RACL: Risk Aware Closed-Loop Agent Simulation with High Fidelity

Qiujing Lu Ruoxuan Bai Shu Li Honglin He Shuo Feng
Email: fshuo@tsinghua.edu.cn

Department of Automation, Tsinghua University

Background

The creation of realistic and responsive simulated agents is essential for using simulation as a viable tool for the development and testing of autonomous driving.

However, human driving behavior is characterized by high uncertainty due to diverse intentions and driving styles, posing a major scientific challenge in creating generative models. Additionally, the low average accident rate among human drivers, about 1.9×10^{-6} per mile, results in limited incident data, further complicating the development of data-driven models.

Current methods often focus on either normal driving conditions or safety-critical scenarios, leaving the effective integration of both into simulation models as an unresolved challenge.

Motivation and Approach

We introduce Risk Aware Closed-Loop agent simulation(RACL), a comprehensive framework that respects the safety-critical states and captures the natural progression of risk.

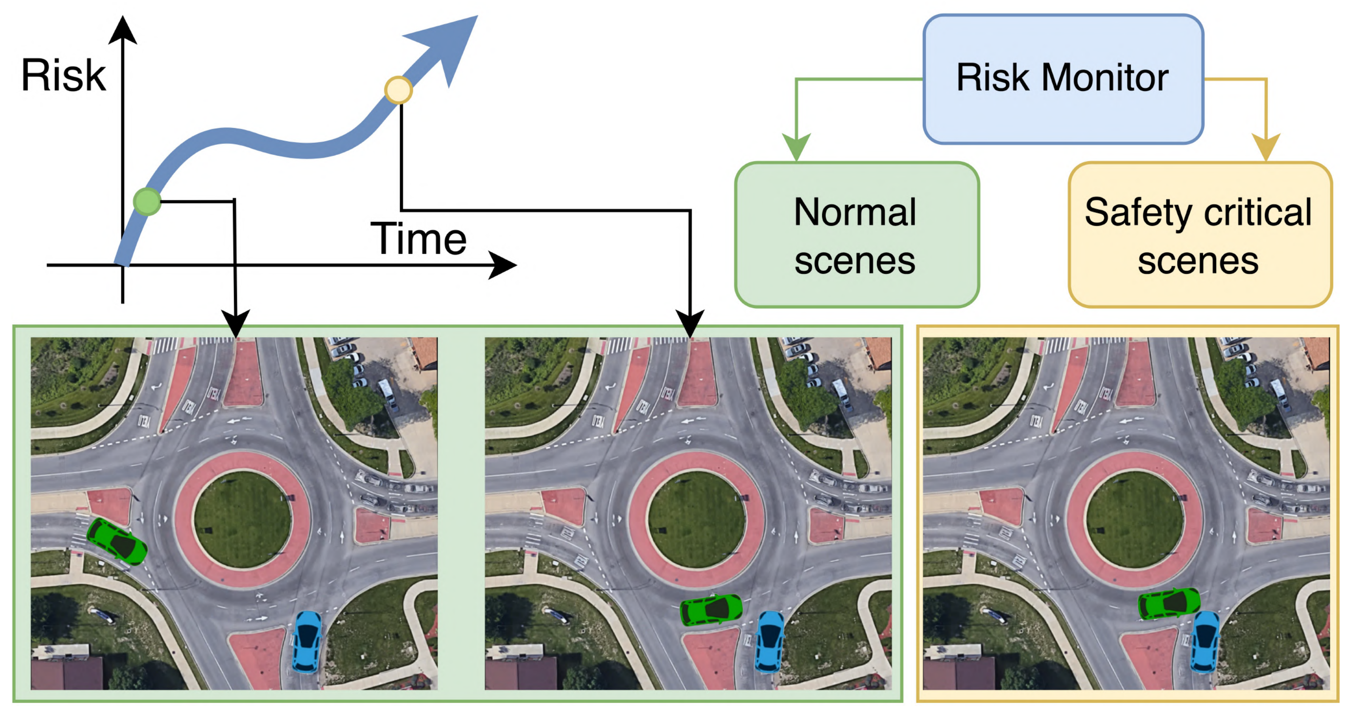

Figure 1. RACL is designed to enhance the generation of realistic driving scenarios by integrating risk assessment into the simulation process. It uses a learnt predictor to estimate the risk of the whole scene at each timestep. Once high risk is detected, it automatically switches from the normal driving policy to risky driving policy for generating realistic safety-critical scenes.

- Proposed a framework for searching and generating risky states, utilizing accident data efficiently.
  - Introduced a risk monitoring mechanism that tracks the evolution of risk throughout the simulation process.
  - Implemented optimization strategies for transitioning modes to ensure a smooth shift from normal to high-risk scenarios.
- By distinctly modeling normal and risk states, we ensured efficient utilization of limited crash data and attained a high level of realism in simulating both modes.

RACL framework

During the generation phase, the risk monitor analyzes the current state and past information $X^t \dots X^{t-H}$. Depending on the assessed risk level, RACL chooses between two pathways:(1) For low risk, it employs a normal motion predictor $D(\theta)$ for next step's action.(2) For high risks, it utilizes a VAE encoder $p(\beta)$ and $D(\theta)$ to identify an optimal risky future state X^{t+T*}. Upon determining this state, the framework generates subsequent motions using a goal-conditioned model and then a risky motion policy.

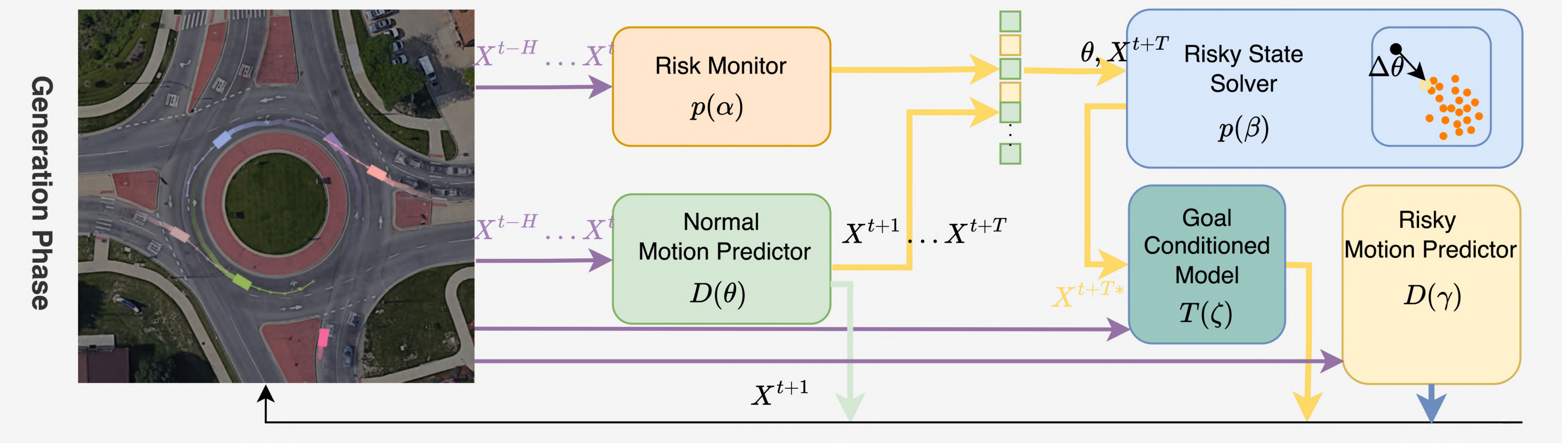

Figure 2. Generation phase of RACL

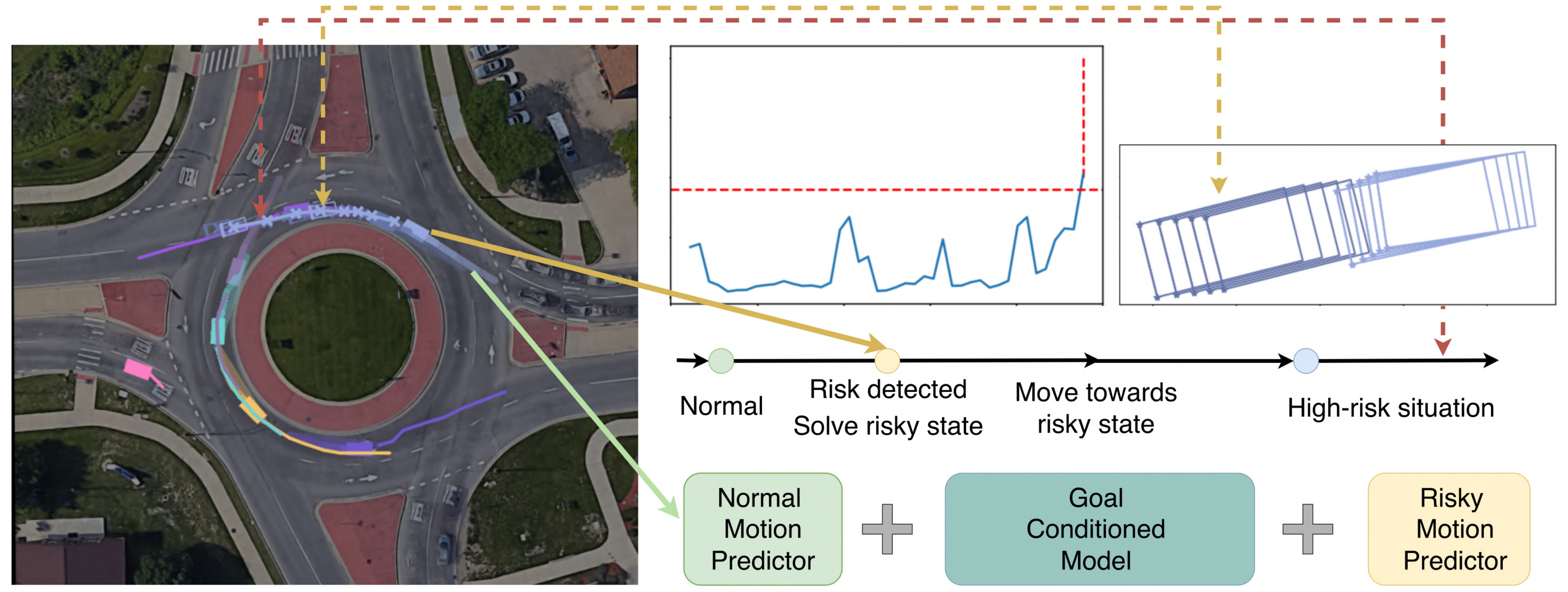

Figure 3. Details of the simulation trace rollout involving a rear-end crash scenario

Model Training

For a given moment t, the training goal is to maximize the likelihood of the subsequent T steps given the history of the past H steps:

$$_{\theta,\gamma,\zeta}\mathbb{E}_{X^{t+T}\dots X^{t-H}\sim p_{data}}\mathcal{L}(\theta,\gamma,\zeta|X^{t+T}\dots X^{t-H}) = p_{\theta,\gamma,\zeta}(X^{t+1}\dots X^{t+T}|X^t\dots X^{t-H}) = D_\gamma 1(X^t \in S) + D_\theta 1(X^{t+T} \in S^c) + T_\zeta 1(X^t \in S^c, X^{t+T} \in S)$$

Results: Qualitative Results

Our approach generates realistic interactions for various accident types.

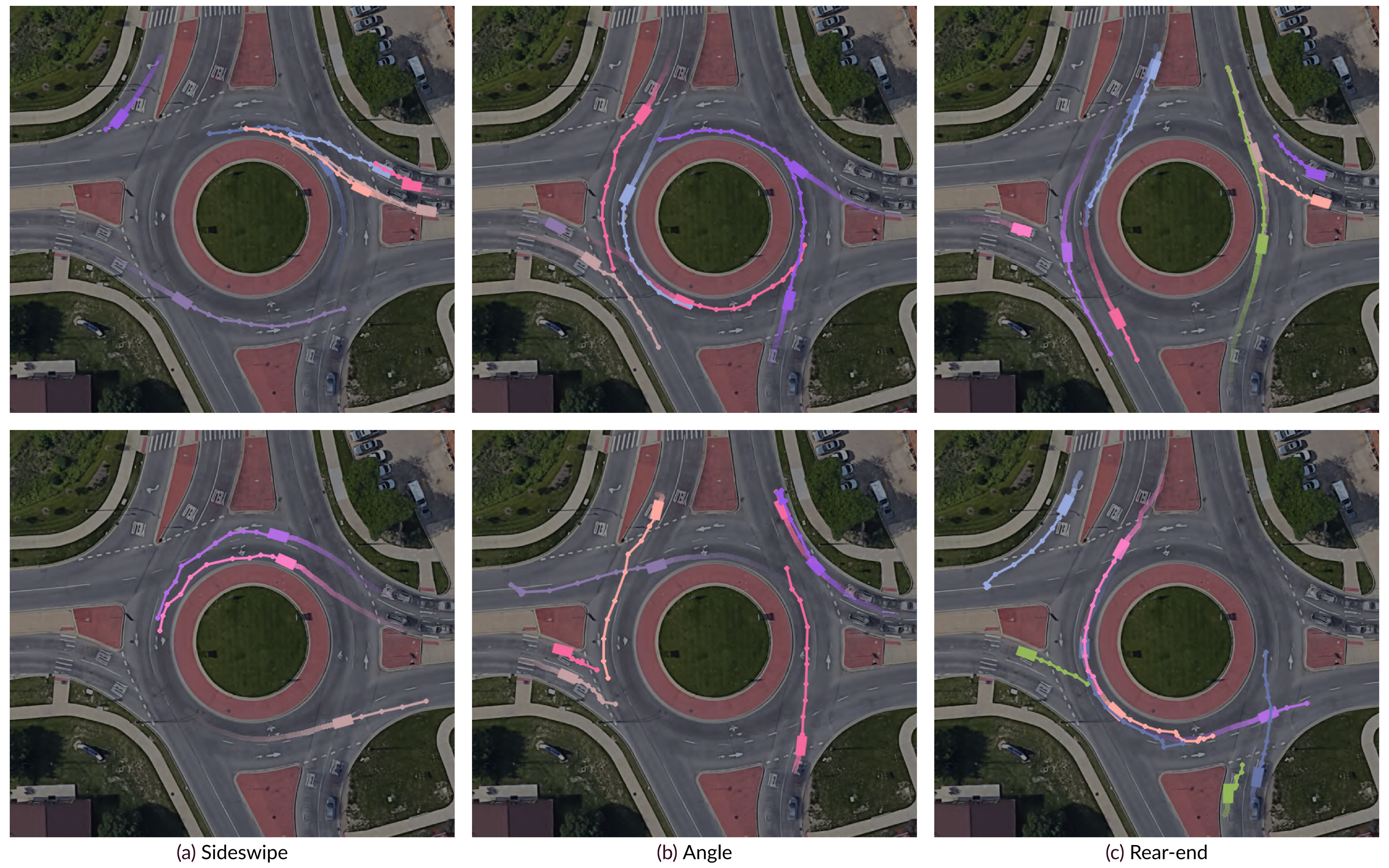

Figure 4. Sampled traces centered at 4 seconds before the noted accident with shadow lines to indicate past trajectories and dotted lines for future paths. The top section depicts Neural NDE, while the bottom section presents RACL.

Results: Quantitative Comparison

We compare our approach with other State-Of-The-Art methods on diverse datasets.

Method	D_{KL}(Speed)↓	D_{KL}(Distance)↓	D_{KL}(Yielding$_v$) ↓	D_{KL}(Yielding$_d$) ↓	D_{KL}(PET)↓
SUMO*	0.126	0.089	0.087	0.107	-
NeuralNDE[2]	0.008	0.004	0.005	0.005	0.017
RACL	0.005	0.003	0.005	0.005	0.016

Table 1. Quantitative evaluation of simulation traces at the two-lane roundabout. Results of SUMO are queried from [2].

References

[1] Ruoxuan Bai, Jingxuan Yang, Weiduo Gong, Yi Zhang, Qiujing Lu, and Shuo Feng. Accurately predicting probabilities of safety-critical rare events for intelligent systems. *arXiv preprint arXiv:2403.13869*, 2024.

[2] Xintao Yan, Zhengxia Zou, Shuo Feng, Haojie Zhu, Haowei Sun, and Henry X Liu. Learning naturalistic driving environment with statistical realism. *Nature communications*, 14(1):2037, 2023.