Game-theoretic Modelling of Integrated Longitudinal and Lateral Vehicle Maneuvers

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Research Overview

Objectives:

1. Model microscopic vehicle behaviour in a realistic manner.
2. Capture the decision-making logic of human drivers.
3. Jointly considering car-following and lane-changing maneuvers.
4. Focus on discretionary lane change only.

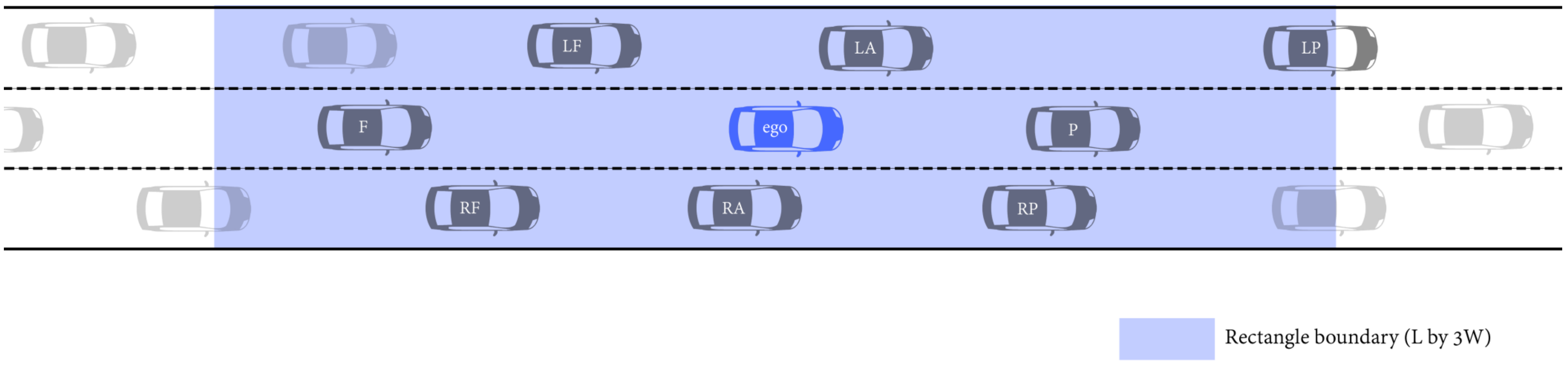
Research Overview

Assumptions:

1. Rationality: Drivers are rational.
2. Predictability: Drivers can foresee a short time interval into the future and will use this prediction to make optimal decisions.
3. Heterogeneity: Each human driver has his/her own preference on the weighting of their costs.

Identify Game Opponents

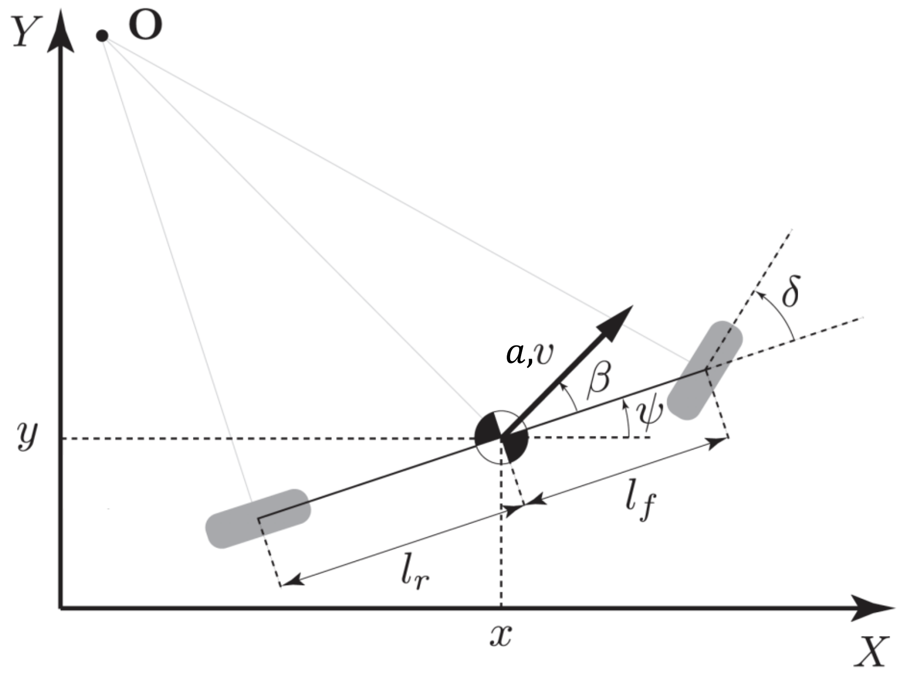
- A set of N players
- At most 8 players can be identified



System Dynamics

Kinematic Bicycle Model:

- States: x-position, y-position, velocity, heading ($\mathbf{z} = [x, y, v, \psi]$)
- Controls: acceleration, steering angle ($\mathbf{u} = [a, \delta]$)
- State dynamics based on $\mathbf{z}(k+1) = \boldsymbol{f}\big(\mathbf{z}(k), \mathbf{u}(k)\big) + \mathbf{z}(k)$



Receding Horizon Cost Optimization

The optimal control $\mathbf{u}^*$ is derived such that the cost function J is minimized during the planning period $[t_0, t_f)$ subject to the state dynamics and the initial condition.

