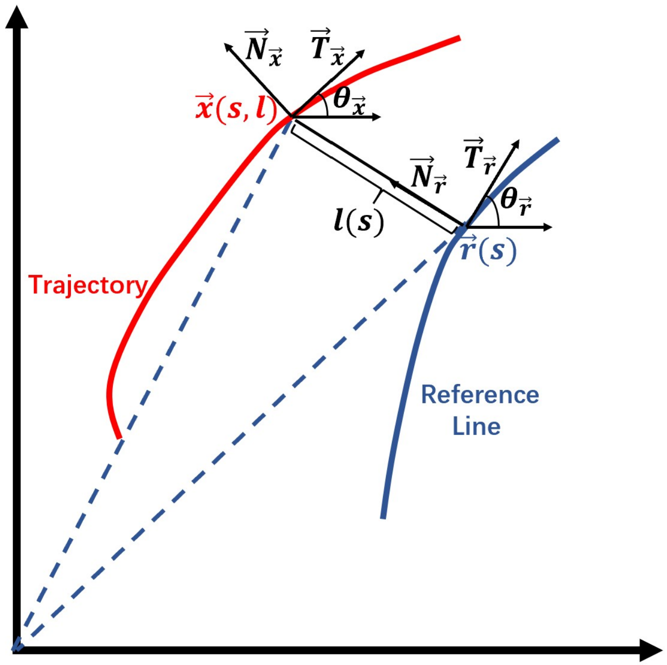
- **Frenét Frame (SLT) [5]:**

$$\begin{cases} \text{Path:} & l = p(s) \\ \text{Speed Profile:} & s = q(t) \end{cases}$$



[5] M. Werling, J. Ziegler, S. Kammel, and S. Thrun, "Optimal trajectory generation for dynamic street scenarios in a fren´et frame," in 2010 IEEE International Conference on Robotics and Automation, 2010, pp. 987–993.

Trajectory Functions

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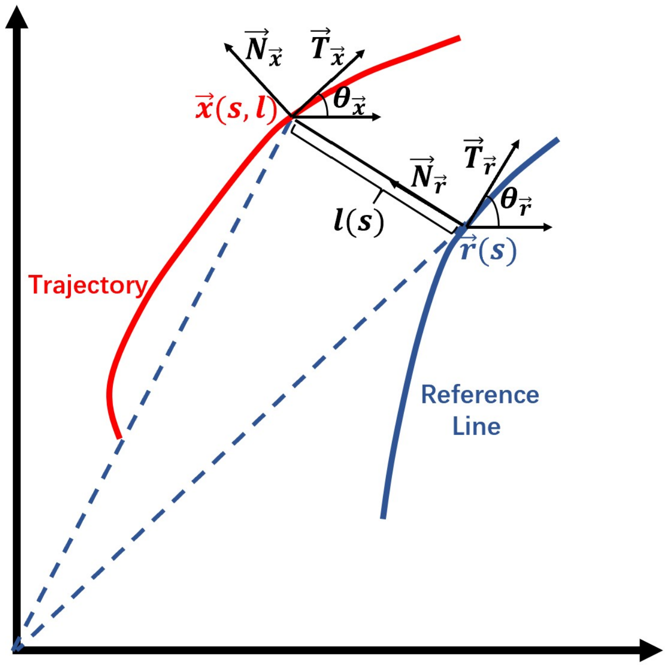
- **Control:**

$$[f, g, \arctan(\frac{g'}{f'}), \frac{|f'g'' - f''g'|}{(f'^2 + g'^2)^{3/2}}, u', u'']^{\mathrm{T}} = \boxed{[x, y, \theta, \kappa, v, a]^{\mathrm{T}}}$$

$$[p, q, p', p'', q', q''] \mapsto \boxed{[x, y, \theta, \kappa, v, a]}$$



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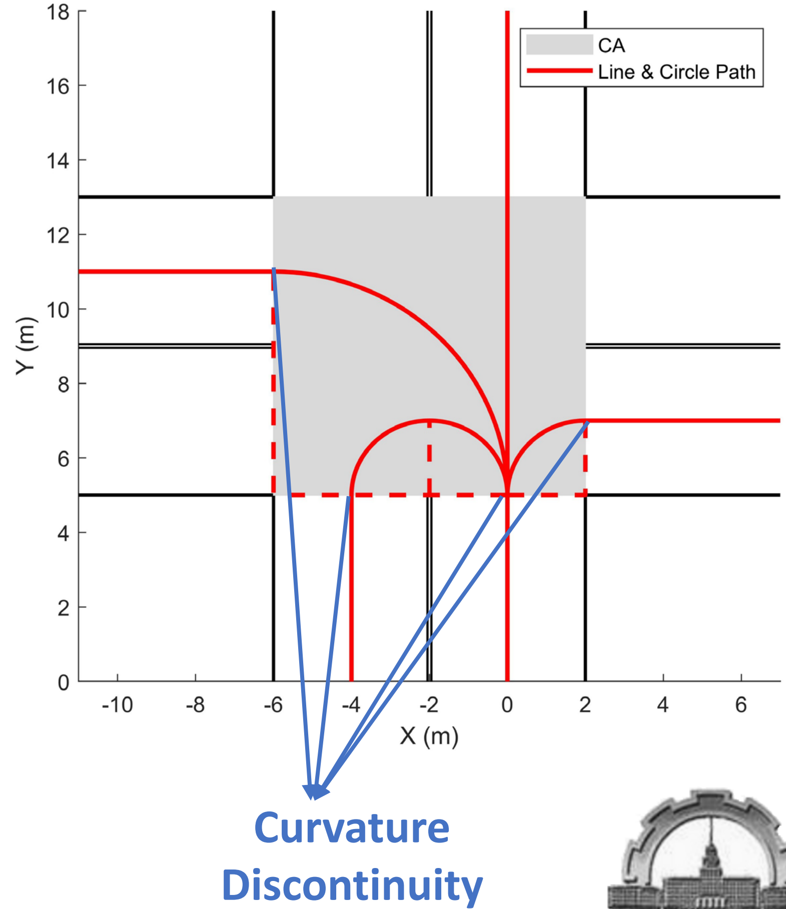
❖ Reference Path Generator

- Find the reference path functions $x = f(s), y = g(s)$ for each vehicle
- Sampling on Line & Circle Path



