RounD-KITTI: Merging Realistic Traffic Behavior with KITTI-Calibrated Sensors in CARLA

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***Abstract*—Evaluating autonomous vehicle performance in complex traffic scenarios requires both calibrated sensors and realistic traffic conditions. However, existing traffic datasets focus on vehicle trajectories but lack comprehensive sensor data, while perception datasets provide sensor data but offer limited traffic diversity. To bridge this gap, we introduce an open-source toolset that generates perception datasets in CARLA by embedding real-world vehicle trajectories within a simulated sensor environment. This approach produces sensor data that accurately mirrors real-world traffic dynamics, providing a valuable resource for testing AI-driven autonomous systems in complex scenarios such as roundabouts, where sensor-based perception is essential for safe AV navigation.**

***Index Terms*—Real-world Scenario, CARLA, Roundabout, AI-driven autonomous systems, Datasets, Sensor-based perception**

I. Introduction

The development of autonomous vehicles (AVs) heavily relies on high-quality datasets for perception, sensor fusion, and motion planning. Real-world datasets like KITTI[1], offer high-quality sensor data from urban scenes but lack customizable and varied traffic scenarios, limiting their applicability for testing AVs under controlled and varied conditions. In contrast, naturalistic traffic datasets like RounD[2] capture real roundabout behaviors but cannot be dynamically modified to test AV strategies, and they include no sensor data. Finally, synthetic SUMO[3]-based city-wide traffic scenarios such as LUST [1] or MOST [2], provide realistic and dynamically alterable urban traffic, but at a scale that is not adapted to perception or motion planning for AVs. This gap calls for an AV-oriented simulation toolset capable of producing realistic, calibrated, and alterable data for perception and motion planning.

CARLA[4], an open-source autonomous driving simulator, has emerged as a powerful tool for generating synthetic scenarios with ground-truth annotations. CARLA has the capability to model precise motion planning, engine patterns, urban environments as well as on-board sensors, making CARLA better suited to research on AVs than SUMO. However, CARLA lacks reference scenarios that simultaneously incorporate realistic motion planning, sensor-based perception, and decision-making dynamics.

[1]http://www.cvlibs.net/datasets/kitti/
[2]https://round-dataset.com/
[3]https://eclipse.dev/sumo/
[4]https://carla.org/

We propose in this paper a methodology to create such reference scenario, incorporating real-world traffic datasets in CARLA, while ensuring accurate sensor perception. Our approach consists of three key modules: (i) Dataset integration & trajectory reconstruction, where we integrate real-world scenario data and correct vehicle trajectories in CARLA; (ii) the motion control calibration, where we adjust the CARLA internal motion control parameters and algorithms (e.g. PID & steering patterns) ensuring spatial and temporal accuracy between the dataset and CARLA. (iii) sensor mapping, where we equip CARLA vehicles with calibrated sensor parameters corresponding to realistic sensor campaigns. This includes mapping LiDAR and cameras to replicate real-world sensing conditions from the sensor campaign. In this paper, we focus on a roundabout scenario RounD for steps (i) and (ii) and rely on the KITTI sensor dataset for step (iii). Fig.1 outlines the general workflow of our methodology. We finally demonstrate the benefit of such a realistic CARLA reference scenario for the evaluation of AV roundabout hazard management. We notably showcase that relying on unrealistic motion planning or sensor perception provides overoptimistic situation assessments leading to inaccurate decision making by the AV. The CARLA dataset is released as open-source[5].

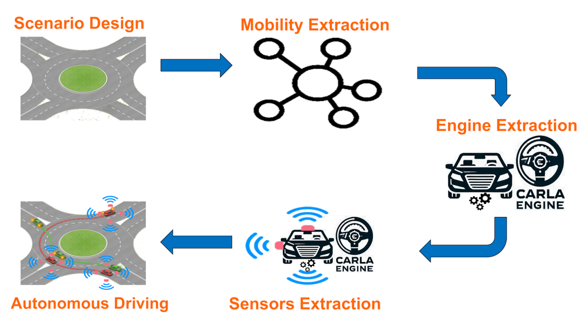


Fig. 1: Methodology workflow for integrated simulation

The paper is structured as follows: Section II provides an overview of related work on AV dataset generation. Section III describes the environment mapping and mobility extraction process. Section IV presents the individual vehicle control dynamics model. Section V details the sensor setup. Section VI discusses the simulation experiment and its evaluation. Section **??** concludes the paper and outlines future research directions.

