Safety-driven Interactive Planning for Neural Network-based Lane Changing

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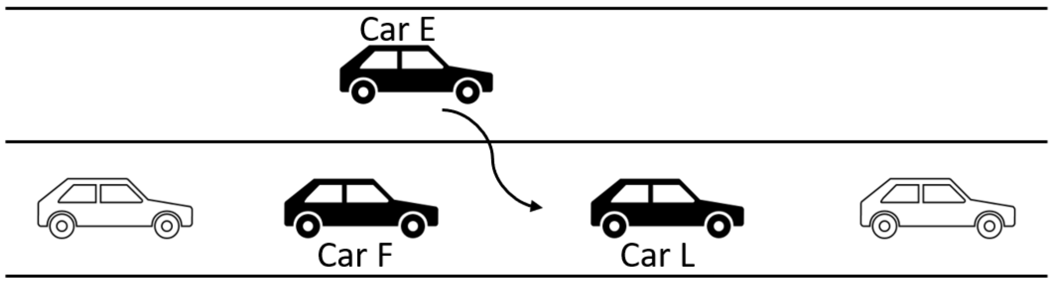
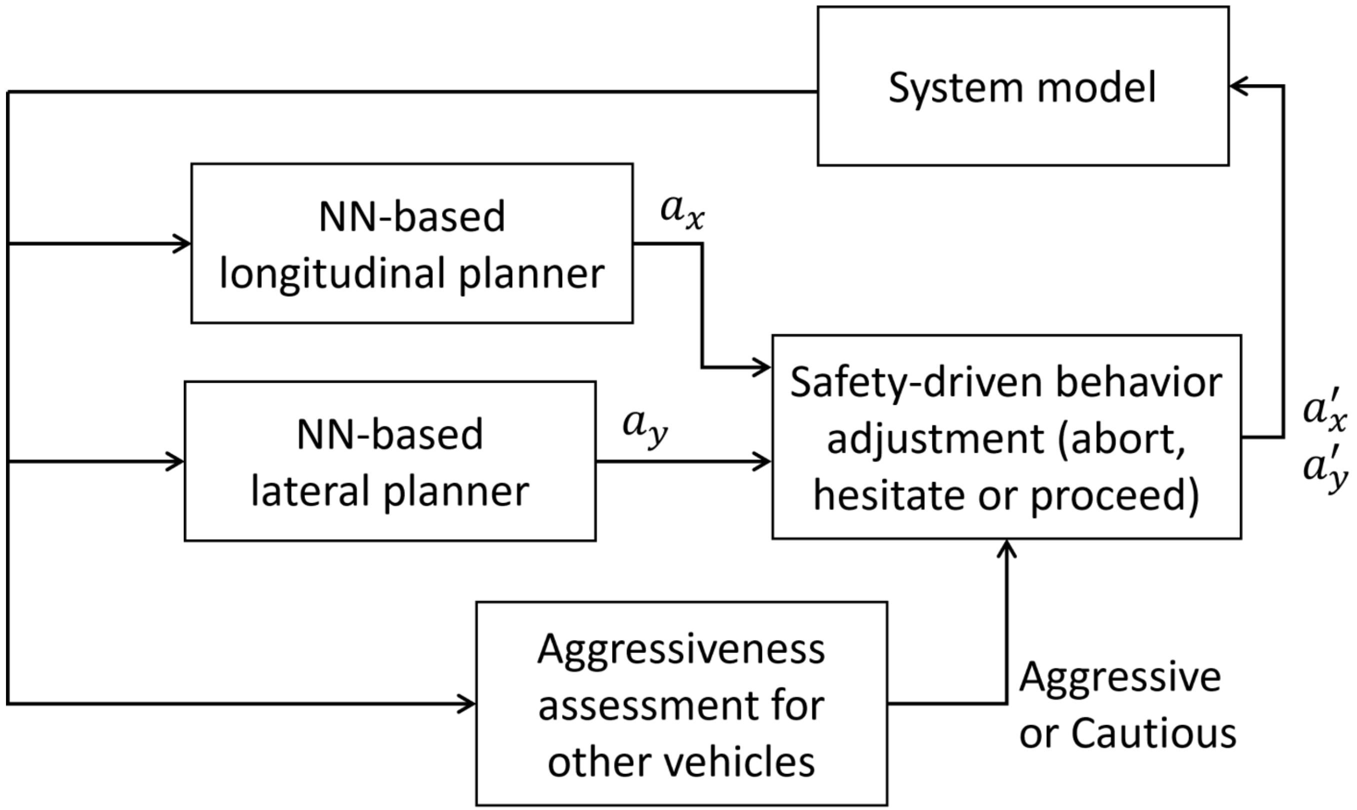
Motivation and Goal