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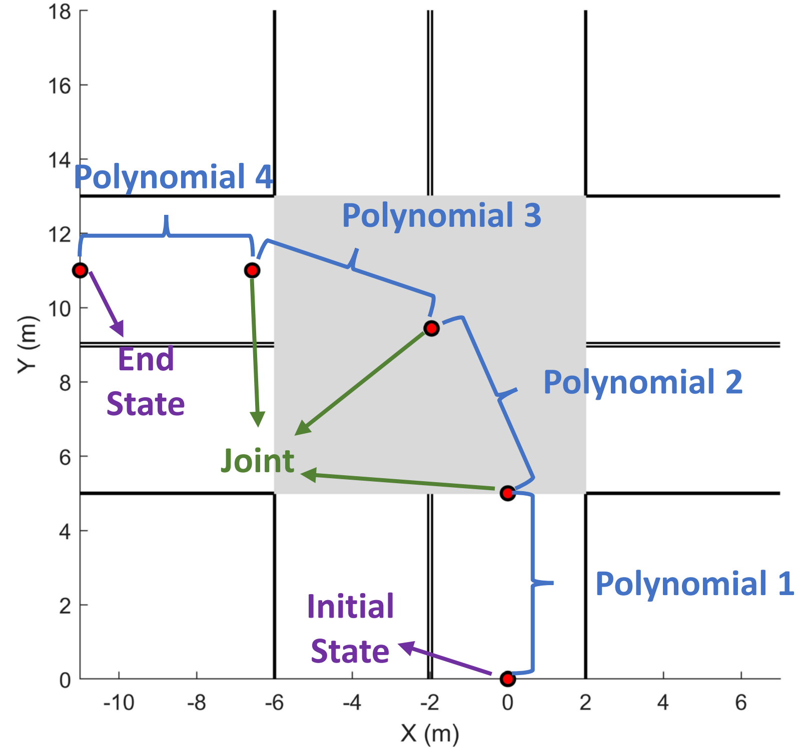
  Knots→ parameterization (spline)



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- **Find the reference path functions x = $f(s)$, $y = g(s)$ for each vehicle**
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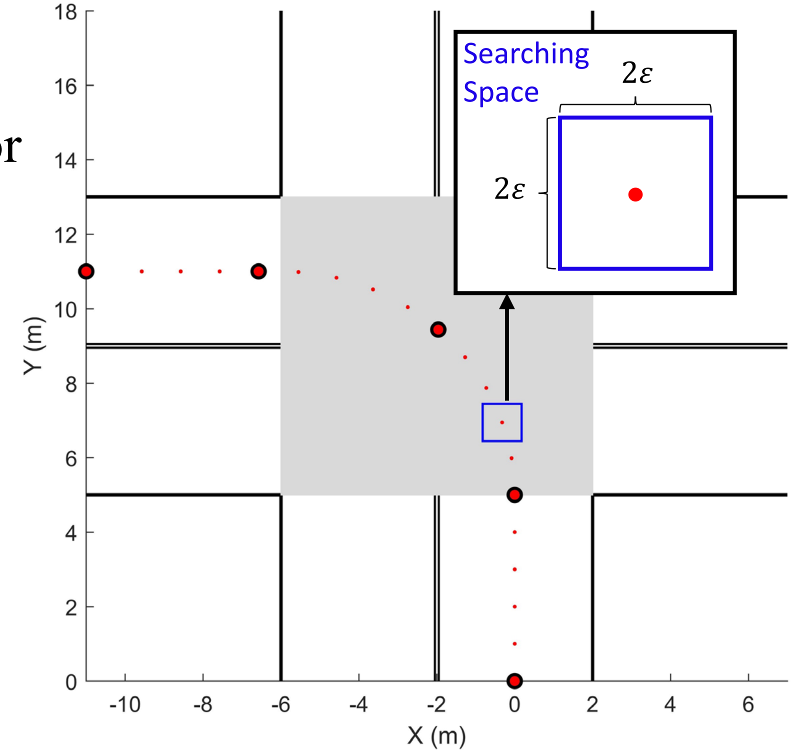
Knots→ parameterization (spline)

Anchor Points→ keep the vehicle behavior

$$|f(s_{a,j}) - x_{a,j}| \le \varepsilon$$

$$|g(s_{a,j}) - y_{a,j}| \le \varepsilon$$



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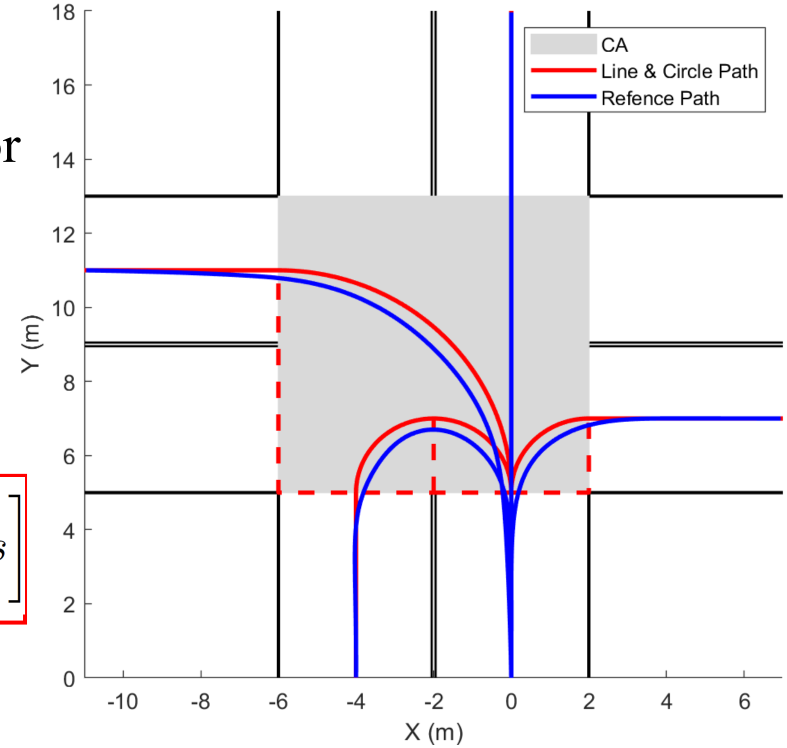

- **Smooth Optimization**

$$\text{Min.}\ \boxed{\sum_{z=2}^{3} w_{\mathrm{s},z}^{\mathrm{P}} \left[\int \left(f^{(z)}\right)^{2}(s)\mathrm{d}s + \int \left(g^{(z)}\right)^{2}(s)\mathrm{d}s\right]}$$

Curvature and Derivative of curvature

Reference Path Generator

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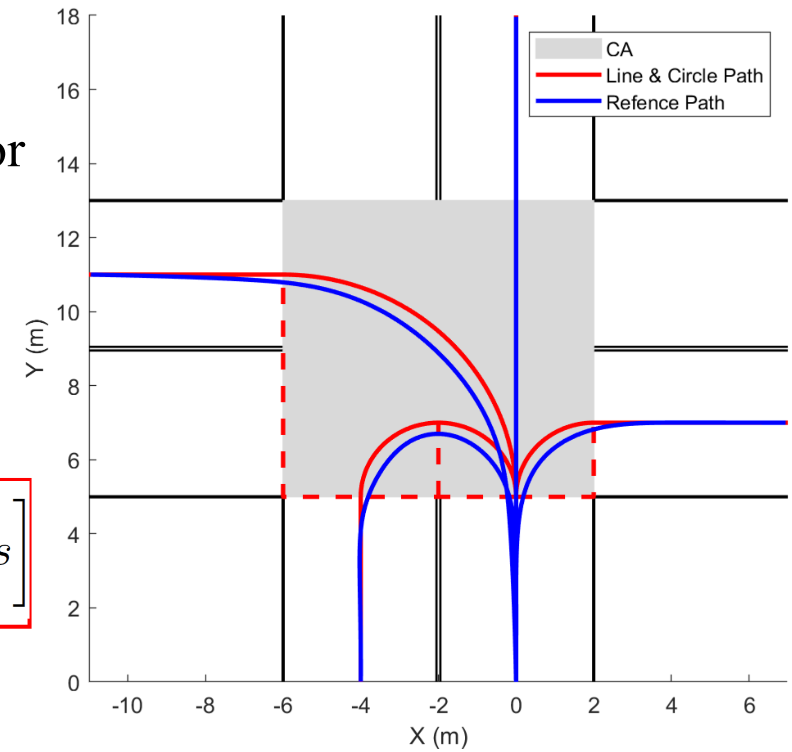