[5]https://gitlab.eurecom.fr/cats/carla/round-carla

II. Related Work

Autonomous Driving (AD) research heavily relies on high-fidelity datasets that accurately capture both real-world traffic behaviors and sensor data characteristics. Most autonomous driving systems fuse sensor readings from multiple sensors, including cameras, LiDAR, radar, GPS, wheel odometry, and IMUs. Previously released autonomous driving datasets have included sensor readings obtained by multiple sensors. *Geiger et al.* introduced the multi-sensor KITTI Dataset [3], which provides synchronized stereo camera as well as LiDAR sensor data, enabling tasks such as 3D object detection and tracking, visual odometry, and scene flow estimation. *Caesar et al.* also introduced the multi-sensor nuScenes Dataset [4] with more extensive data by incorporating five radar sensors, while *Sun et al.* introduced Waymo dataset with mutli-LiDAR strategy by adding five high-resolution LiDAR sensors. For AD data perception, In KITTI-CARLA [5], a synthetic dataset is generated within a simulated environment in CARLA, using a vehicle equipped with sensors identical to those in the KITTI dataset [3], providing ground truth for semantic segmentation, instance segmentation, and odometry poses.

Considering naturalistic traffic behavior, RounD [6] presents naturalistic trajectory dataset that introduces a fresh compilation of natural real-world road user trajectory data from German roundabouts. The dataset is gathered using a camera-equipped drone technology, overcoming occlusion challenges inherent in traditional traffic data collection methods. The extracted tracks contain positions, headings, speeds, accelerations, and object classifications, processed from recorded videos using deep neural networks.

Existing datasets such as KITTI and RounD provide valuable insights for perception, motion planning and AD research. However, they each have limitations: KITTI lacks dynamic and interactive traffic scenarios, while RounD, despite offering naturalistic vehicle trajectories, cannot be dynamically altered to test AD features (e.g. AI models) under controlled, alterable and reproducible conditions.

As illustrated in Table I, realistic AD simulations require datasets that include naturalistic, alterable, robotic-ego control, sensor perception, and robotic background traffic scenarios. However, no single dataset strategy fully meets all these metrics. RounD dataset typically satisfies only two of these requirements. The KITTI-CARLA fulfills three complementary metrics. To address these limitations, we propose in this work a RounD-KITTI scenario in CARLA, which integrates the naturalistic dataset RounD for traffic scenarios and the calibrated KITTI sensors for perception. This combined approach enables a more comprehensive and realistic simulation framework that fulfills all key requirements for AD simulations, including realistic environment, dynamic interactions, high-fidelity sensor data, and controlled scenario variations.

III. Dataset Integration

The first step in our methodology ensures that real-world vehicles environment and trajectories from the RounD dataset are accurately replicated in CARLA.

TABLE I: Existing simulation methodologies for AD

	naturalistic	**alterable**	**control**	**perception**	**background**
Traffic Dataset	✓	x	x	x	✓
SUMO	x	✓	x	x	LuST [1]/MoST [2]
CARLA	x	✓	✓	✓	autopilot
KITTI/ NuScenes/ Waymo	✓	x	x	✓	✓
KITTI-CARLA	x	✓	✓	✓	x
This work	✓	✓	✓	✓	✓

A. Map Reconstruction

The first step is to design a roundabout in CARLA that closely matches one of the four roundabouts available in the RounD dataset. Using the latitude and longitude coordinates of the selected roundabout, we exported its OpenStreetMap (OSM) representation. As road configurations in OSM lack the precision needed for CARLA simulations, we leveraged MathWorks' RoadRunner to modify the roundabout design by adjusting entry/exit curvature, lane width, and geometry to match the coordinate projection of the RounD dataset. Fig. 2 illustrates the steps followed to create the scenario design.