- Challenging interactive task
  - Lane changing in dense traffic
  - Safety-efficiency dilemma
  - Transition period with mixed traffic
- Neural network-based planner
  - Improve performance
  - Save effort for system modeling
  - Challenges in ensuring safety
- Goal: prevent over-conservative planning, while ensure safety



Safety-driven Interactive Planning Framework

- Neural network-based planners for longitudinal and lateral motion planning
- Neural network to assess the aggressiveness of the following vehicle F
- Safety analysis and behavior adjustment



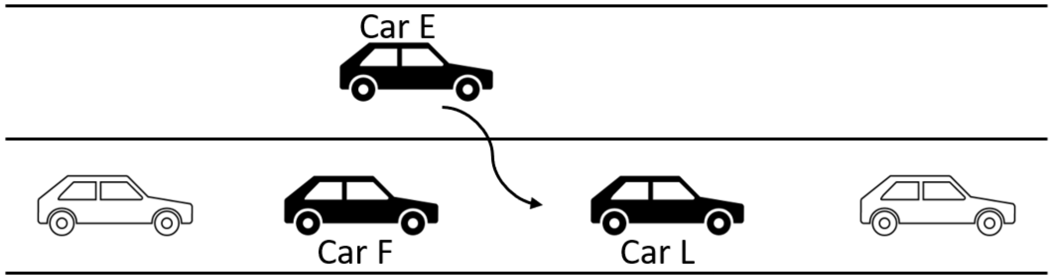
Longitudinal and Lateral Planners

- Supervised learning with synthesized dataset
- More comprehensive datasets can improve the system performance, while safety is always ensured by other components in the framework

notation	definition
inputs	
p_x	longitudinal position of the ego vehicle
p_y	lateral position of the ego vehicle
v_x	longitudinal velocity of the ego vehicle
v_y	lateral velocity of the ego vehicle
$p_{x,l}$	longitudinal position of the leading vehicle L
$v_{x,l}$	longitudinal velocity of the leading vehicle L
$p_{x,f}$	longitudinal position of the following vehicle L
$v_{x,f}$	longitudinal velocity of the following vehicle L
outputs	
a_x	longitudinal acceleration of the ego vehicle
a_y	lateral acceleration of the ego vehicle

Aggressiveness Assessment and Behavior Prediction

- Assumption: the following vehicle F follows the ego vehicle E when it is cautious and follows the leading vehicle L when it is aggressive [1].
- Let a_1 and a_0 denote the predicted accelerations when it is cautious or aggressive, respectively.
- The following vehicle's behavior is predicted by comparing its true acceleration $a^*_{x,f}$ with the predicted a_1 and a_0.

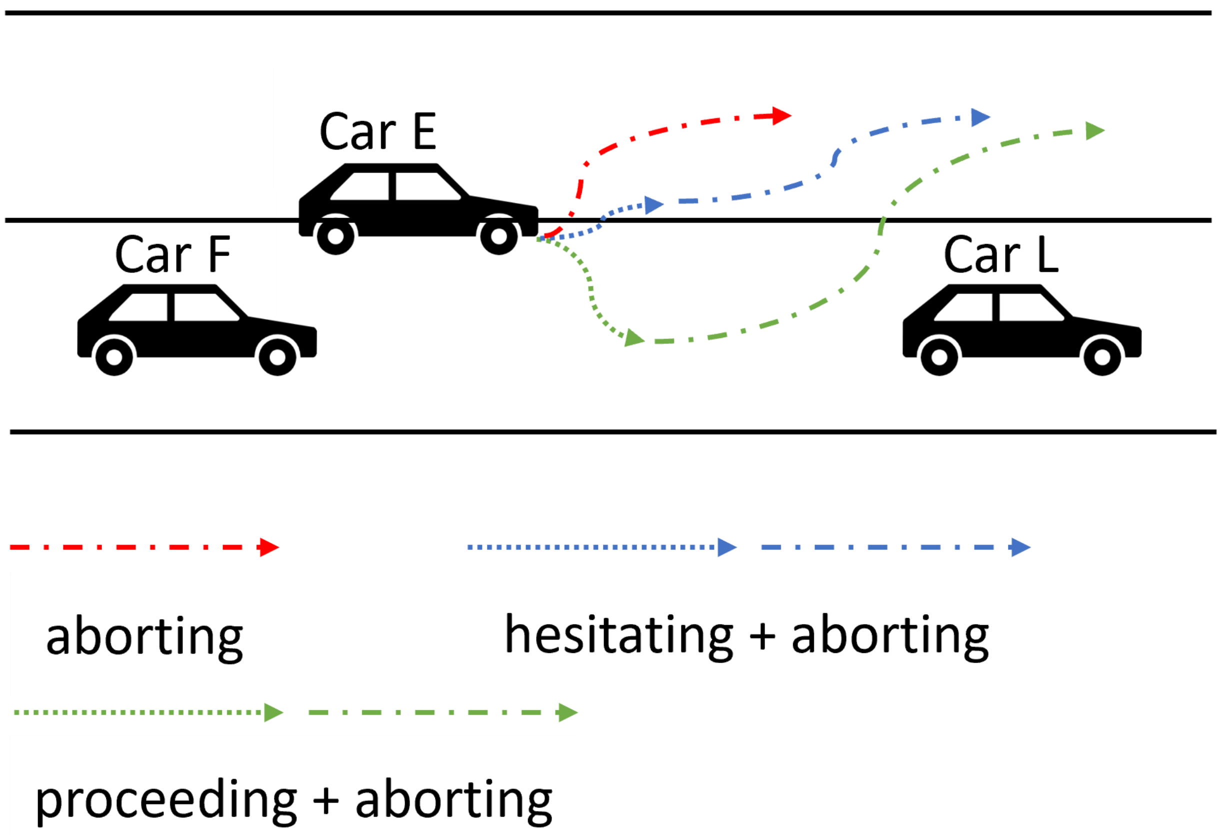


$$\begin{cases} |a^*_{x,f} - a_1| < |a^*_{x,f} - a_0| - a_{th} \rightarrow \text{vehicle } F \text{ is cautious} \\ |a^*_{x,f} - a_0| < |a^*_{x,f} - a_1| - a_{th} \rightarrow \text{vehicle } F \text{ is aggressive} \\ -a_{th} \leq |a^*_{x,f} - a_0| - |a^*_{x,f} - a_1| \leq a_{th} \rightarrow \text{uncertain} \end{cases}$$

[1] Jinning Li, Liting Sun, Wei Zhan, and Masayoshi Tomizuka. 2020. Interaction aware behavior planning for autonomous vehicles validated with real traffic data. In Dynamic Systems and Control Conference, Vol. 84287. American Society of Mechanical Engineers, V002T31A005.

Safety Analysis and Motion Adjustment

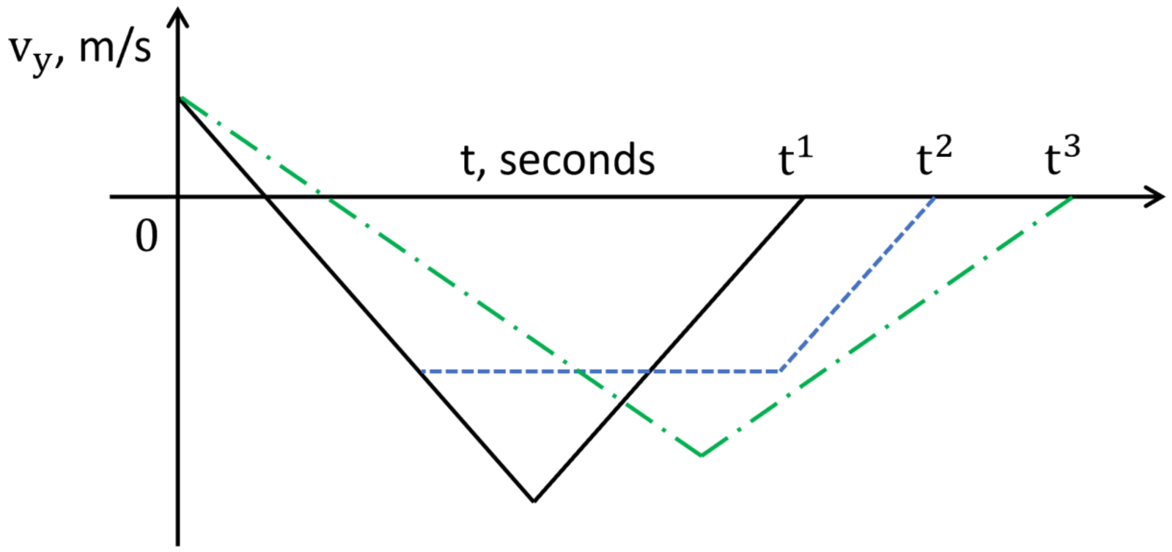
- Three strategy choices with decreasing preference
  - Proceed to change lanes
  - Hesitate around the current lateral position
  - Abort the lane changing and return back to the original lane
- Ensure safety with pre-computed safe evasion trajectory



Safe Evasion Trajectory (Lateral Motion)

- Safe evasion trajectory is pre-computed and updated periodically.

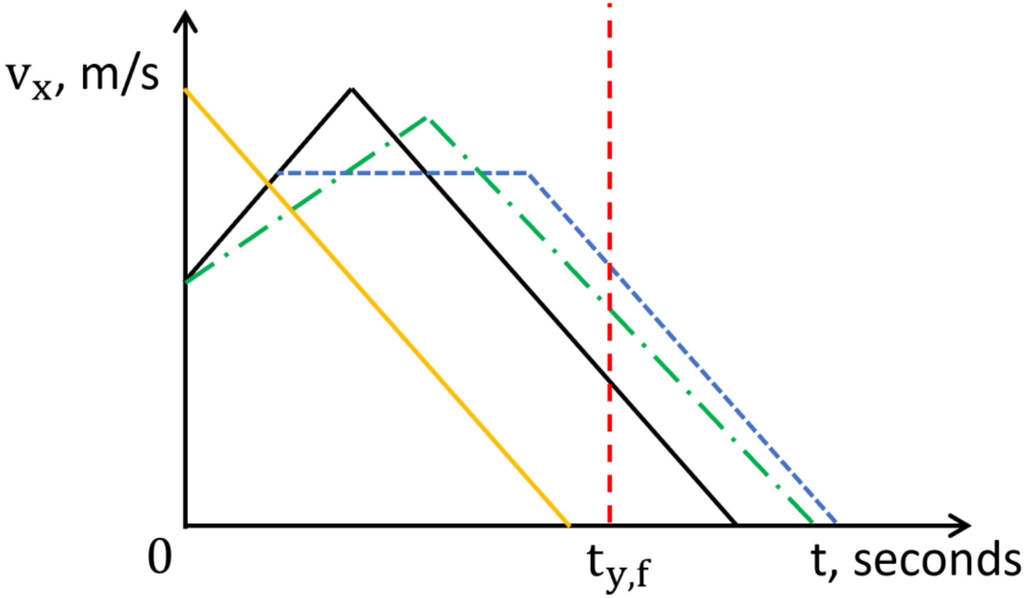
- Lateral motion:
- Leave the target lane as soon as possible
- It is safe if longitudinal position difference is large than vehicle length when ego vehicle is occupying the target lane.



Safe Evasion Trajectory (Longitudinal Motion)

- Safe evasion trajectory is pre-computed and updated periodically.

- Longitudinal motion:
- Get closer to the leading vehicle as soon as possible, keep safe and maintain the distance
- Leave larger space to prevent collision with the following vehicle



Evaluation with Synthetic Examples

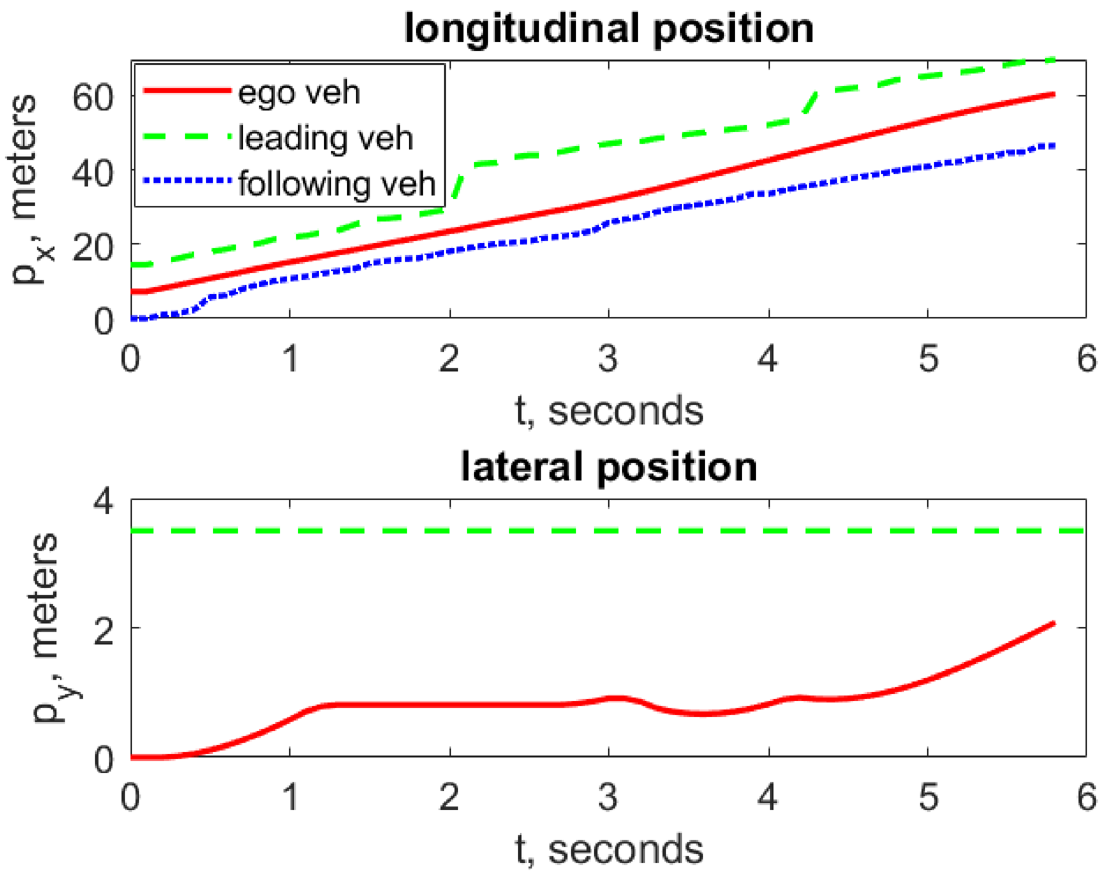
- $a_{x,l}$ is longitudinal acceleration of leading vehicle
- δp is the initial longitudinal distance between leading vehicle and ego vehicle

experimental settings	methods	lane changing time	final lateral position	success rate	collision rate
$-6 \leq a_{x,l} \leq 4$, $7 \leq \delta p \leq 37$	MPC	1.90 s	**3.44 m**	**92.61%**	7.39%
	only NN	**1.70 s**	3.25 m	89.59%	10.41%
	SafIn NN	1.90 s	2.73 m	80.31%	**0%**
$-6 \leq a_{x,l} \leq 0$, $7 \leq \delta p \leq 37$	MPC	1.90 s	**3.46 m**	**87.46%**	12.54%
	only NN	**1.68 s**	3.30 m	82.37%	17.63%
	SafIn NN	2.08 s	2.44 m	67.89%	**0%**
$-6 \leq a_{x,l} \leq 4$, $7 \leq \delta p \leq 17$	MPC	1.90 s	**3.44 m**	83.06%	16.94%
	only NN	**1.73 s**	3.24 m	**84.53%**	15.47%
	SafIn NN	1.97 s	2.23 m	61.51%	**0%**
$-6 \leq a_{x,l} \leq 0$, $7 \leq \delta p \leq 17$	MPC	1.90 s	**3.46 m**	71.82%	28.18%
	only NN	**1.71 s**	3.29 m	**74.32%**	25.68%
	SafIn NN	2.34 s	1.66 m	38.76%	**0%**

Our approach ‘SafIn NN’ results in zero collision rate in all simulations regardless whether the following vehicle is aggressive or not.

Evaluation with Real-world Challenging Dataset

- 48 challenging scenarios in real-world dataset collected by Pony.ai
- Always remain safe under our ‘SafIn NN’ planner, despite our planner is never trained or optimized with the dataset
- 12 collisions under ‘only NN’ planner



Evaluation of Aggressiveness Assessment

- It is classified as easy, medium or hard based on $|a_1 - a_0|$.
- With larger a_{th}, the uncertain rate is higher and the error rate is lower for all three different difficulty levels.
- For easy cases, the performance can be considerably greater.

$$\begin{cases} |a^*_{x,f} - a_1| < |a^*_{x,f} - a_0| - a_{th} \rightarrow \text{vehicle } F \text{ is cautious} \\ |a^*_{x,f} - a_0| < |a^*_{x,f} - a_1| - a_{th} \rightarrow \text{vehicle } F \text{ is aggressive} \\ -a_{th} \leq |a^*_{x,f} - a_0| - |a^*_{x,f} - a_1| \leq a_{th} \rightarrow \text{uncertain} \end{cases}$$

	$a_{th} = 0$	$a_{th} = 0.15$	$a_{th} = 0.25$	$a_{th} = 0.5$	$a_{th} = 1$
easy					
uncertain rate	0%	2.28%	4.05%	9.16%	19.3%
error rate	4.61%	3.6%	3.05%	2.01%	0.91%
medium					
uncertain rate	0%	18.38%	31.33%	56.32%	79.65%
error rate	36.73%	28.82%	24.53%	15.87%	7.16%
hard					
uncertain rate	0%	65.26%	74.16%	85.57%	94.39%
error rate	49.76%	17.18%	12.76%	7.1%	2.74%

Evaluation of Aggressiveness Assessment

- Despite the positive error rate, our overall approach is quite robust and does not result in collisions in all experiments
- Occasional mis-prediction is highly likely to be corrected later with a high prediction frequency.
- It is more challenging when the following vehicle is far away from the ego vehicle. However, these scenarios are less critical.

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hard					
uncertain rate	0%	65.26%	74.16%	85.57%	94.39%
error rate	49.76%	17.18%	12.76%	7.1%	2.74%

Discussion on MPC and Neural Network-based Planners

- ‘only NN’ has similar performance as MPC
  - NN planners are learned from synthesized data of the system under MPC
  - In this work, MPC is assumed to have perfect system model
- Our safety-driven interactive planning framework can be incorporated with any state-of-the-art neural network-based planners
- With more high-quality training data, ‘SafIn NN’ will perform better

Conclusion

- Safety-driven interactive planning framework for neural network-based lane changing
  - Safety-driven behavior adjustment module for safety assurance
  - Aggressiveness assessment module for avoiding over-conservative planning

- Ongoing work
- Leverage connectivity technology to further improve performance
- Safe planning given probabilistic prediction