$$\mathbf{u}^*_{[t_0,t_f)} = \arg\min_{\mathbf{u}} J(\mathbf{z}, \mathbf{u}, t|\mathbf{z}(t_0))$$

$$J(\mathbf{z}, \mathbf{u}, t|\mathbf{z}(t_0)) = \sum_{t=t_0}^{t_f} \eta^{t-t_0} \mathcal{L}(\mathbf{z}(t), \mathbf{u}(t), t)$$

The running cost $\mathcal{L}$:

$$\mathcal{L}(\mathbf{z}, \mathbf{u}, t) = \sum_k \alpha_k \mathcal{L}_k(\mathbf{z}, \mathbf{u}, t)$$

Cost Function – Speed

The car following behaviour is modelled according to the Intelligent driving model (IDM). The cost function then minimizes the discrepancy between the actual speed and the equilibrium speed.

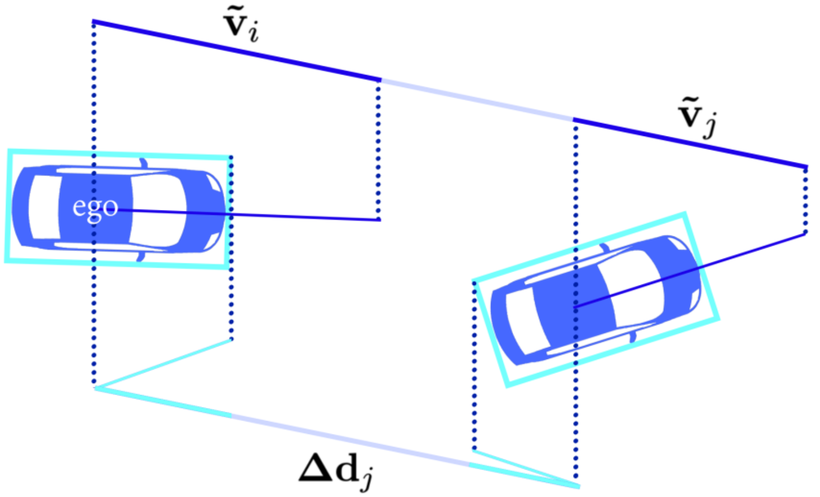
$$\mathcal{L}_{speed} = (v_{\text{eq}} - v_i)^2$$

$$v_{\text{eq}} = \min\left\{v_d, \frac{s - s_0}{T}\right\}$$

Cost Function – Safety

The safety cost is applied to all surrounding opponents in the set N which penalizes low time to collision (TTC) between the vehicles.

$$\mathcal{L}_{safety} = \sum_{j \in N} \exp\left(-TTC_j\right)$$



Cost Function – Comfort

To optimize comfort, we penalize excessive control inputs.

