OCTOBER 1 - 5, 2023

IEEE/RSJ International Conference on Intelligent Robots and Systems

Adversarial Driving Behavior Generation Incorporating Human Risk Cognition for Autonomous Vehicle Evaluation

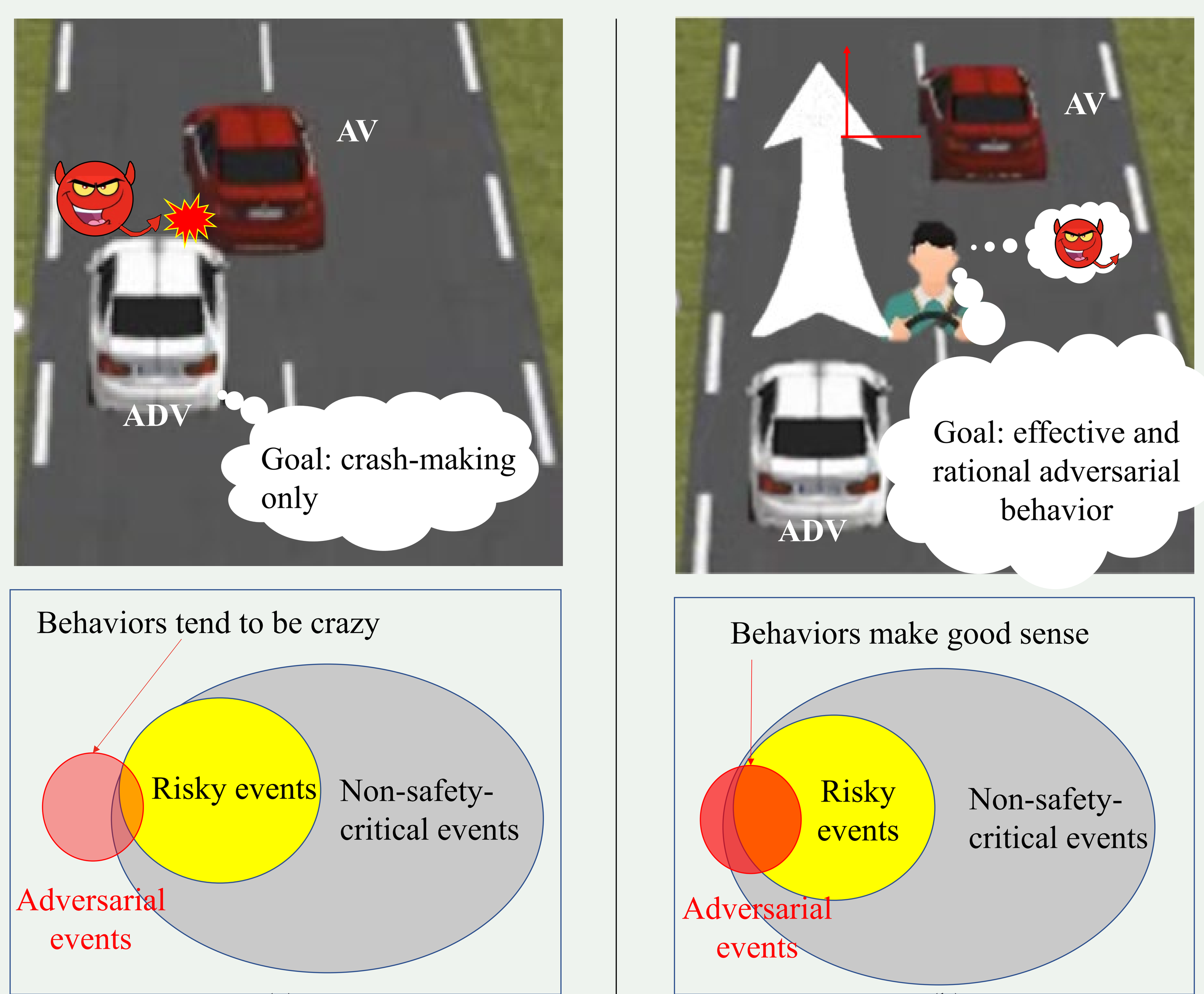
*Zhen Liu, Hang Gao, Hao Ma, Shuo Cai, Yunfeng Hu, Ting Qu, Hong Chen, Xun Gong**

School of Artificial Intelligence
Jilin University

Abstract

- This paper focuses on the development of a novel framework for generating adversarial driving behavior of background vehicle interfering against the AV to expose effective and rational risky events.
- The adversarial behavior is learned by a reinforcement learning (RL) approach incorporated with the cumulative prospect theory (CPT) which allows representation of human risk cognition.
- The extended version of deep deterministic policy gradient (DDPG) technique is proposed for training the adversarial policy while ensuring training stability as the CPT action-value function is leveraged.
- A comparative case study regarding the cut-in scenario is conducted on a high fidelity Hardware-in-the-Loop (HiL) platform and the results demonstrate the adversarial effectiveness to infer the weakness of the tested AV.