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Curvature and Derivative of curvature

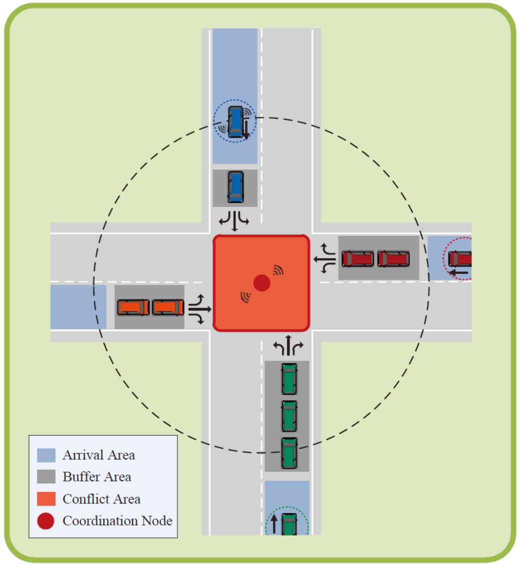
- **Solver:**

  Quadratic Programming (QP)

  → finding the optimal spline coefficients → reference path

❖ Reference Speed Profile Generator

- **Find reference speed functions $u(t)$ for vehicles**



❖ Reference Speed Profile Generator

- **Find reference speed functions $u(t)$ for vehicles**
- **The collision-set coordination**

  →only one vehicle can occupy CA simultaneously

$$\boxed{\boxed{\left[t_1^{\mathrm{In}} \quad t_1^{\mathrm{Out}}\right]} \cap \boxed{\left[t_2^{\mathrm{In}} \quad t_2^{\mathrm{Out}}\right]} = \varnothing}$$

Occupation time of Vehicle 1 — Occupation time of Vehicle 2

- Find reference speed functions $u(t)$ for vehicles
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Reference Speed Profile Generator

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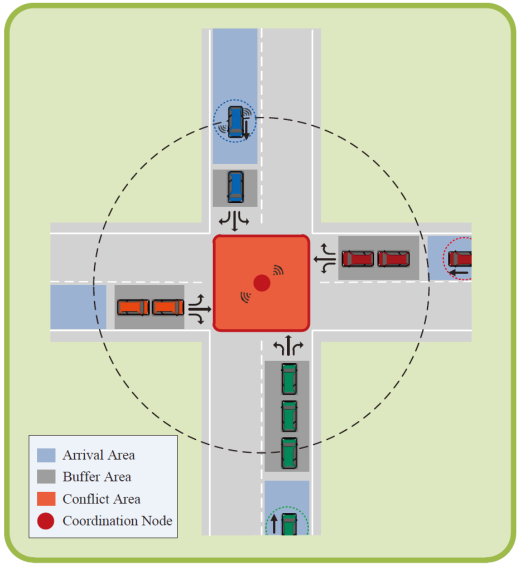
Two integer $\alpha, \beta \in \{0,1\}$

$$s_i^{\mathrm{Out}} - \boxed{\alpha_i} \times M \le u_i(t) \le s_i^{\mathrm{In}} + \boxed{\beta_i} \times M$$

$$\boxed{\alpha_{i_1} + \alpha_{i_2}} + \boxed{\beta_{i_1} + \beta_{i_2}} \le 3$$



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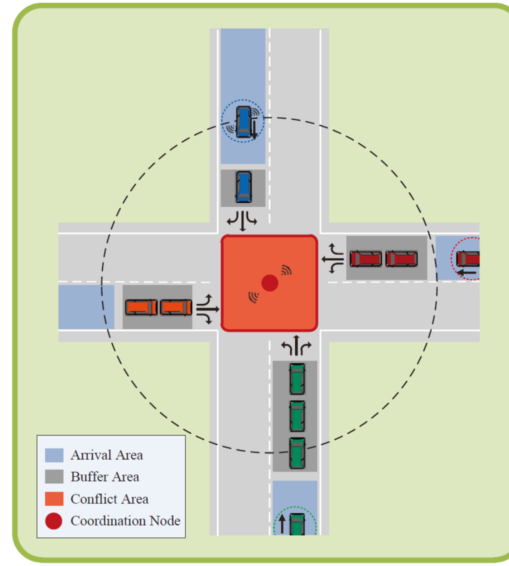
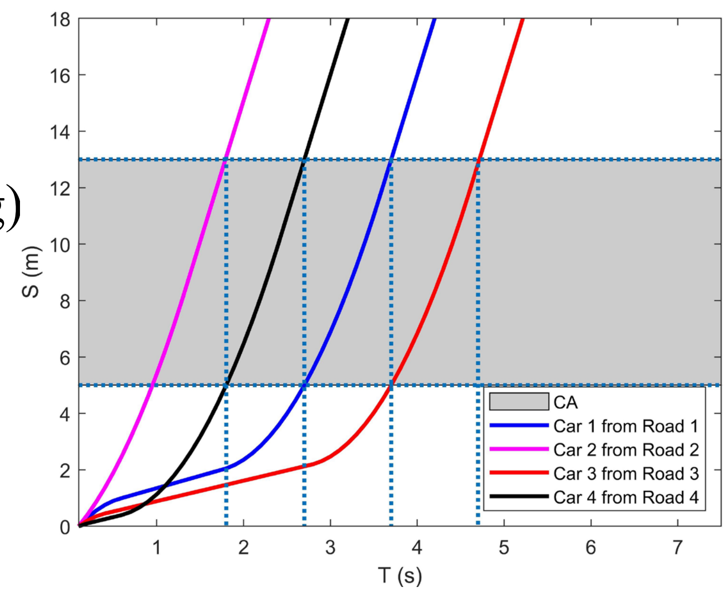
- **Optimization** (mixed integer programming)

Throughput $$C_{\mathrm{p,ref}}^{\mathrm{S}}(u) = w_{\mathrm{p}}^{\mathrm{S}} \int \left(u'(t) - \boxed{v_{\mathrm{eff}}}\right)^2 \mathrm{d}t$$

Smoothness $$C_{\mathrm{s,ref}}^{\mathrm{S}}(u) = \sum_{z=2}^{3} \left[w_{\mathrm{s},z}^{\mathrm{S}} \int \left(u^{(z)}\right)^2 (t)\mathrm{d}t \right]$$