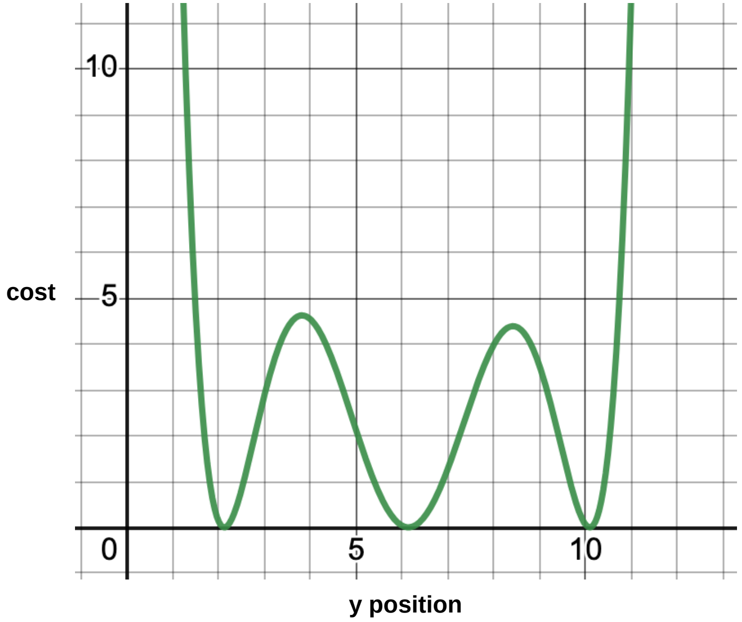
$$\mathcal{L}_{acceleration} = a_i^2$$

$$\mathcal{L}_{steering} = \delta_i^2$$

Cost Function – Centring

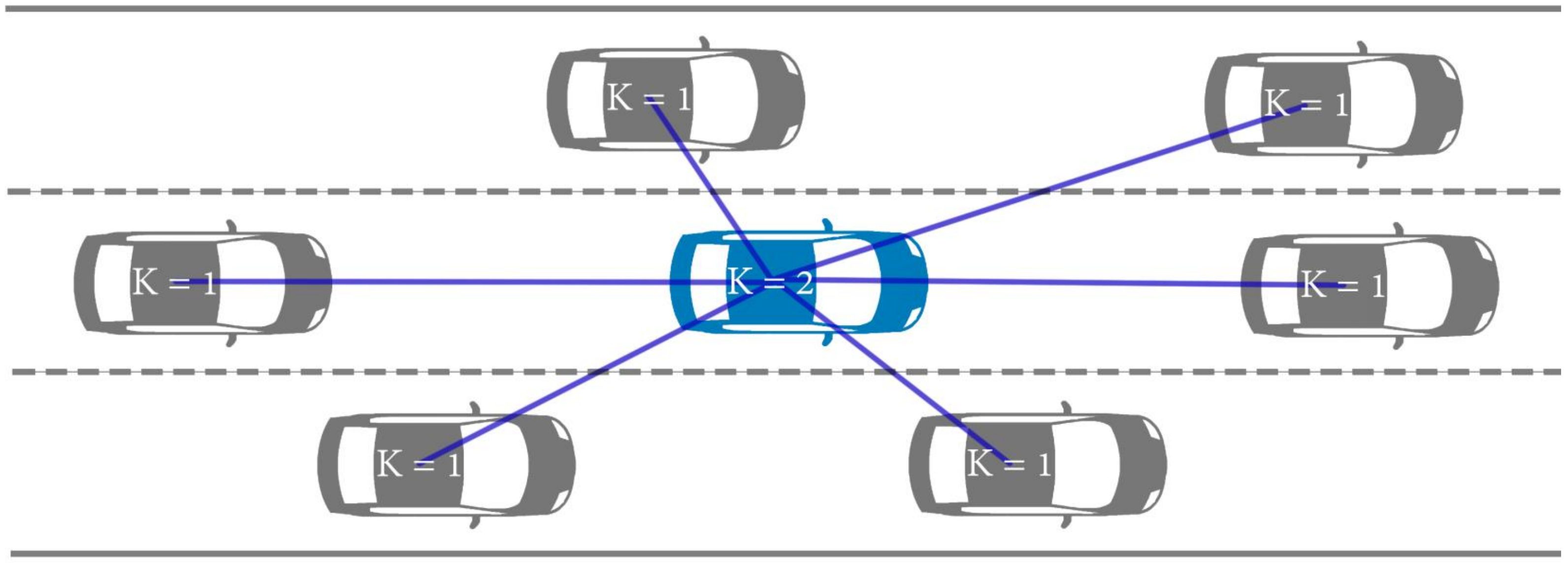
The centring cost penalizes the vehicle if it deviates from the centre of the lane in which it is classified to be in. It can be thought of as a lane keeping cost.

$$\mathcal{L}_{centre} = \prod_{c \in L} \frac{(y_i - c)^2}{c}$$



Level-K Game Theory

- Complete information level-k game.
- Vehicle with level K assumes all its opponents have levels K-1 and will act accordingly.



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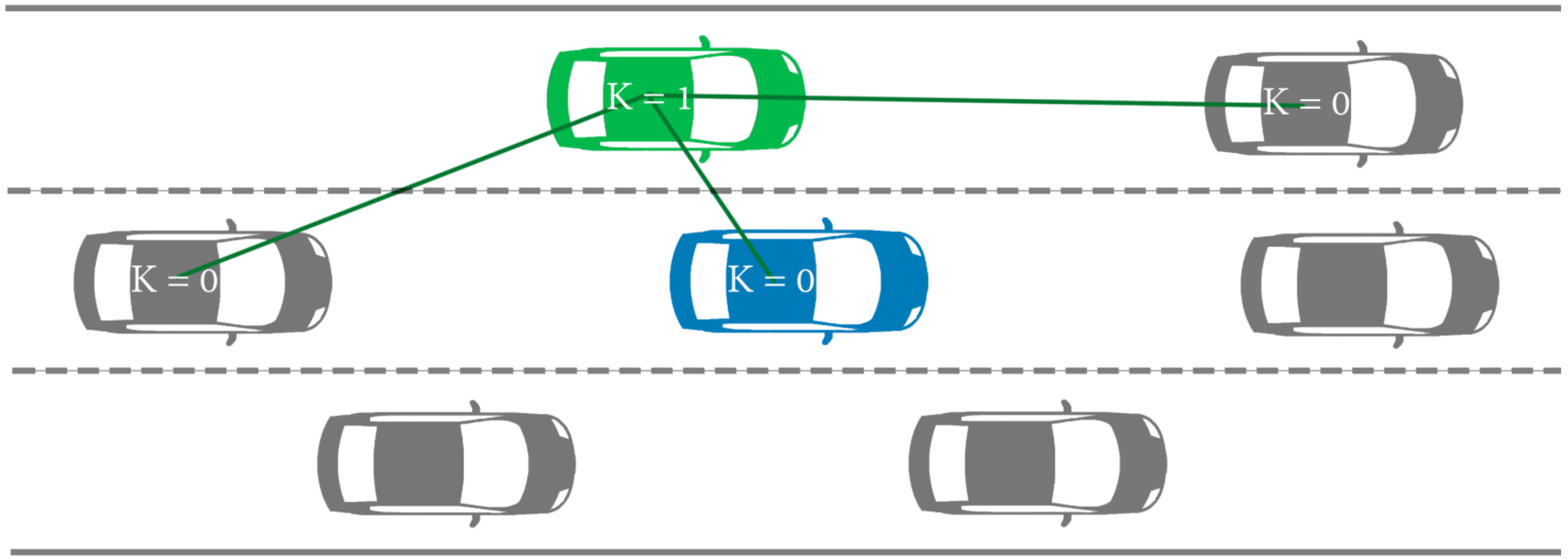


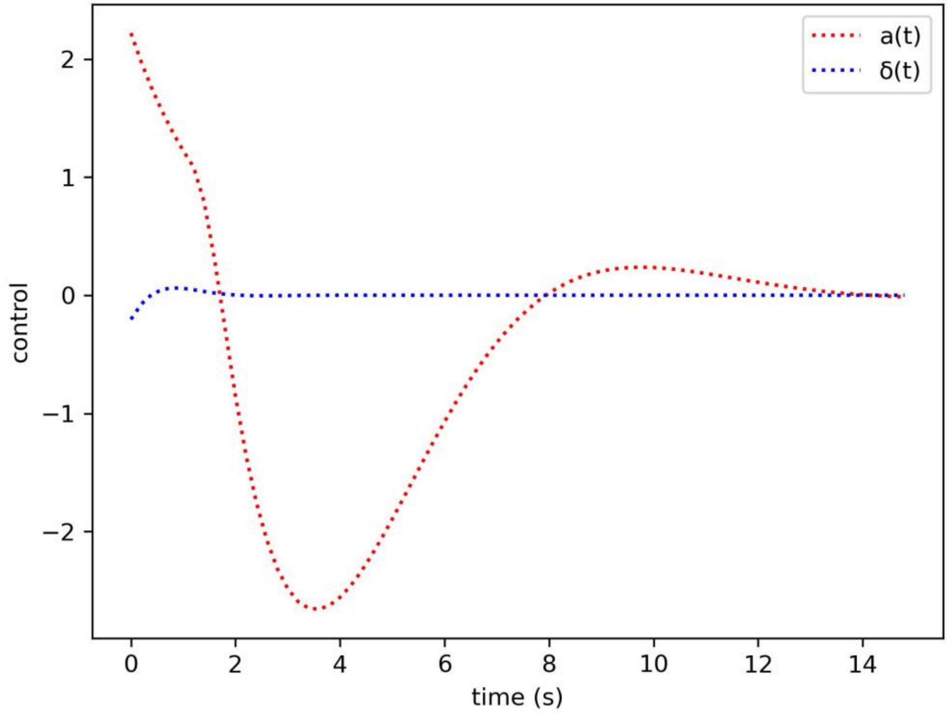
Test scenario – 1 lane

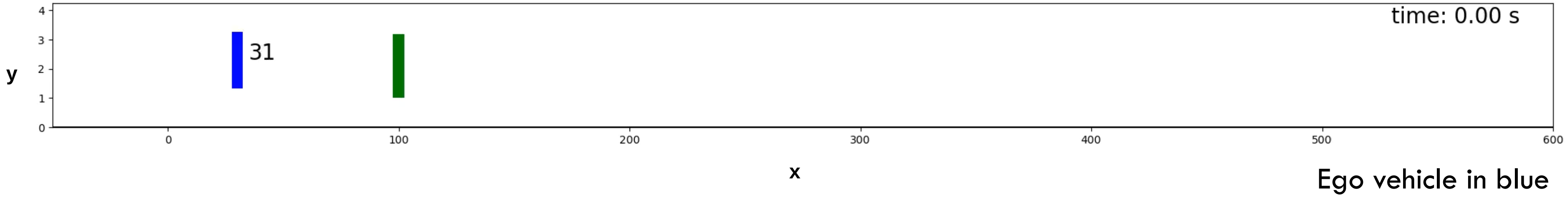
- Global optimization
- 0.2 s interval, 15 s duration
- 5 step prediction horizon, 1 step control horizon
- Computation time: 1.02 s

- Discount factor: 1
- Desired speed: 35 m/s
- Ego vehicle weights:

Speed	Safety	acceleration	steering	Lane centre
0.1	0.3	0.006	0.001	0.01

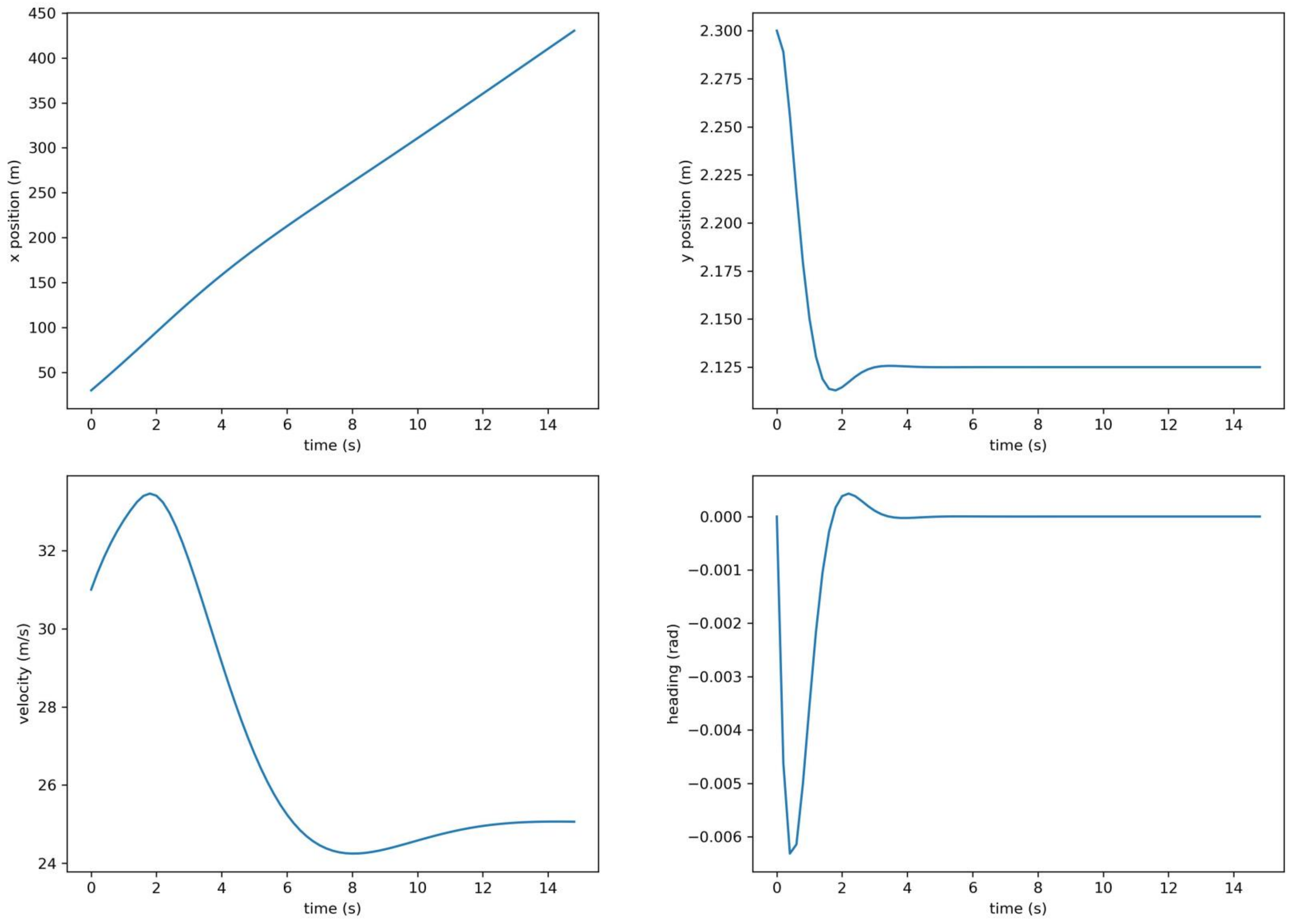
Test scenario – 1 lane





Ego vehicle in blue

Test scenario – 1 lane



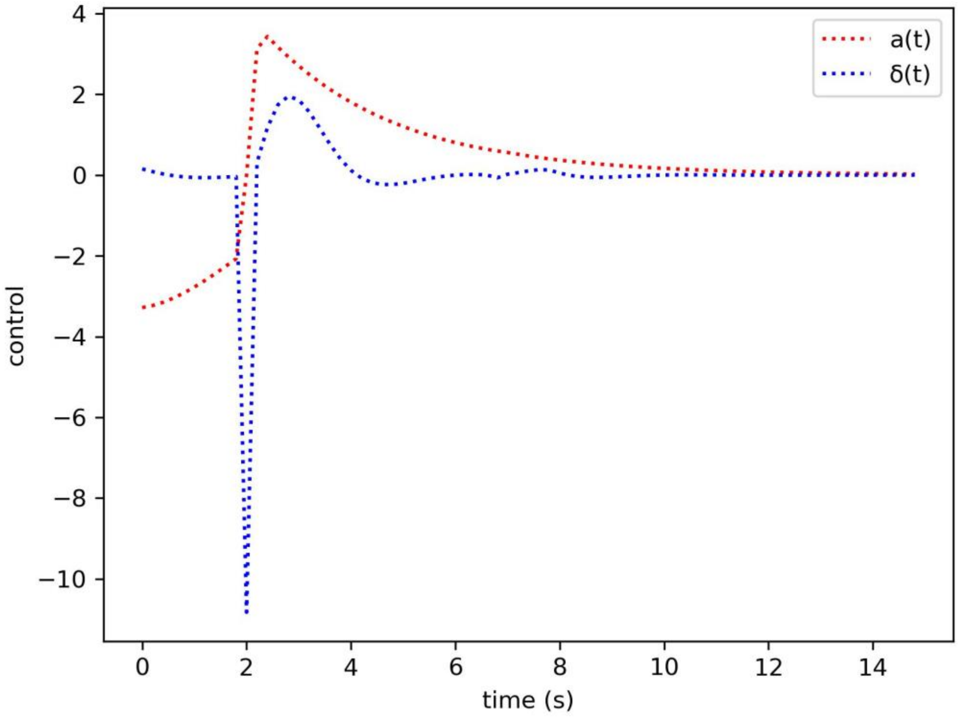
Test scenario – 2 lanes

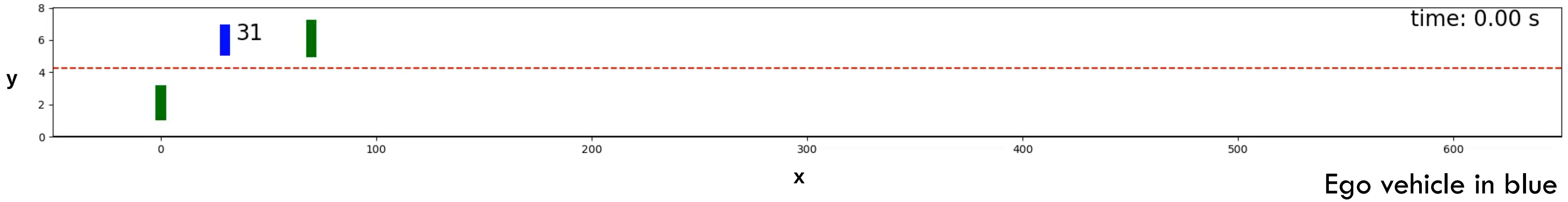
- Global optimization
- 0.2 interval, 15 second duration
- 5 step prediction horizon, 1 step control horizon
- Computation time: 1.35 s

- Discount factor: 1
- Desired speed: 35 m/s
- Ego vehicle weights:

Speed	Safety	acceleration	steering	Lane centre
0.06	0.1	0.06	0.01	0.05

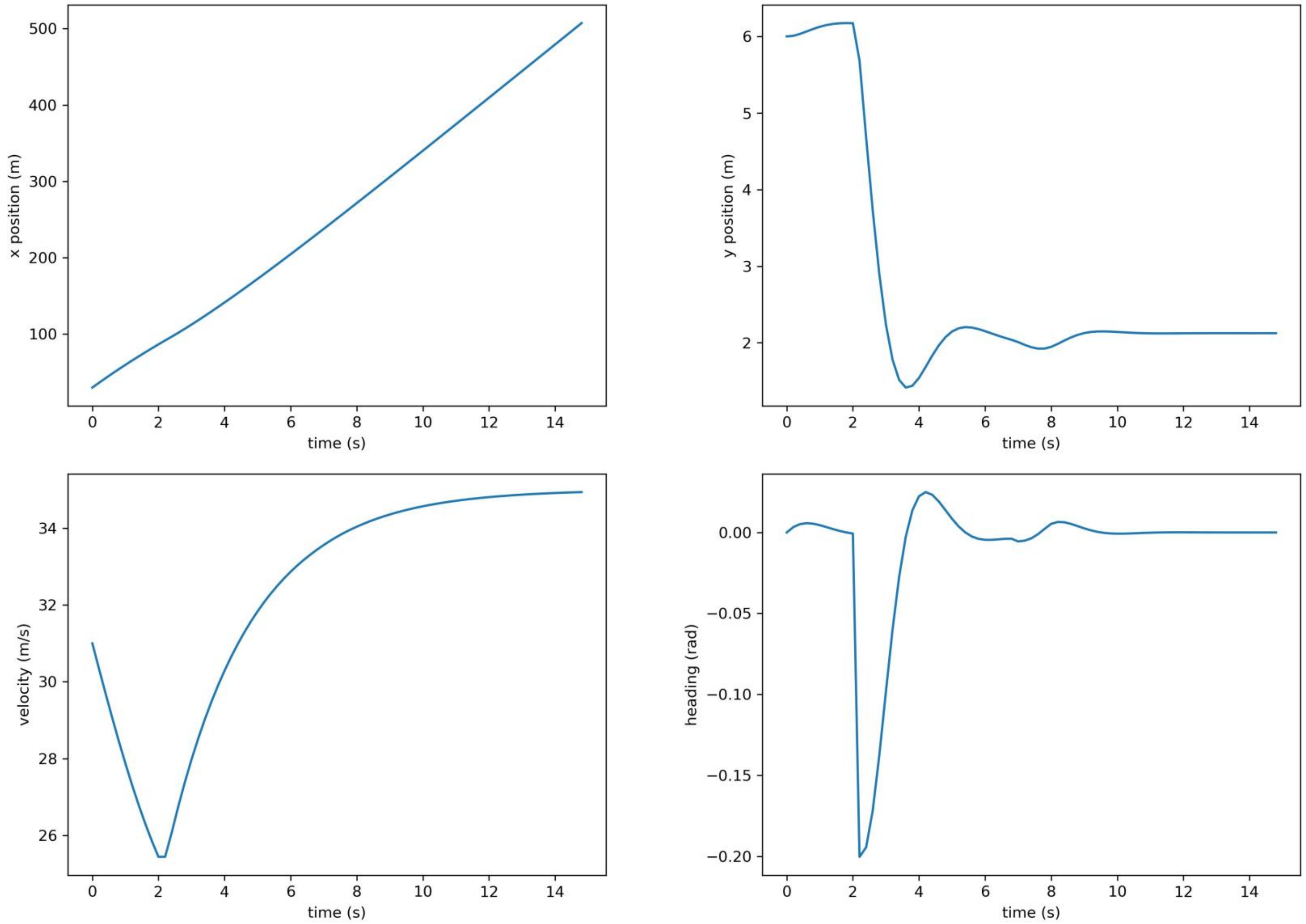
Test scenario – 2 lanes





Ego vehicle in blue

Test scenario – 2 lanes



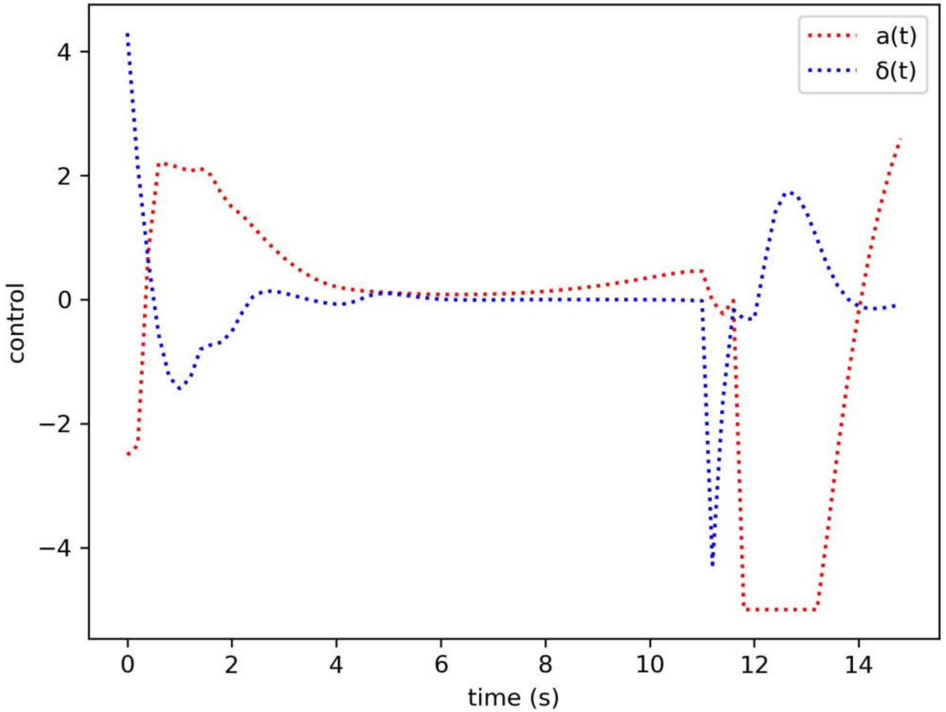
Test scenario – 3 lanes

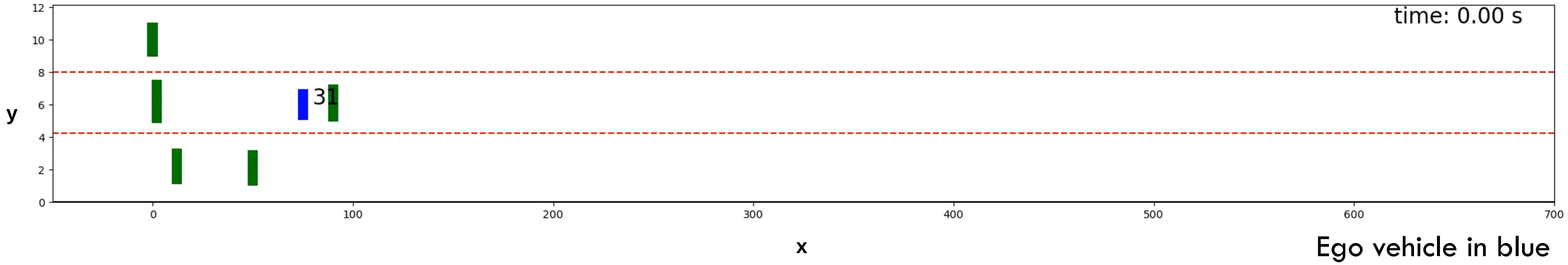
- Global optimization
- 0.2 interval, 15 second duration
- 5 step prediction horizon, 1 step control horizon
- Computation time: 6.00 s

- Discount factor: 1
- Desired speed: 35 m/s
- Ego vehicle weights:

Speed	Safety	acceleration	steering	Lane centre
0.01	0.3	0.006	0.001	0.006

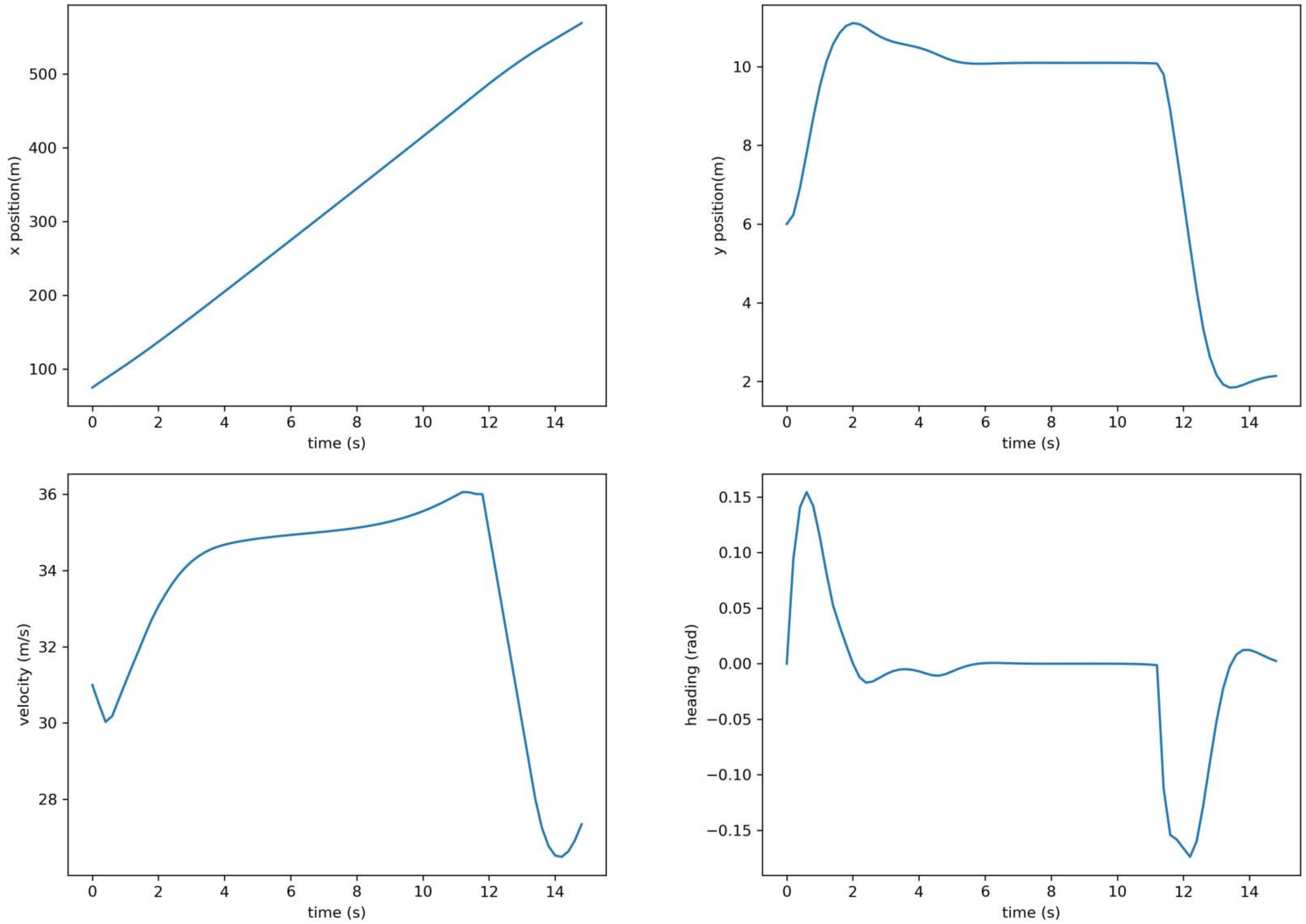
Test scenario – 3 lanes





Ego vehicle in blue

Test scenario – 3 lanes



Model Calibration

HighD dataset:

- Vehicle trajectory over a highway segment (~400m)
- Vehicle data (x, y, vx, vy, ax, ay) at 25hz

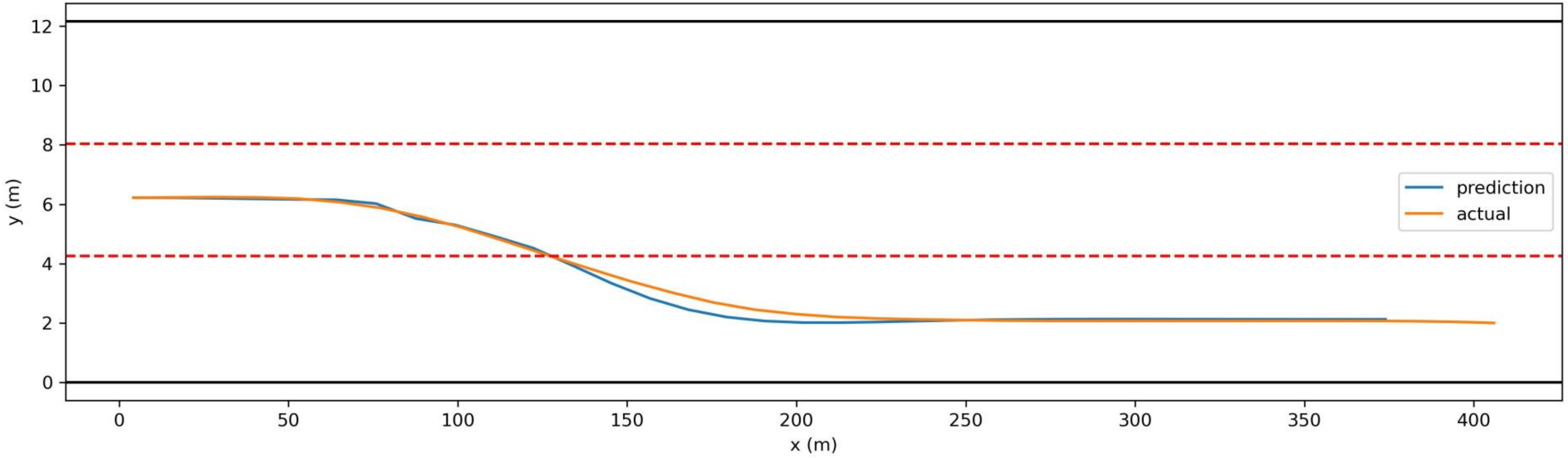
Input: consecutive states [x(t), y(t), v(t), psi(t)] & [x(t+1), y(t+1), v(t+1), psi(t+1)]

Output: parameters of the cost function $[\eta, v_d, \boldsymbol{\alpha}]$

Model Calibration

Optimization algorithm: differential evolution

Similarity measure: Fréchet distance



Trajectory 1422 from the HighD 50_tracks

Conclusion

Significance:

- We hope to understand driver preferences.
- The framework we propose improves existing microscopic models by taking into account interactions between vehicles.

Future study:

- We want to use the calibrated model as a testbed for designing optimal controller for AVs.

Thank you! Questions?

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