Motivation

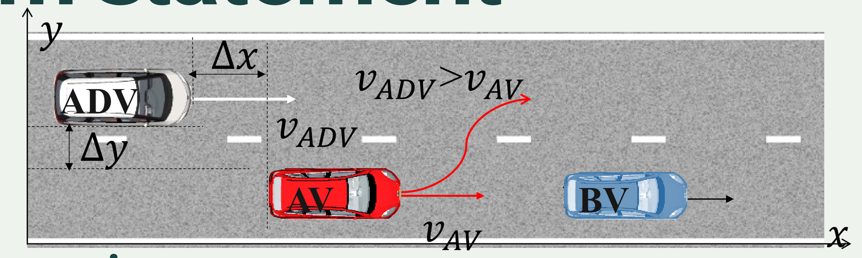


(a) (b)

- Contribution
  - Cumulative prospect theory (CPT) allows representation of human risk cognition.
  - CPT-RL can generate effective adversarial driving behavior by underestimating collision probability.
  - CPT-DDPG is proposed for solving CPT-RL while ensuring training stability as the CPT action-value function is leveraged.
  - A comparative case study demonstrate the adversarial effectiveness to infer the weakness of the tested AV.

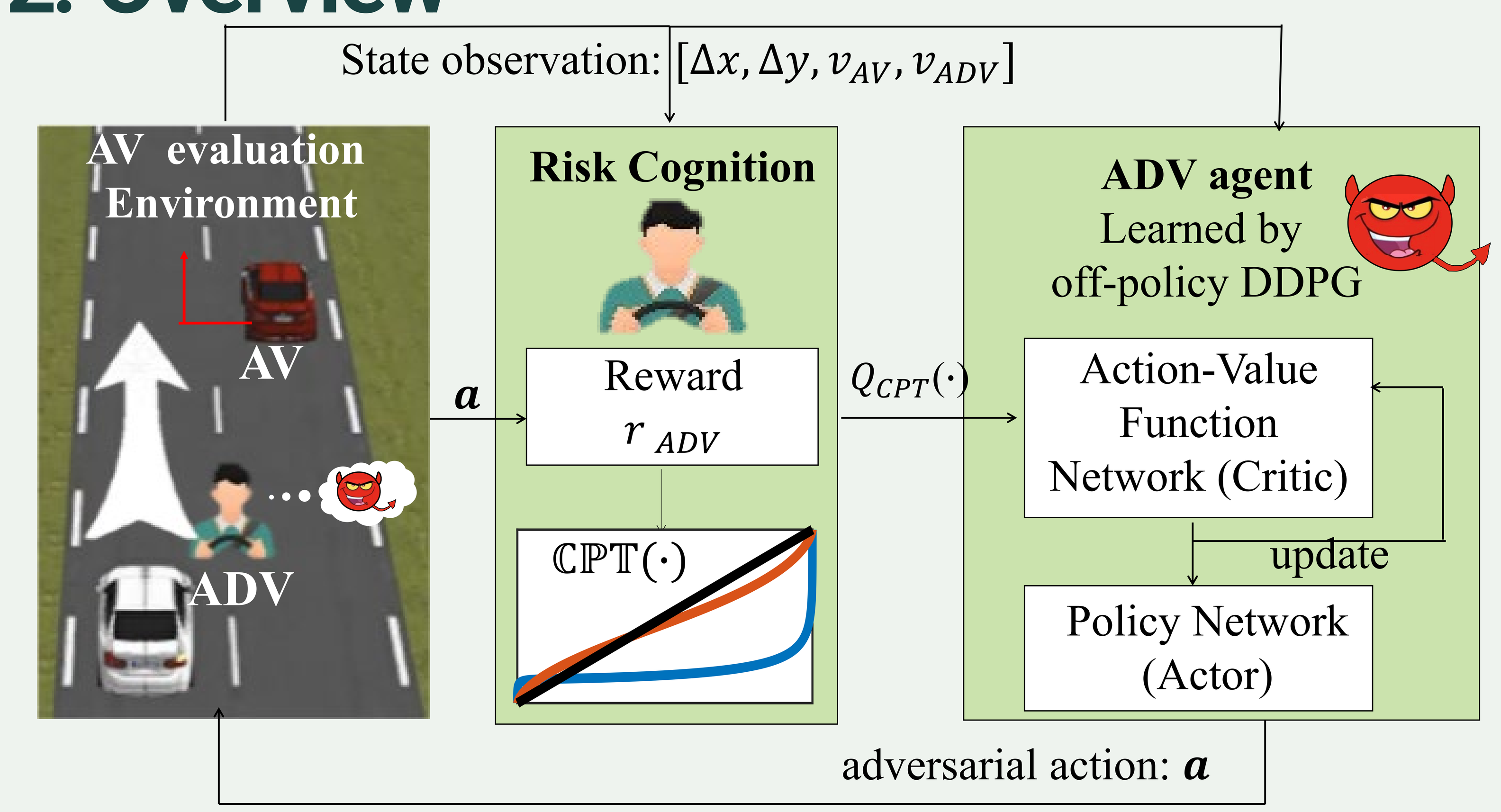
Method

1. Problem Statement



- Lane-changing Scenario
- It is assumed that when the AV decides to cut in, the initial speed of ADV is faster than that of AV.
- ADV's speed v_{ADV}, the AV's speed v_{AV}, the relative longitudinal distance Δx and relative lateral distance Δy between ADV and AV.

2. Overview

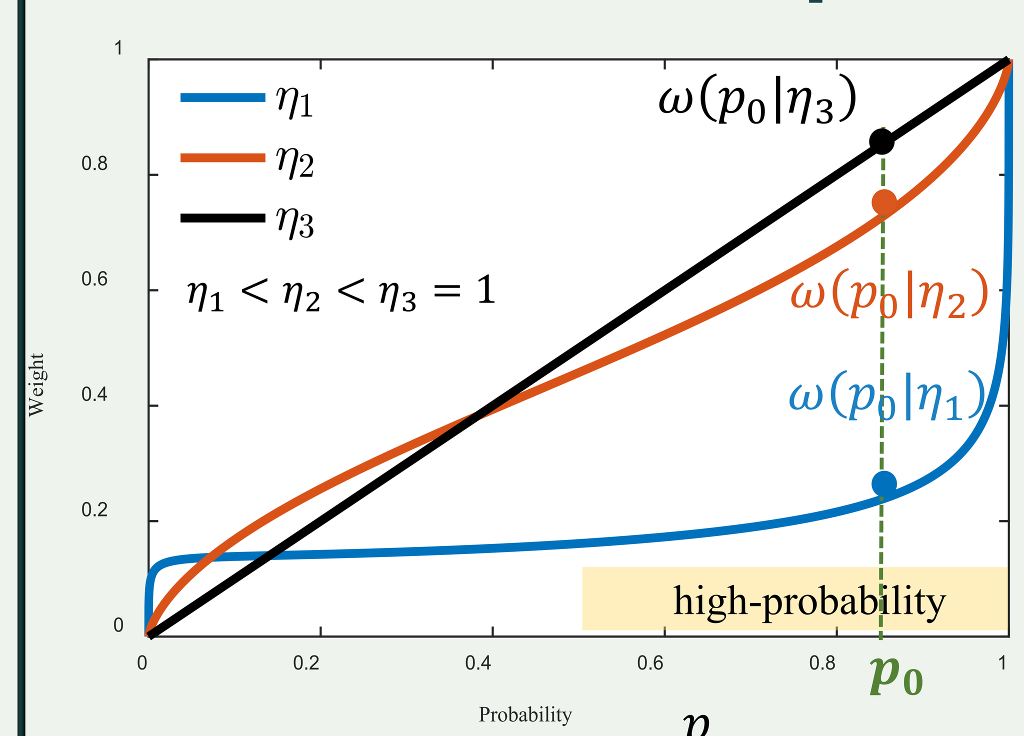


- We propose a framework based on CPT to generate adversarial behavior for testing autonomous vehicle.

$$r_{ADV} = \varphi_1 \frac{v_{ADV} - \underline{v}_{ADV}}{\bar{v}_{ADV} - \underline{v}_{ADV}} + \varphi_2 r_c \qquad \mathbb{C}\mathrm{PT}(r_{ADV}, \eta)$$

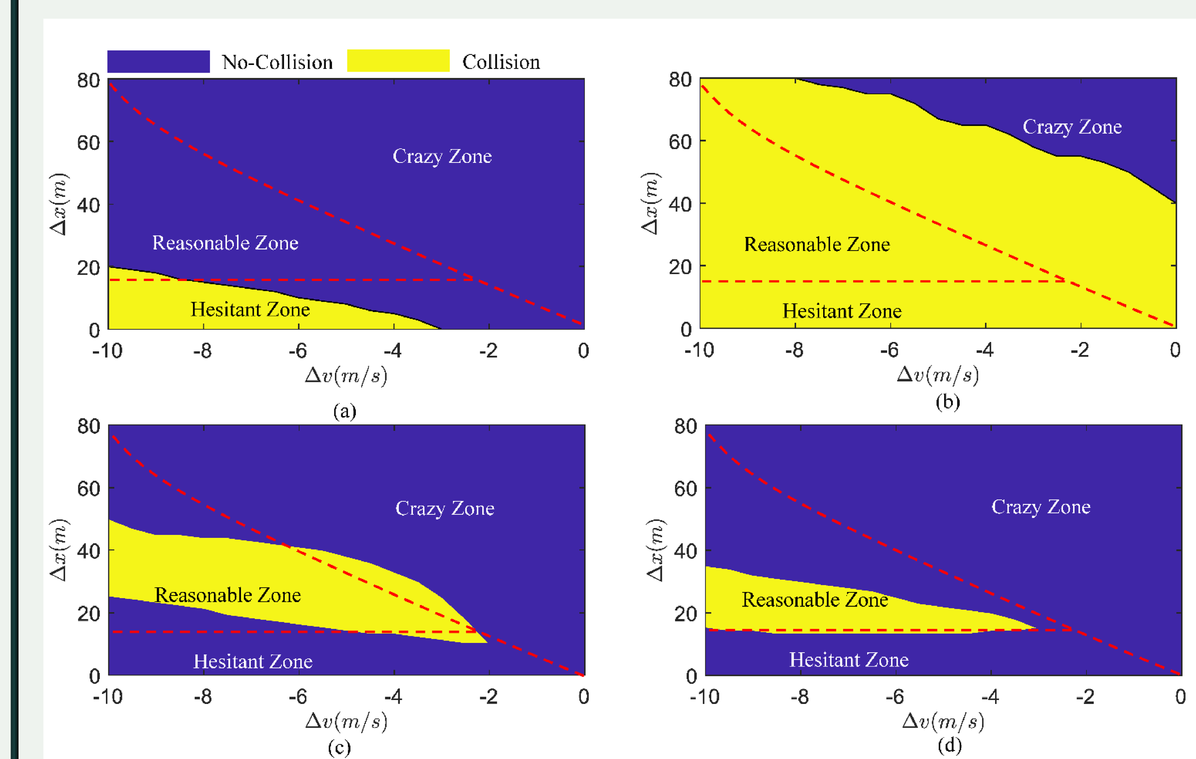
where φ_1 and φ_2 are weights, $\underline{v}_{ADV}$ and $\bar{v}_{ADV}$ are denoted as the lower bound and upper bound of ADV's longitudinal speed respectively. The collision penalty $r_c = -1$ if collision happened, otherwise $r_c = 1$.

3. Cumulative Prospect Theory(CPT)



The impact of η on human risk cognitive probability ω(p). Small η value leads to underestimated occurrence probability by human: Given a high-probability event with a probability p_0, and η_1<η_2<η_3= 1, the human objective outcome probability ω(p) satisfies $\omega(p_0|\eta_1)$ <$\omega(p_0|\eta_1)$ < $\omega(p_0|\eta_1)$ = p_0.

Results



(a): Conservative ADV

$$r_{ADV} = \varphi_1 \frac{v_{ADV} - \underline{v}_{ADV}}{\bar{v}_{ADV} - \underline{v}_{ADV}} + \varphi_2 r_c,$$

(b): Hostile ADV

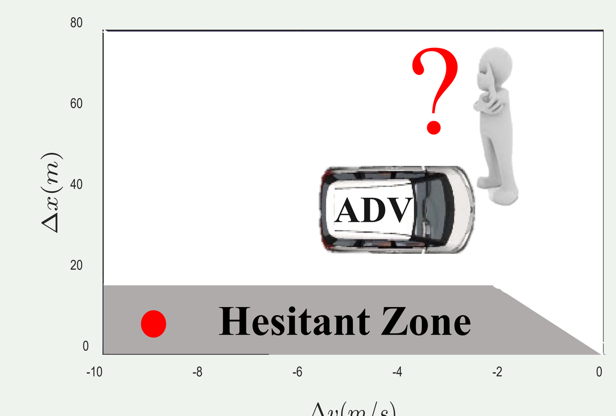
$$r_{ADV}^{Hostile} = \begin{cases} 1, & if\ collision \\ -1, & if\ no\ collision \end{cases}$$

(c): CPT-RL (η=0.1) ADV

$$r_{ADV} = \varphi_3 \frac{v_{ADV} - \underline{v}_{ADV}}{\bar{v}_{ADV} - \underline{v}_{ADV}} + \varphi_4 r_c \qquad \mathbb{C}\mathrm{PT}(r_{ADV}, \eta = 0.1)$$

(d): CPT-RL (η=0.9) ADV

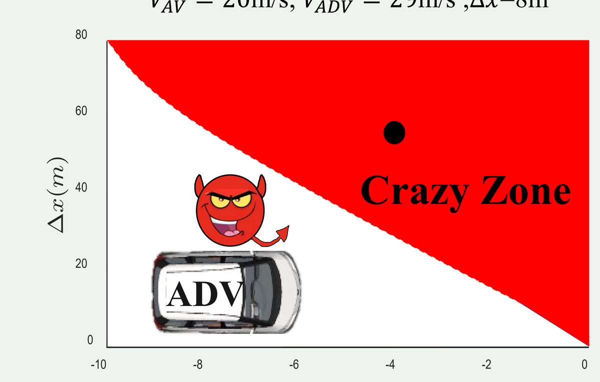
$$r_{ADV} = \varphi_3 \frac{v_{ADV} - \underline{v}_{ADV}}{\bar{v}_{ADV} - \underline{v}_{ADV}} + \varphi_4 r_c \qquad \mathbb{C}\mathrm{PT}(r_{ADV}, \eta = 0.9)$$



Case one: initial boundary conditions: V_{AV} = 20m/s; V_{ADV} = 29m/s ;Δx=8m

Cause of collision in Hesitant Zone: only ADV decelerates too cautiously and loses the opportunity to overtake AV.

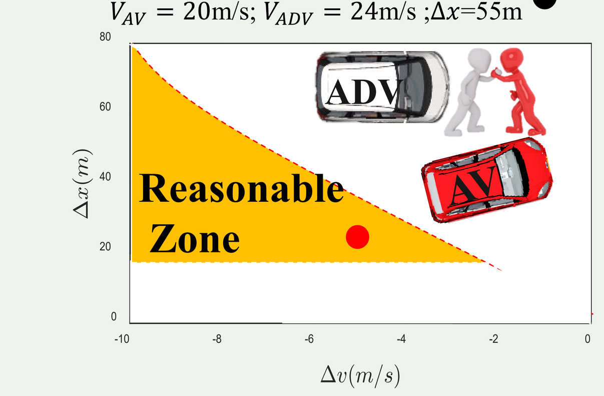
- The conservative ADV has weak adversarial effectiveness.



Case two: Initial boundary conditions: V_{AV} = 20m/s; V_{ADV} = 24m/s ;Δx=55m

Cause of collision in Crazy Zone: ADV accelerate aggressively with obvious hostile intents to AV.

- The hostile ADV has bad adversarial effectiveness.



Case three : initial boundary conditions: V_{AV} = 20m/s; V_{ADV} = 25m/s ;Δx=25m

Cause of collision in Reasonable Zone: ADV underestimating collision probability, driving mistakes, etc.

- The CPT-RL ADV has good adversarial effectiveness.

Conclusions

- We develop a CPT-RL approach for adversarial behavior generation towards the task of AV evaluation.
- The approach leverages human risk cognition to achieve rational exposure of safety-critical events. The stable training process is guaranteed via the proposed CPT-DDPG algorithm.
- Experimental results demonstrate that the CPT-RL is able to offer personalized adversarial patterns and facilitate effective AV evaluation.