Acceleration, jerk



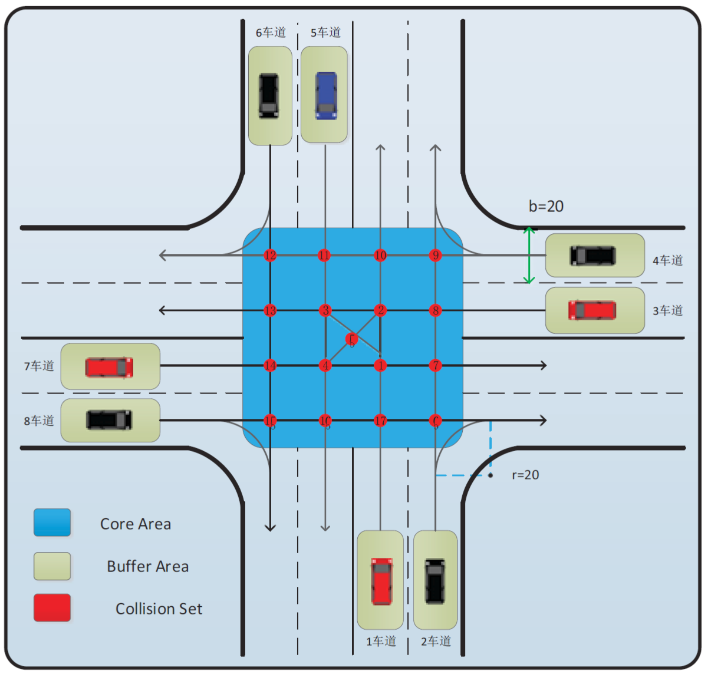


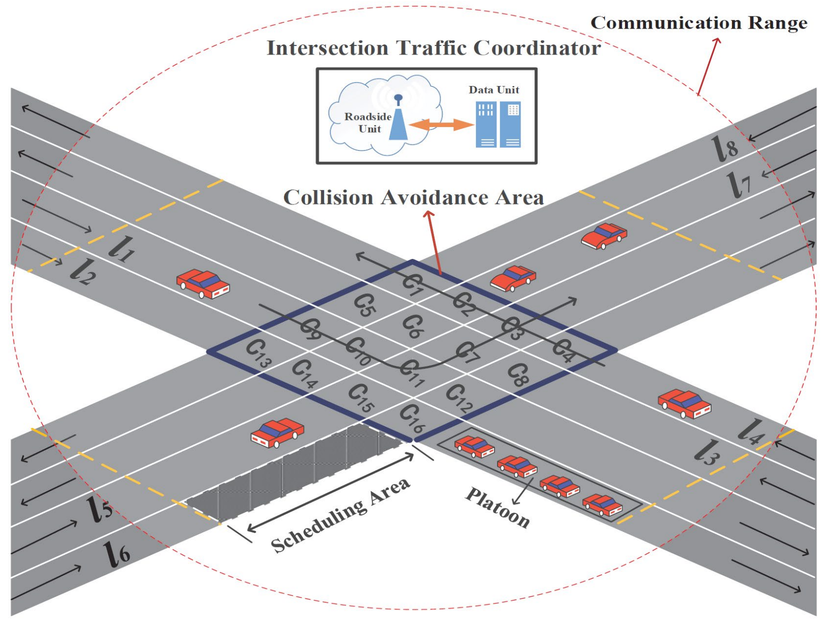
Reference Speed Profile Generator

- **Single-collision-set strategy**

❖ Reference Speed Profile Generator

- **Multi-collision-set strategy [6,7]**
  - based on the road structure
  - based on the number of roads and lanes





[6] C. Liu, Y. Mo, B. Gao and T. Zhang, "Low Complexity Coordination Strategies at Multi-Lane Intersections," 2019 IEEE Globecom Workshops (GC Wkshps), 2019, pp. 1-6.
[7] B. Qian, H. Zhou, F. Lyu, J. Li, T. Ma and F. Hou, "Toward Collision-Free and Efficient Coordination for Automated Vehicles at Unsignalized Intersection," in IEEE Internet of Things Journal, vol. 6, no. 6, pp. 10408-10420, Dec. 2019.

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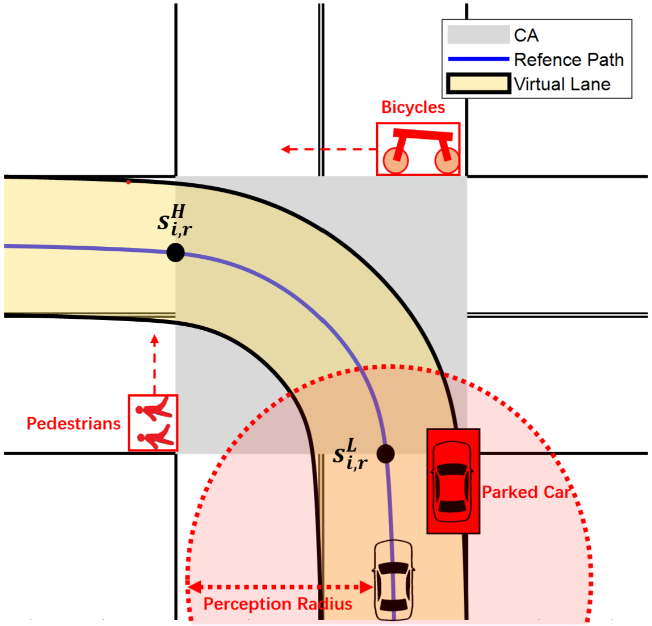
❖ Low-level Planner

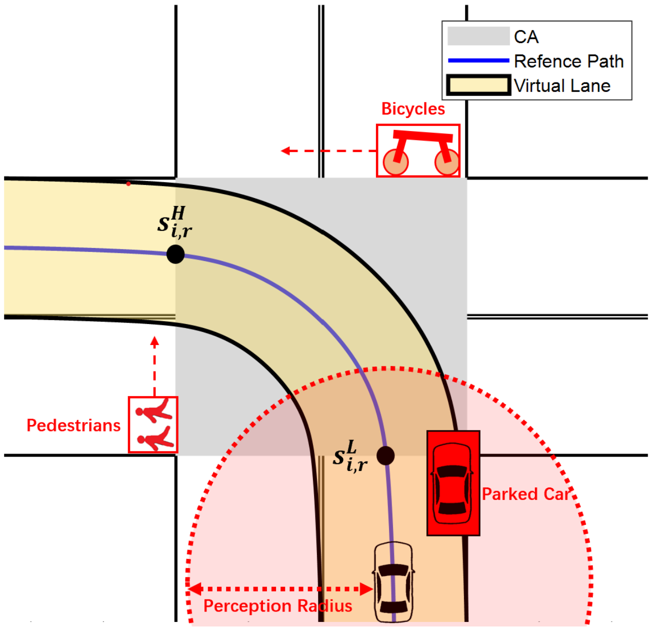
- **Consider various obstacles**

  -- pedestrians, bicycles, parked cars.



❖ Low-level Planner

- **Consider various obstacles**
  -- pedestrians, bicycles, parked cars.
- **Limited perception field**
  -- replanning iteratively
  (deal with the oncoming obstacles)



❖ Low-level Planner

- **Consider various obstacles**

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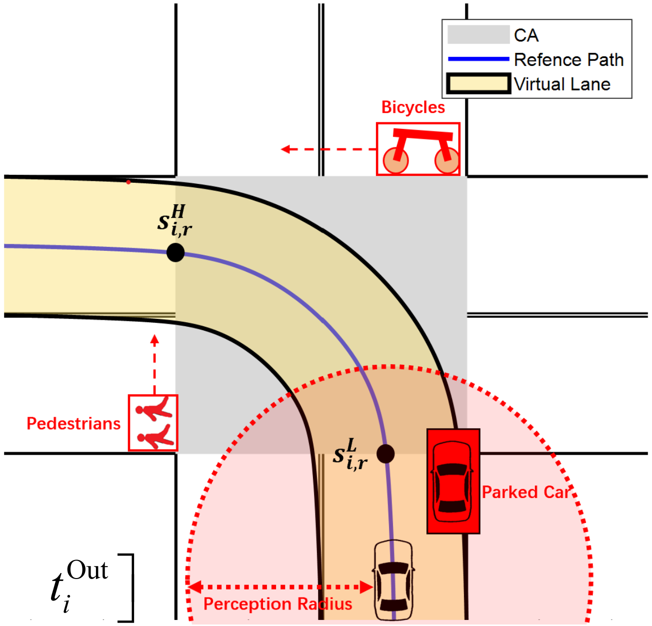
  (deal with the oncoming obstacles)
- **Follow instructions from high-level planner**

  -- path → within the virtual lane

  -- speed profile → within the time limitation $\left[t_i^{\text{In}} \quad t_i^{\text{Out}}\right]$



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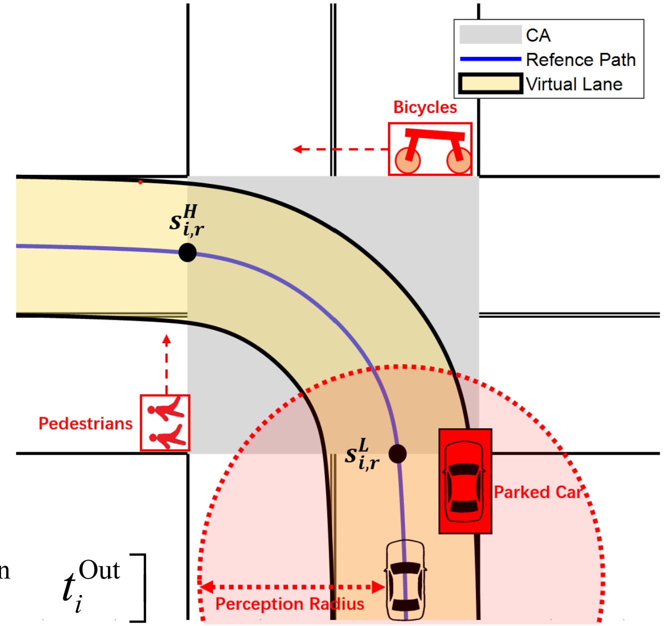
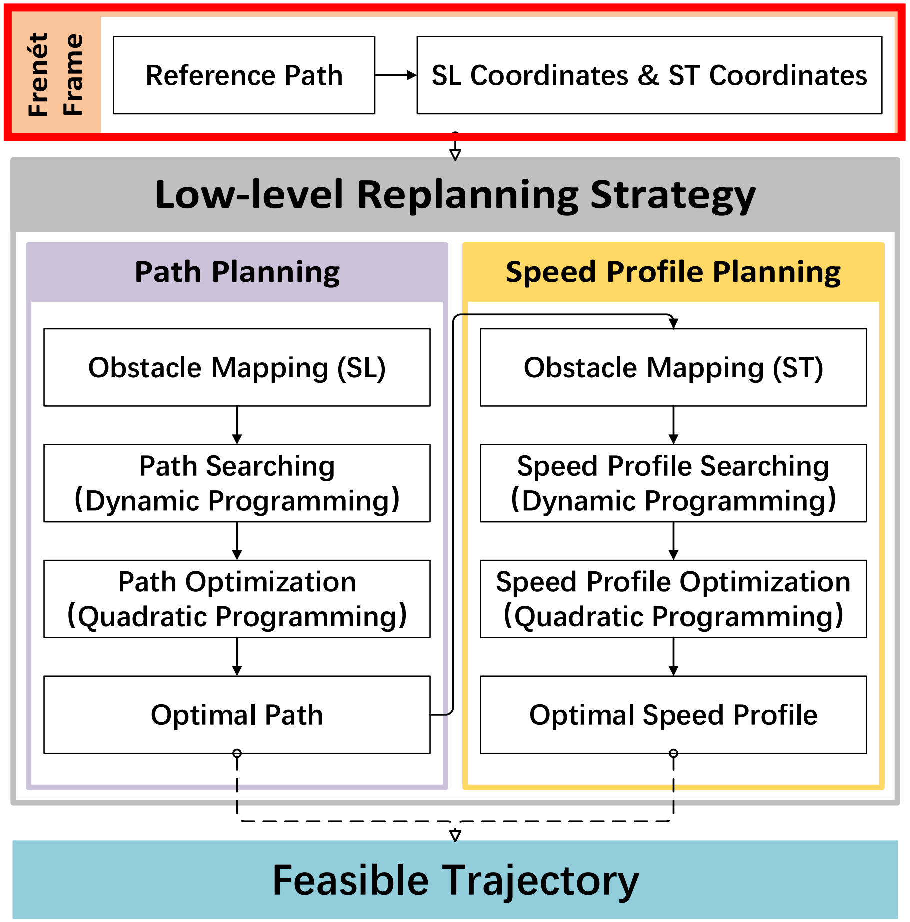


Impact	Path planning	Speed Profile Planning
smoothness	$C_{\mathrm{s}}^{\mathrm{P}} = \sum_{z=2}^{3} \left[w_z^{\mathrm{P}} \int \left(p^{(z)}\right)^2 (s) \mathrm{d}s \right]$	$C_{\mathrm{s}}^{\mathrm{S}} = \sum_{z=2}^{3} \left[w_z^{\mathrm{S}} \int \left(q^{(z)}\right)^2 (t) \mathrm{d}t \right]$
vehicle behavior	$C_{\mathrm{b}}^{\mathrm{P}} = w_4^{\mathrm{P}} \int p^2(s) \mathrm{d}s$	$C_{\mathrm{b}}^{\mathrm{S}} = w_4^{\mathrm{S}} \int \left(q(t) - u_{i,r}(t)\right)^2 \mathrm{d}t$
collision avoidance	$C_{\mathrm{c}}^{\mathrm{P}} = \sum_{j=1}^{N_{\mathrm{o}}} \begin{cases} \mathrm{Inf} & d_j^{\mathrm{s}} < d_{j,\min}^{\mathrm{s}} \ \& \ d_j^{\mathrm{l}} < d_{j,\min}^{\mathrm{l}} \\ 0 & else \end{cases}$	$C_{\mathrm{c}}^{\mathrm{S}} = \sum_{j=1}^{N_{\mathrm{o}}} \begin{cases} \mathrm{Inf} & d_j^{\mathrm{s}} < d_{j,\min}^{\mathrm{s}} \\ 0 & else \end{cases}$

compare with the reference trajectory

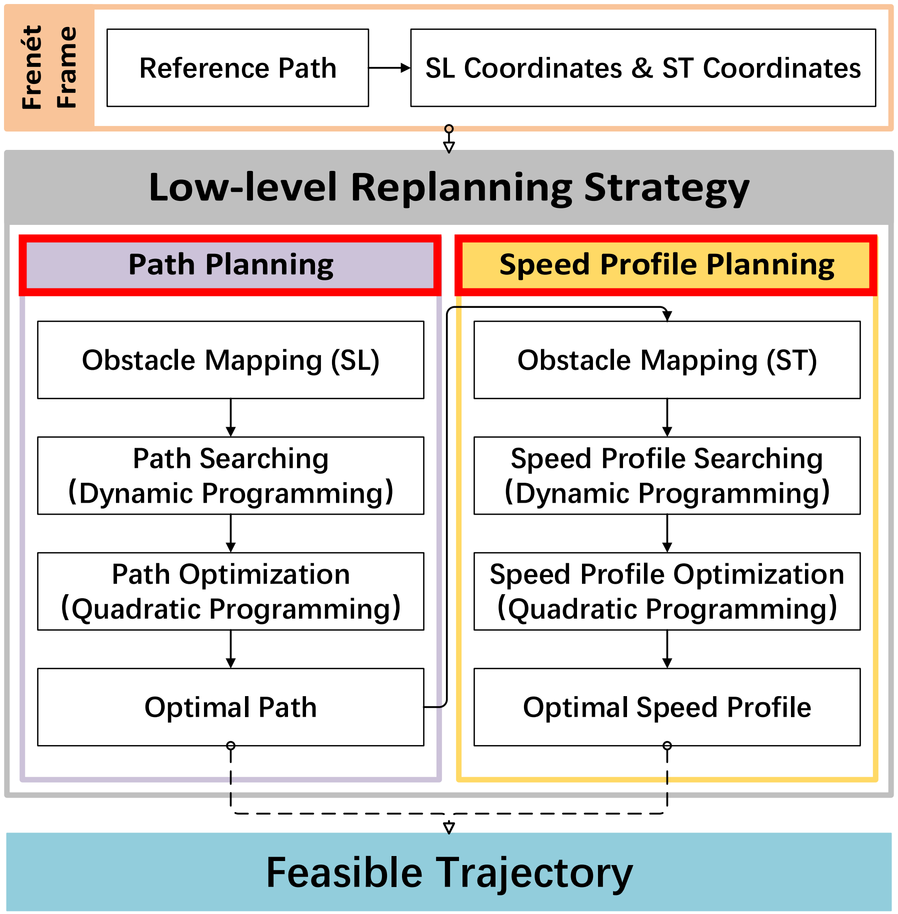
compare the distances and safe distances with obstacles

Low-level Planner [4][5]



- **Frenét Frame**
  - based on reference path

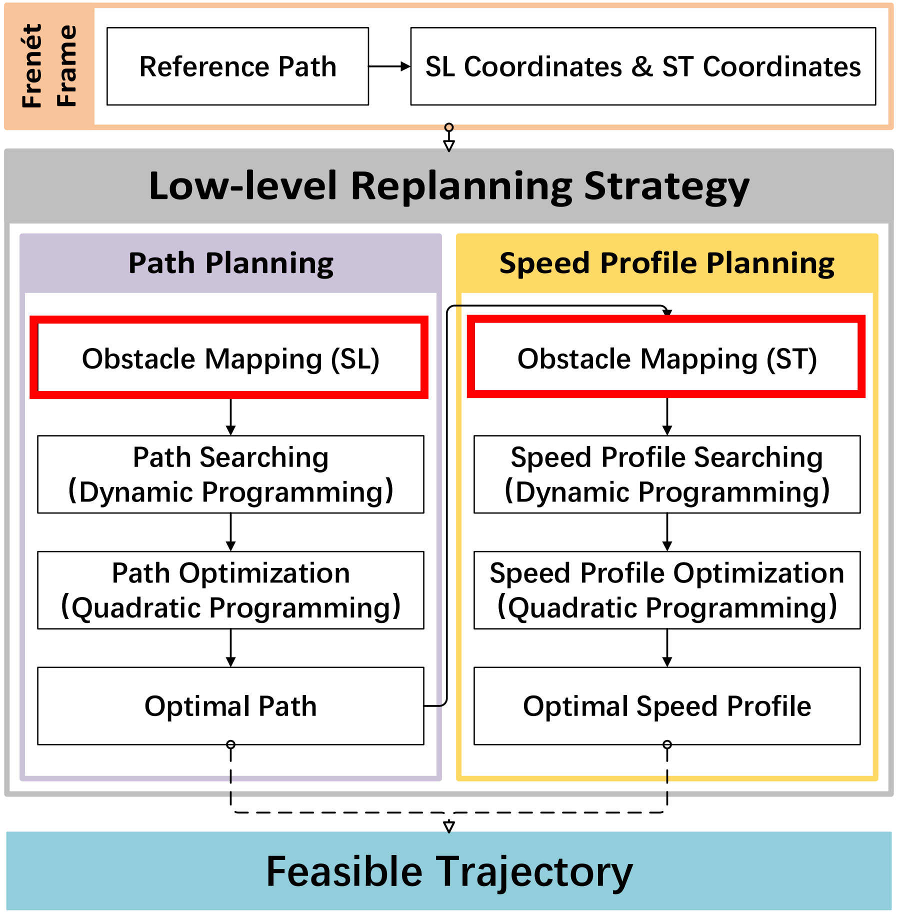
❖ Low-level Planner [4][5]



- **Frenét Frame**
  - based on reference path
- **Planning Strategy:**
  - Path-speed iterative algorithm [8]

[8] Wenda Xu, Junqing Wei, J. M. Dolan, Huijing Zhao, and Hongbin Zha, “A real-time motion planner with trajectory optimization for autonomous vehicles,” in 2012 IEEE International Conference on Robotics and Automation, 2012, pp. 2061–2067.

❖ Low-level Planner [4][5]



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  - Expectation Maximum (EM) [9]