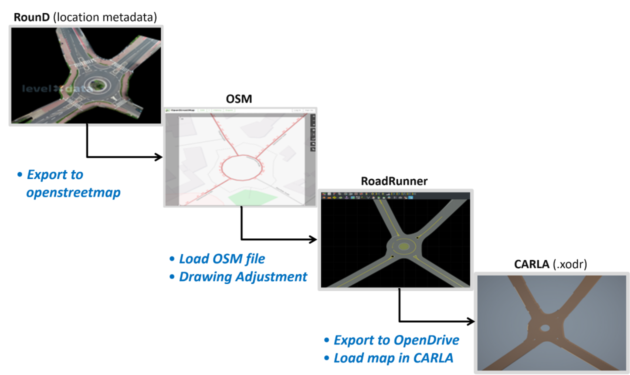


Fig. 2: Road scenario design in CARLA

B. Trajectory Correction

Collected by drone-based computer vision techniques, the RounD dataset provides highly precise vehicle trajectories with an average positional error of less than 10 cm. While this level of accuracy is generally sufficient it presents challenges in our case, where exact position is crucial for maintaining matching vehicle dynamics between CARLA and RounD. During our preparation phase, vehicle steering was directly controlled by the provided trajectory data. However, as shown in Fig. 3, some trajectories contained circular path anomalies, causing the vehicle to sharply turn left and hit the road shoulder. These trajectory artifacts likely stem from minor positional errors in the dataset, which, when mapped to CARLA's physics-based steering model, led to unrealistic vehicle behavior. To mitigate this issue, we developed a trajectory correction algorithm that: (i) detects trajectory mismatches by identifying abrupt, unrealistic steering deviations, (ii) eliminates erroneous waypoints, (iii) extrapolates corrected waypoints by generating new points that align smoothly with the original trajectory direction, ensuring natural vehicle motion. This correction process enhances trajectory feasibility within CARLA, preventing abnormal patterns and improving simulation accuracy.

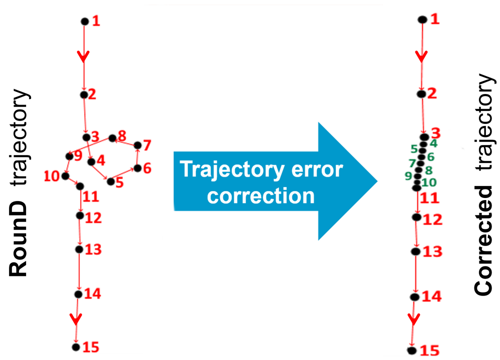


Fig. 3: New waypoints after fixing trajectory errors

C. Time Step Synchronization

To ensure spatiotemporal consistency, we synchronized CARLA with RounD dataset's 25 frames per second (fps) timestep. This required updating CARLA at 25 ticks per second so that each vehicle's position, speed, and heading were precisely aligned with the dataset. Maintaining such exact update rate ensures that vehicle dynamics in CARLA faithfully replicate real-world motion patterns from the RounD dataset. Following only the assigned waypoints led some vehicles to arrive either too early or too late, potentially causing collisions. To resolve this, we implemented a Model Predictive Controller (MPC) to resynchronize CARLA and RounD data points, reconstructing the exact RounD trajectories (see Fig.4).

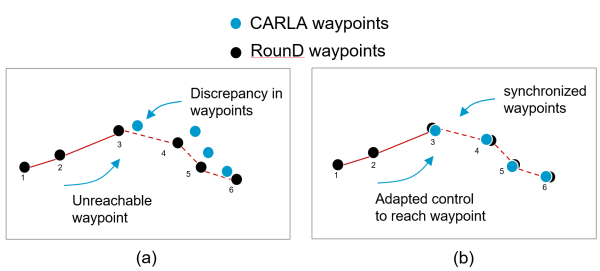


Fig. 4: MPC-based trajectory re-synchronisation

IV. Motion Control Calibration

In the second phase, we refined vehicle motion control to ensure realistic speed and steering dynamics within the CARLA environment matching RounD trajectories. Accurately replicating real-world vehicle behavior is inherently complex, making the choice of a suitable vehicle model critical. We selected the *Tesla Model-3* as our reference vehicle in this study.

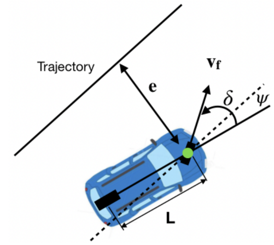


Fig. 5: Kinematic bicycle model [source: www.shuffleai.blog].

A. Steering Control

For steering and lateral control, we adopt a simplified bicycle model, as illustrated in Fig. 5. The steering input is denoted as δ, the heading error with relative to the trajectory as $\Delta\psi$, and the cross-track error as e. According to the *Stanley Control Law*, the cross-track error represents the perpendicular distance between the trajectory and the center of the front axle. As described in [7], Eq. (1) defines the steering input as a path-tracking solution applicable to any vehicle model. However, the control behavior varies based on two key gains: K_e for Cross-track error gain, and K_v for Speed-dependent gain.

$$\delta(t) = \Delta\psi(t) + tan^{-1}(\frac{K_e e(t)}{K_v + v(t)}) \tag{1}$$

B. Initial Speed Challenge

Unlike RounD vehicles, which start at non-zero speeds (13–56 km/h), CARLA vehicles spawn at rest. To bridge this gap, we developed a holistic strategy to compute the required throttle input, speed, and distance necessary to match the initial speeds observed in RounD. As a preliminary step, we constructed an adaptive model by applying throttle inputs as a step function, increasing from 30% to 72% in 0.2% increments. We then recorded three key parameters: (i) Velocity (m/s) at steady-state, (ii) Time (frames at 25 FPS) and (iii) Distance (m) traveled until steady-state.

Table II summarizes the extracted data, serving as a lookup table for identifying vehicle dynamics during acceleration.

TABLE II: System Identification Parameters for Vehicle Dynamics at gaining speed phase

CARLA steady-state Dynamic model parameters			
Throttle t_g	***Velocity*** (km/h) v_0	***Frame*** f_g	***Distance***(m) d_g
30.0%	11.81	345	34.98
30.2%	11.93	346	35.45
30.4%	12.06	347	35.89
30.6%	12.18	348	36.36
30.8%	12.30	348	36.71
....	....	....	....
....	....	....	....
71.2%	55.68	465	216
71.4%	56.02	465	217.6
71.6%	56.35	466	219
71.8%	56.66	464	218
72.0%	57.04	467	222

*Specific for Tesla M3 blueprint in CARLA simulator.

Whenever loading a new vehicle trajectory from the RounD dataset, the lookup table is used to determine the appropriate initialization parameters:

- Throttle t_g: throttle input required to reach the desired initial speed v_0
- Frame offset f_g: adjusted CARLA spawn time to account for acceleration delay, computed as f_C = f_R - f_g
- Distance offset d_g: adjusted CARLA spawn position before the original RounD position, computed as p_C = p_R - d_g (moving backward along the trajectory).

C. Speed Control

To regulate a vehicle's speed and acceleration, we finally need to account for nonlinear dynamics, either through a transfer function or an adaptive state-space model. A first-order control system is notably characterized by a first-order differential equation that defines the relationship between input and output in the frequency domain (s-domain). Eq. (2) represents *Moradi et al.* [8] transfer function for a vehicle's throttle input $U(s)$ to its velocity output $V(s)$, where $kappa$ is the gain, and τ is the time delay of the first-order dynamics:

$$\frac{V(s)}{U(s)} = \frac{\kappa}{\tau s + 1} \tag{2}$$

The state-space representation of a single-input, single-output (SISO) Linear Time Invariant (LTI) system is shown in (3), where $x(t)$ is the system's state, $u(t)$ is the input and $y(t)$ is the i output.

$$\begin{cases} \dot{x}(t) = ax(t) + bu(t) \\ y(t) = cx(t) + du(t) \end{cases} \tag{3}$$

By simplifying (3) under the assumptions $a, c \neq 0$, $b = 1$, $d = 0$, and considering velocity $v(t)$ as the new state, we obtain the state-space model for LTI control as per Eq. (4):

$$\begin{cases} a_x(t) = av(t) + cu(t) \\ y(t) = v(t) \end{cases} \tag{4}$$

We adopted the speed control model from [8] with one key modification: replacing the passenger comfort constraint with the RounD dataset's recorded speed, this approach allows us to generate throttle and brake values for each vehicle in CARLA based on RounD dataset's frame-specific speed and acceleration. To validate our approach, we analyzed speed compliance and time synchronization. Fig.6 illustrates a speed comparison for a randomly selected vehicle (veh-95 from the RounD dataset):

- **Preparation Phase** (Left): The vehicle spawns at a specific distance and gradually accelerates to match the initial dataset speed at the corresponding frame.
- **Tracking Phase** (Right): The speed control function maintains close alignment with the dataset's speed over time, demonstrating the accuracy of our approach.

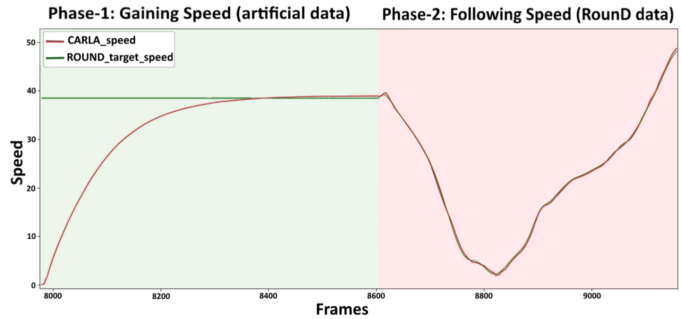


Fig. 6: MPC-based RounD speed matching

V. Sensors Matching

The third phase of our methodology equips CARLA vehicles with KITTI-like calibrated sensors to enable high-fidelity data collection within CARLA. While CARLA lacks vehicle characteristics for KITTI's Volkswagen vehicle in terms of width, height, and physical characteristics (as shown in Fig.7), it yet provides a flexible framework for sensor placement. Without loss of generalities, we placed KITTI sensors on our Tesla *Model-3* vehicle at the exact positions and orientations as in the KITTI dataset, ensuring consistent perception and data collection as for real-world KITTI recordings. To maintain realism and accuracy, we replicate KITTI's sensor configurations, including:

- Velodyne HDL-64E LiDAR (identical mounting position and calibration as in KITTI).
- Two RGB cameras (similar to Point Grey Flea 2) positioned according to the KITTI dataset.

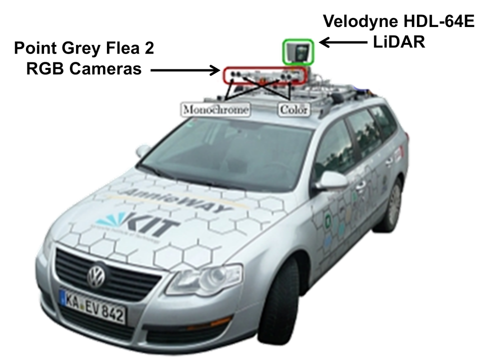


Fig. 7: KITTI-Car equipped with calibrated sensors

Our approach follows KITTI-CARLA's sensor setup and calibration settings [5], yet with one key distinction: unlike KITTI-CARLA, which generates data in artificial towns (TOWN01–TOWN07), our methodology replicates the real-world RounD dataset. This ensures the collected sensor data captures naturalistic driving behaviors as depicted in Fig. 8, including roundabout interactions, yielding, and acceleration patterns. By integrating real-world road topology and traffic dynamics into a synthetic simulation, we bridge the gap between real-world traffic datasets and synthetic sensor simulations. This enhances dataset suitability for autonomous driving research, sensor fusion, and transfer learning applications.

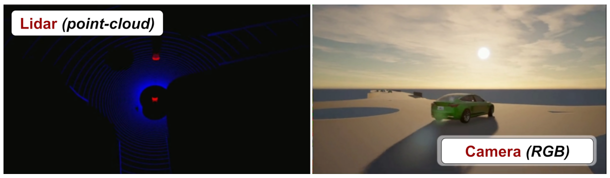


Fig. 8: KITTI-like dataset; Lidar & RGB Camera

VI. Impact Assessment on Autonomous Driving

In this section, we assess the benefit of the designed joint motion control & sensor CARLA scenario matching RounD motion and KITTI perception for repeatable, controllable and realistic autonomous driving simulation-based experiments. Without loss of generality, we rely on a simplified roundabout hazard detection access control algorithm considering perception from sensor input rather than perfect CARLA knowledge on the decision-making algorithm. This assessment does not aim at judging the algorithm itself but rather how imperfect or delayed perception would impact its decision to decide to enter a roundabout.

A. Experiment Setup

Figure 9 represents the roundabout under test and highlights two specific areas: (i) RounD control, where vehicles drive according to RounD trajectories; (ii) Perception-control, where vehicles alter the original RounD trajectories according to the decision-making algorithm. The objective of the latter area is to evaluate if and how sensor-based perception would change if and how the vehicle enters the roundabout compared to RounD (reproducing a human decision).

In this experiment, we leverage two sensor input, LiDAR and RGB cameras, to enable perception-driven decision-making. As a vehicle approaches the roundabout and enters the perception-control zone, it continuously processes sensor data to detect other vehicles, predict their trajectories, and assess traffic gaps. The decision to enter the roundabout is made based on perception inputs and hazard assessment models, ensuring the autonomous system proceeds only when a safe gap is available.

As any access to the roundabout under test is under perception control, we consider two options to assess the impact of realistic sensor perception: (i) perfect knowledge, where the ego vehicle gets an absolute knowledge of any approaching vehicle; (ii) perception-based knowledge, where the ego-vehicle only detects danger based on its own sensors.

Considering the perception-based decision process, once a vehicle enters the perception control zone, it analyzes sensor data from LiDAR and two RGB cameras, configured identically to those in the KITTI dataset. By fusing LiDAR and camera data and leveraging the YOLOv8 model, the ego vehicle not only detects surrounding vehicles but also accurately determines their relative positions in a 2D space. This fusion process enables precise distance estimation between the ego vehicle and other detected vehicles, represented as a 2D vector:

- x-distance: The distance between the ego vehicle's front bumper and the closest detected point along the x-axis. This value is always positive, as the cameras are aligned with the vehicle's heading.
- y-distance: The lateral distance between the ego vehicle and the detected object. Negative values indicate objects to the left, while positive values correspond to objects on the right.

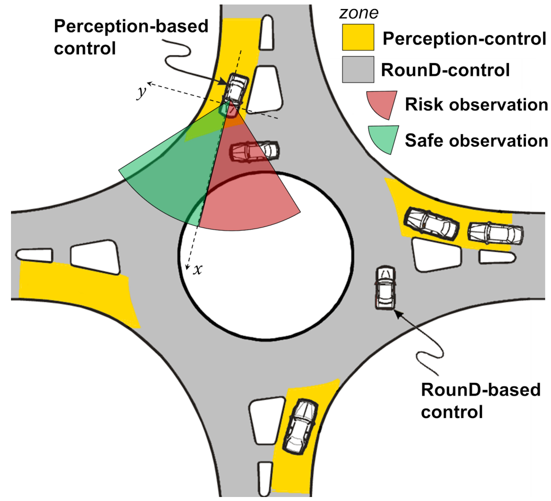


Fig. 9: Perception-based control

Without loss of generality, the control strategy follows a conservative approach: if the ego vehicle detects an approaching vehicle within a predefined Euclidean distance and in a negative y-position (i.e., approaching from the left), it identifies a collision risk and applies braking. Conversely, if no incoming vehicle is detected, the ego vehicle proceeds safely into the roundabout.

B. Evaluation and Discussion

The RounD dataset contains 256 vehicle trajectories in a roundabout traffic scenario. To evaluate the impact of our proposed approach, we simulated all RounD vehicles and analyzed their behaviors under perception-based control. Following the simulation, we compared the autonomous vehicle (AV) behavior with the original RounD dataset trajectories. This comparison allowed us to assess deviations, collision rates, and overall safety performance, highlighting the effect of perception-based decision-making compared to perfect (unrealistic) knowledge in complex urban environments.

Table III presents the evaluation results for both control strategies: perception-based control and RounD-control (using perfect knowledge). The analysis considers two possible decisions for each vehicle approaching the roundabout: (i) *Brake*, where the ego-vehicle applies braking, and (ii) *Go*, where the ego-vehicle enters the roundabout. For each decision, we further evaluate whether the outcome was safe or resulted in a collision. It is worth noting that a *safe braking* event does not necessarily imply a positive outcome, especially if it involves unnecessary or excessively harsh deceleration compared to the original RounD scenario.

Defining a braking event as a continuous deceleration over 25 consecutive frames, the simulation results are summarized as follows:

TABLE III: Evaluation: RounD-control vs. Perception-control

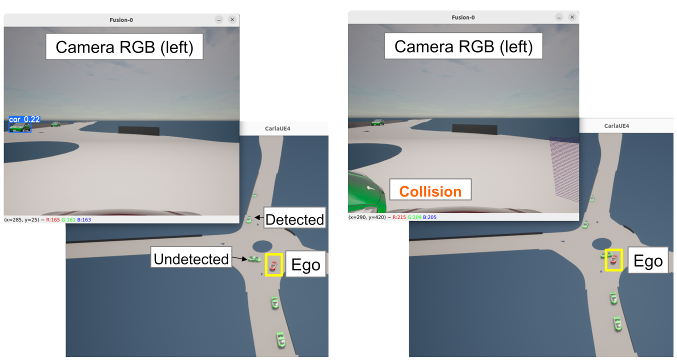
	Brake*		Go	
	Safe	***Collide***	**Safe**	***Collide***
RounD-control	30	0	226	0
Perception-control	41 (Effective: 17, Ineffective: 24)	0	197	18

*Brake in RounD = 25 consecutive frames with speed deceleration

- **RounD-control:** 30 vehicles performed braking maneuvers when approaching the roundabout, consistent with real-world hazard responses observed in the RounD dataset. The remaining 226 vehicles entered the roundabout without any collisions.
- **Perception-control:** 41 vehicles applied braking before entering, indicating increased sensitivity to perceived hazards. