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Generation of Autonomous Vehicle Testing Trajectories for Cut-In Scenario Integrating Data and Kinematics.

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Abstract

- Autonomous vehicle assessment is crucial for technological advancement. Yet, simulated evaluation poses challenges like ensuring physical law compliance and reflecting real-world naturalness and diversity, making simulated testing difficult.
- We present a new approach integrating data-driven methods and kinematic constraints to generate testing trajectories as a probabilistic process with Gaussian distribution. Fusion technology enables relying on initial scene info, enhancing practicality and convenience for AV trajectory generation.
- Ablation studies on kinematic constraints and data separately show the effectiveness of our model.

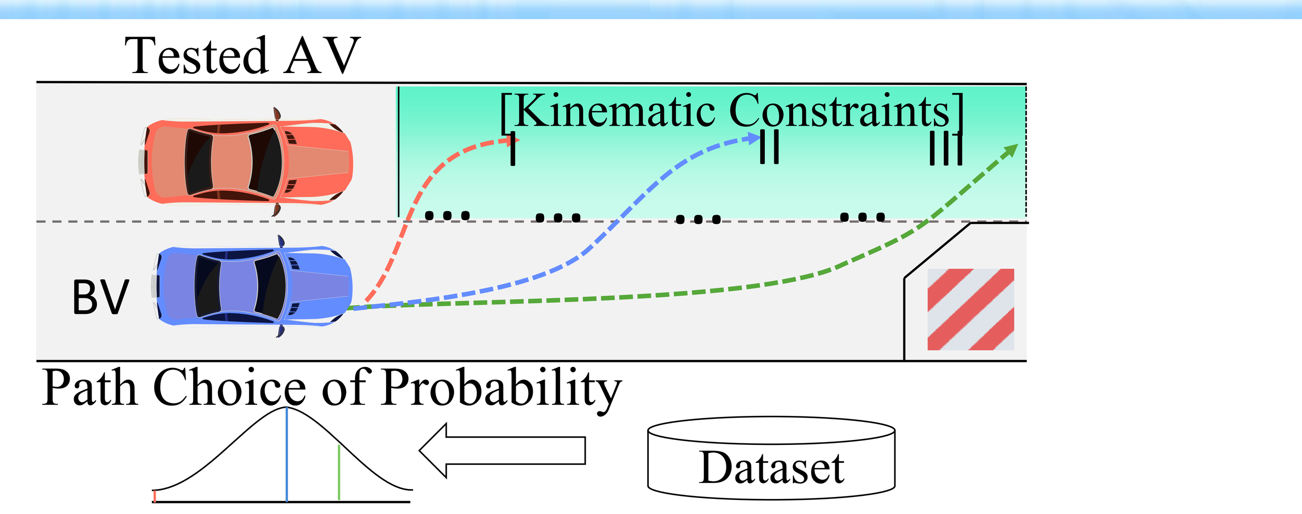


Fig.1. Background vehicle (BV) has decided to change lanes while evaluating the performance of the autonomous vehicle (AV). The kinematically feasible path choices deviate from each other with different probabilities in the naturalistic dataset.

Methods

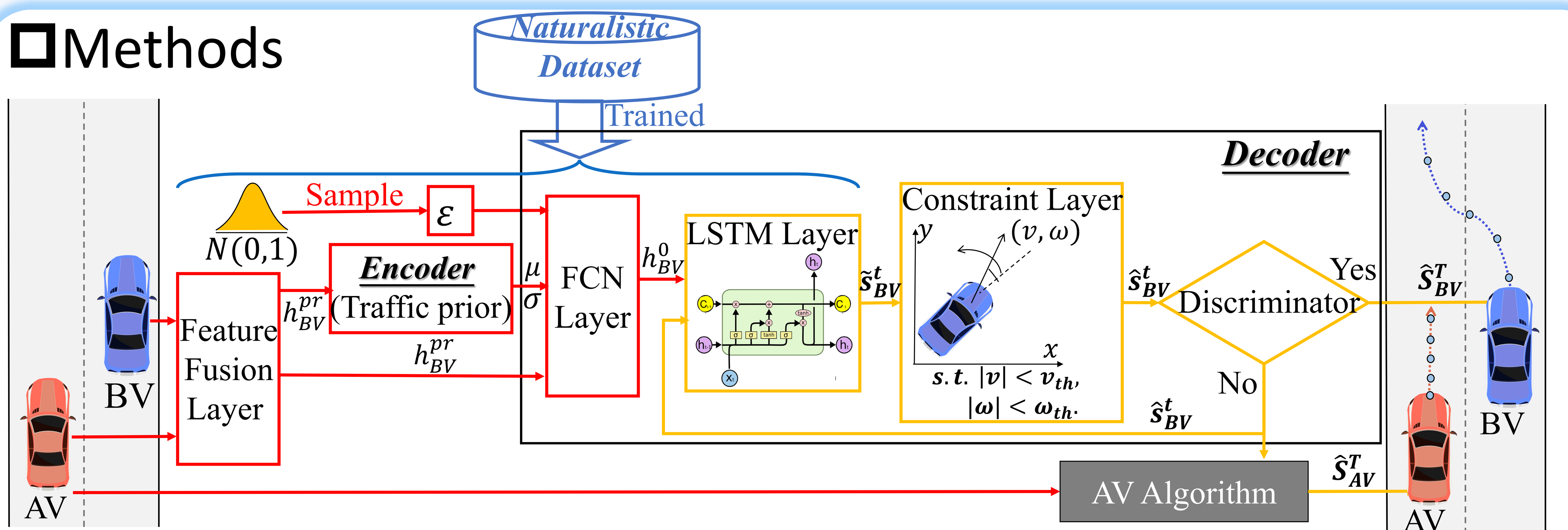


Fig.2. The testing environment framework using Dual-CVAE.

1). The entire network is trained using the naturalistic dataset, following the blue workflow.

Net Parameters ⟵ $W, b = \arg\min L$ ⟵ Integrated Loss of both Vehicles

2). In the testing process, the initial scene is firstly obtained, and a variable ε is sampled from $N(0,1)$ for once, following the red workflow. Then, the encoded hidden vector h_{BV}^{0} is obtained.

Feature Fusion Layer: $h_{BV}^{pr} = W_{BV}^{pr}[s_{BV}^{0}, r^{0}] + b_{BV}^{pr}$, $\quad z_{BV} = \mu_{BV} + \sigma_{BV}\varepsilon$,

Encoder Net: $[\mu_{BV}, \sigma_{BV}] = W_{BV}^{enc} h_{BV}^{enc} + b_{BV}^{enc}$. $\quad h_{BV}^{0} = W_{BV}^{dec}[h_{BV}^{pr}, z_{BV}] + b_{BV}^{dec}$. FCN in Decoder

3). The network generates the BV state s_{BV}^{t} and checks whether it has reached the target lane while AVstate s_{AV}^{t} is updated accordingly, following the yellow workflow.

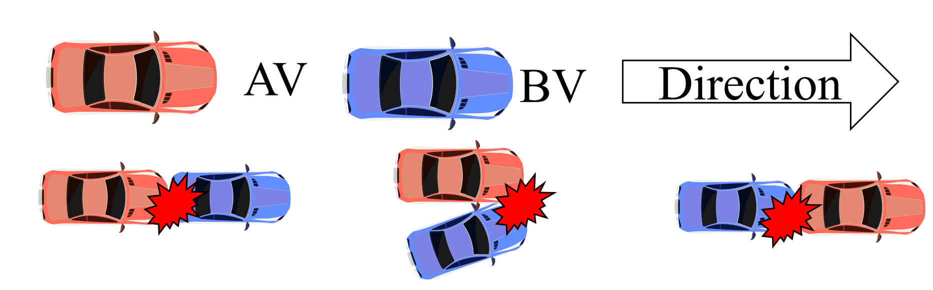
LSTM layer with kinematic constraints: $[\tilde{s}_{BV}^{t+1}, h_{BV}^{t+1}] = LSTM_{BV}^{dec}([\hat{s}_{BV}^{t}, h_{BV}^{t}])$

$\hat{s}_{BV}^{t+1} = \mathcal{K}(\tilde{s}_{BV}^{t+1}, \hat{s}_{BV}^{t})$

Human-Designed Rules: *Stop if* $\hat{y}_{BV}^{t'} >= y_{cen}$, *then* $T = t'$

Results

- Kinematics Ablation study.



(a) AV rear-ends BV (b)Sideswipe (c) BV rear-ends AV

Fig.3. Three different types of collision events might happen in cut-inscenario.

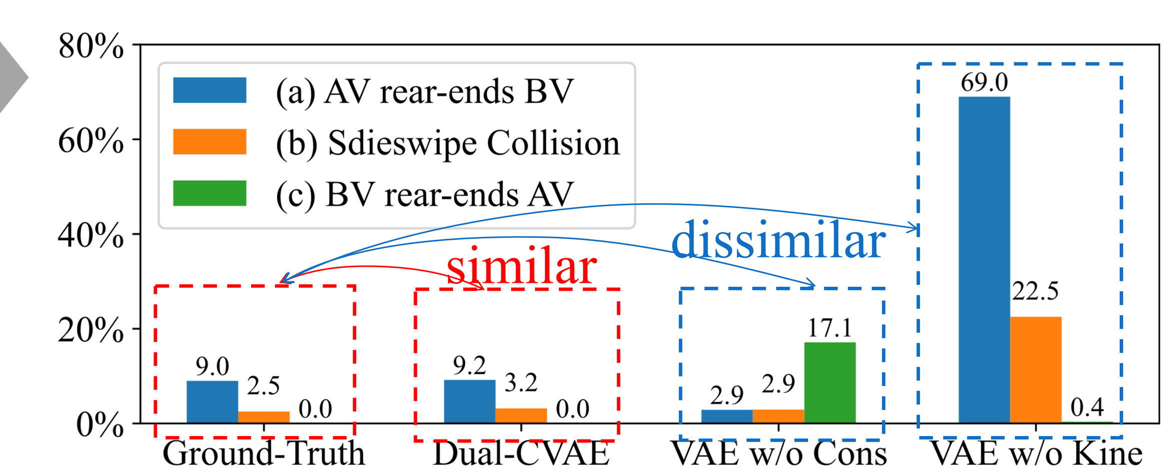


Fig.4. Ablation study of kinematic constraints (VAE w/o Cons) and kinematic model (VAE w/o Kine).

- **Without Kinematics, model behave bad on generating testing trajectories.**

- Data Ablation study.

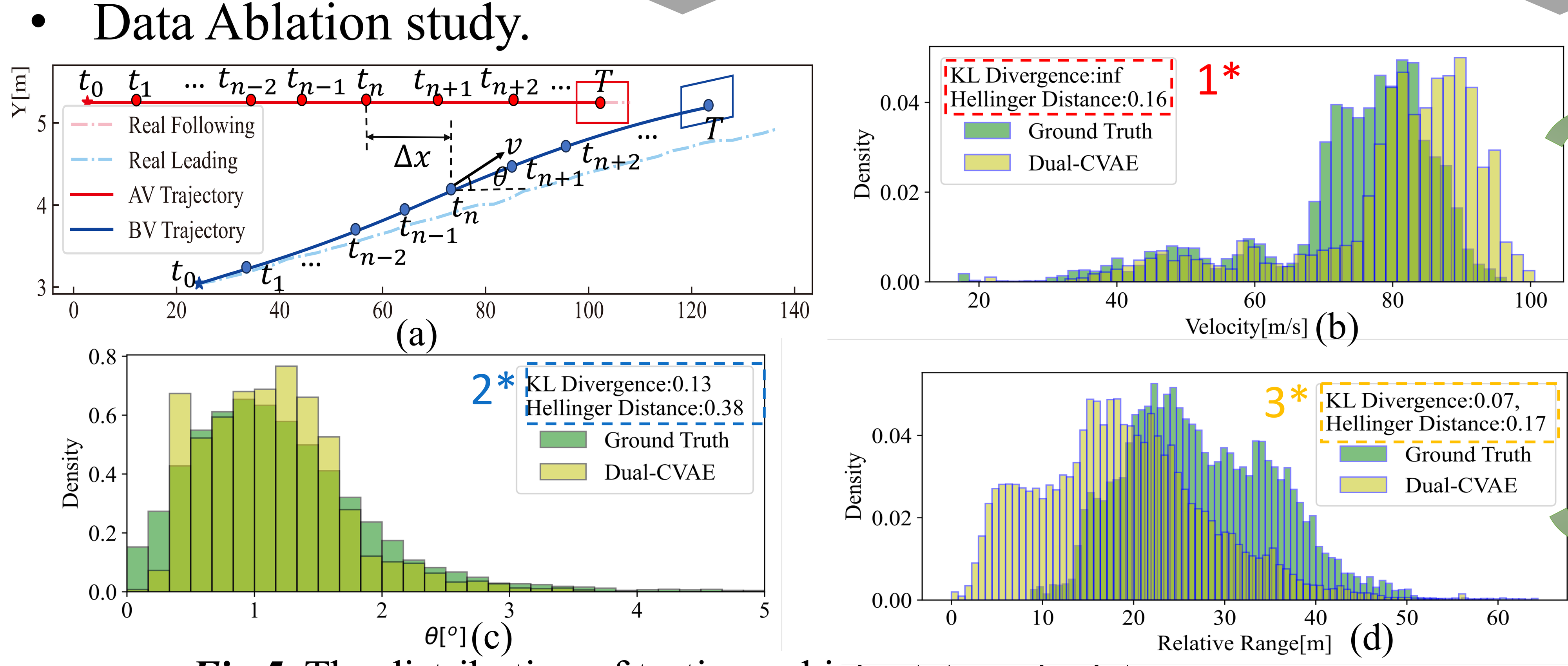


Fig.5. The distribution of testing vehicle state and relative range.

For a set of tested trajectories pairs using initial relationships from real dataset, maneuvers of BV are analyzed. Three key parameters are: Velocity v_{i,t_n}, Heading angle θ_{i,t_n}, Relative Range $\Delta x_{i,t_n}$, as shown in Fig.5. (a)

TABLE I ABLATION STUDY OF DATA-DRIVEN MODEL

D_{KL}|H ↓	SUMO	Quintic	Ours
Velocity v_{BV}	0.44|0.58	+∞|0.48	+∞|**0.16** 1*
Steering ω_{BV}	7.41|5.52	2.13|7.9	**0.13|0.38** 2*
Range Δx	6.31|0.79	0.22|0.24	**0.07|0.17** 3*

The downward arrow ↓ indicates that a smaller indicator is indicative of a superior index.

- **Without Data, model behave bad on generating similar maneuver distributions with real vehicles.**

Contributions and Conclusions

- ***Probabilistic Trajectory Generation.***
  We model trajectory generation as a probabilistic problem, employing Gaussian distributions to introduce realistic variations.
- ***Scene-Dependent Testing Trajectory Generation.***
  Our approach emphasizes the generation of testing trajectories based on initial scene information, different from the conventional methods that rely on historical trajectory data.
- Our method prove that VAE model is effective in creating statistically realistic trajectories and simulating genuine collision events. The generated trajectories closely mimic the planning behaviors of real drivers, as they are trained on human-driven data.
- Future work will focus on integrating the model with large language model to generate realistic and robust testing long-time domain scenarios.