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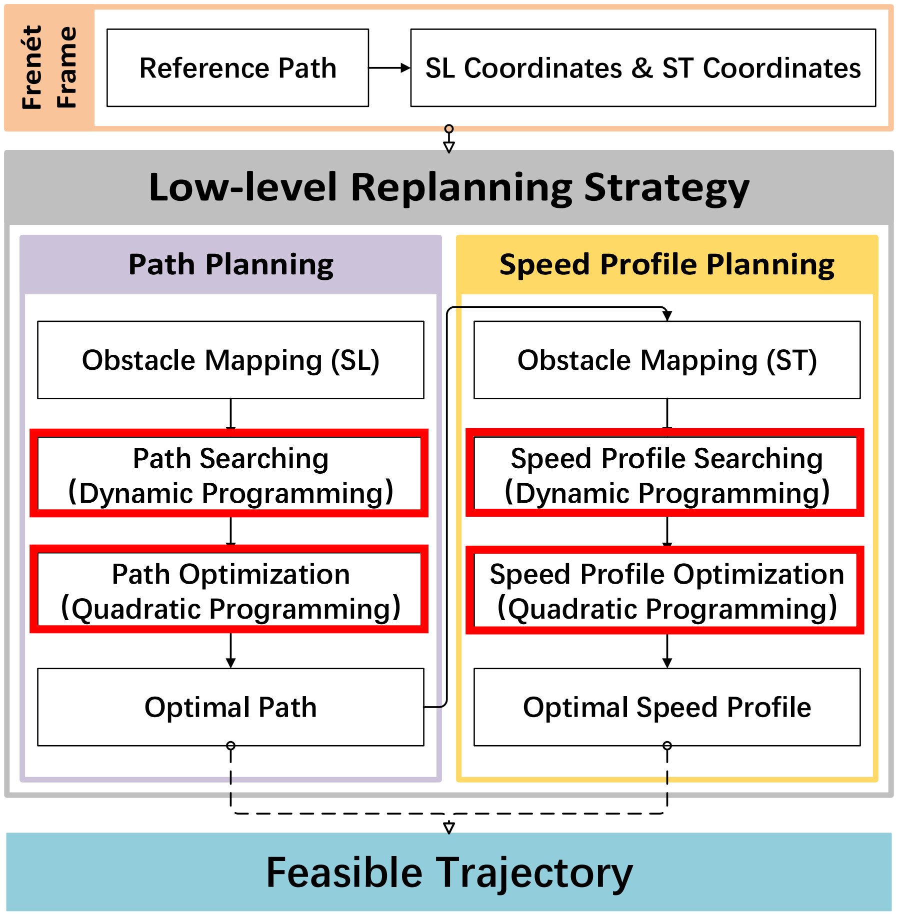
[9] H. Fan, F. Zhu, C. Liu, L. Zhang, L. Zhuang, D. Li, W. Zhu, J. Hu, H. Li, and Q. Kong, “Baidu apollo em motion planner,” arXiv:1807.08048, 2018.

❖ Low-level Planner [4][5]



- **Frenét Frame**
  - based on reference path
- **Planning Strategy:**
  - Path-speed iterative algorithm [8]
- **Obstacle Mapping:**
  - Expectation Maximum (EM) [9]
- **Solver:**
  - Dynamic Programming (DP) + Quadratic Programming (QP)

[8] Wenda Xu, Junqing Wei, J. M. Dolan, Huijing Zhao, and Hongbin Zha, “A real-time motion planner with trajectory optimization for autonomous vehicles,” in 2012 IEEE International Conference on Robotics and Automation, 2012, pp. 2061–2067.
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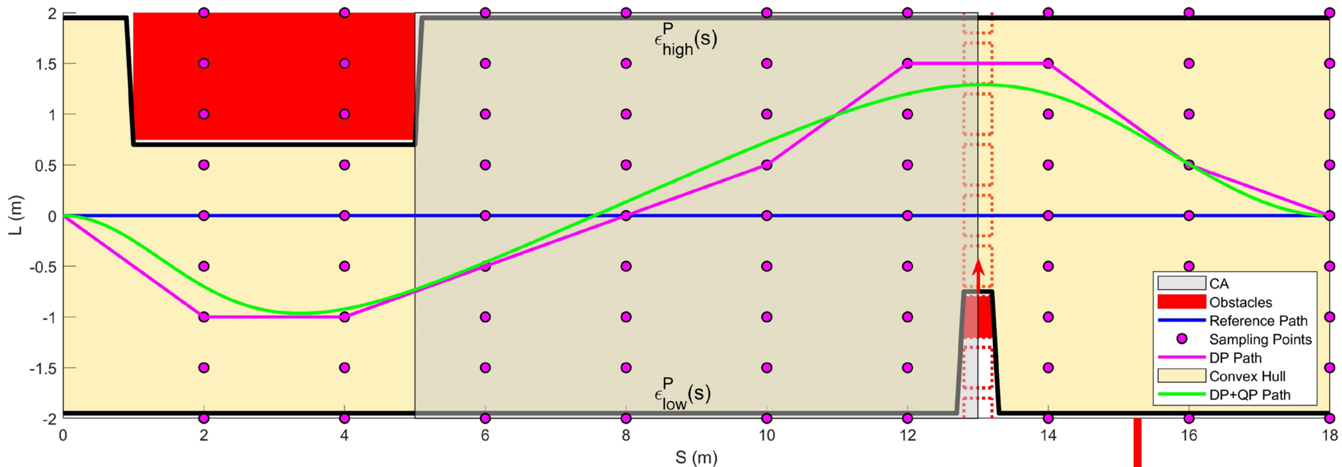
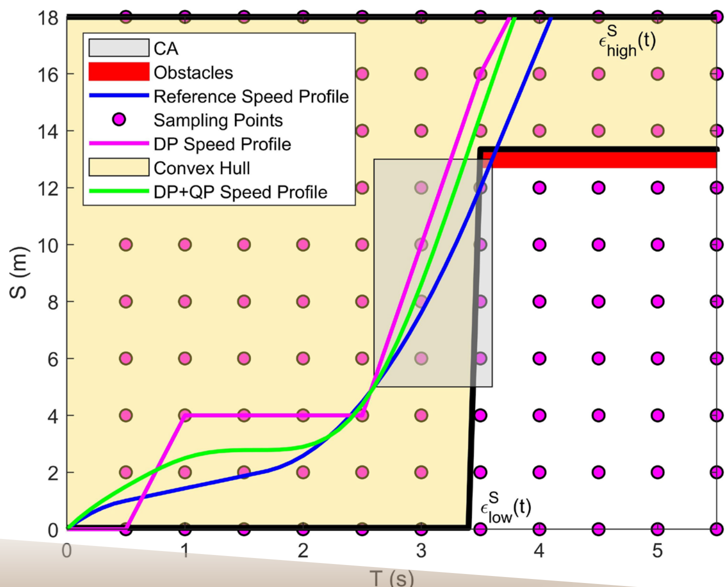
❖ Low-level Planner

Path Planning



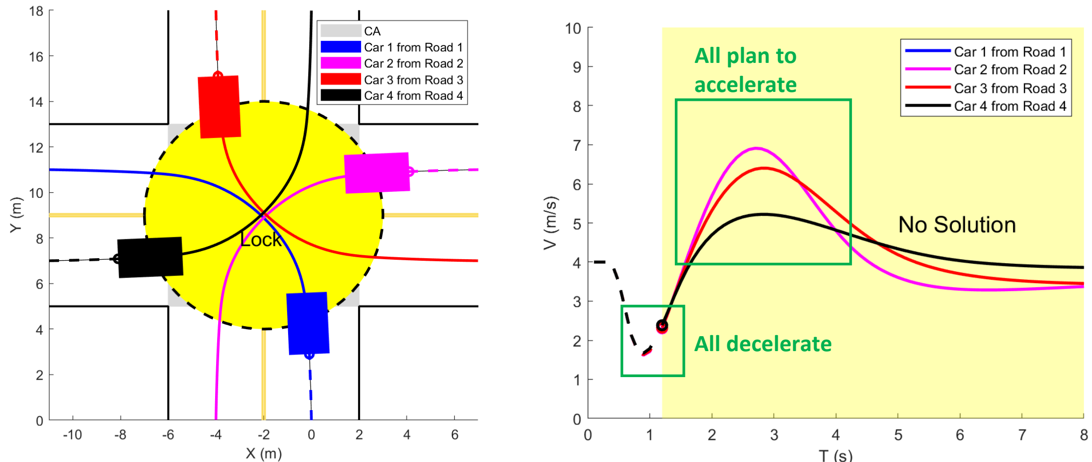
Speed Profile Planning



Within Feasible Regions

❖ Numerical Results for integrated framework

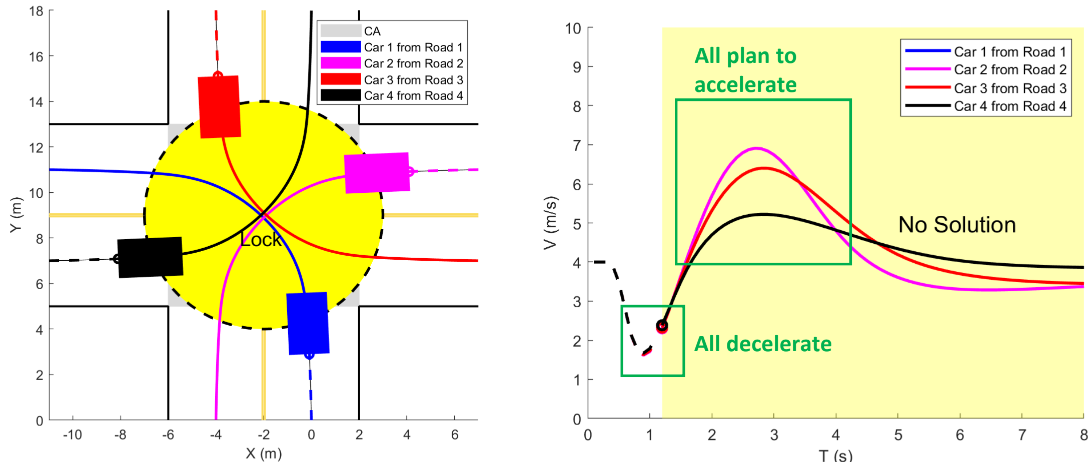
- **Avoid deadlocks**



Only use low-level planner

❖ Numerical Results for integrated framework

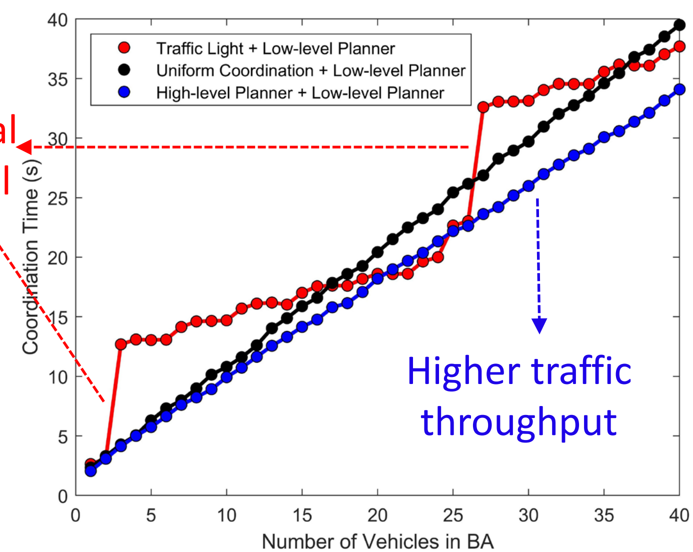
- **Avoid deadlocks**



Only use low-level planner

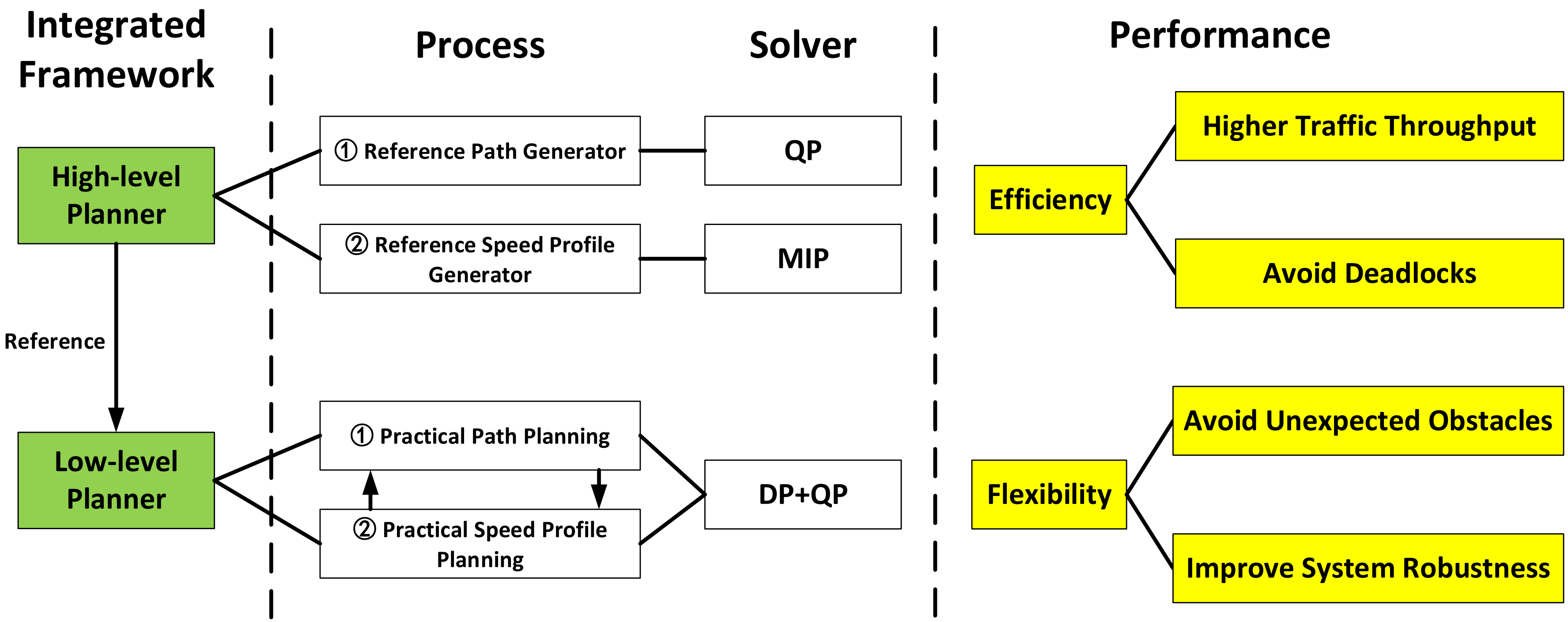
- **Traffic Throughput**
  - traffic lights + low-level planner
  - uniform coordination + low-level planner
  - high-level planner + low-level planner (proposed)

Change interval of traffic signal



OUTLINE:

Conclusion


Integrated Framework
Process
Solver
Performance
High-level Planner
① Reference Path Generator
QP
② Reference Speed Profile Generator
MIP
Reference
Low-level Planner
① Practical Path Planning
② Practical Speed Profile Planning
DP+QP
Efficiency
Higher Traffic Throughput
Avoid Deadlocks
Flexibility
Avoid Unexpected Obstacles
Improve System Robustness

Thanks for Listening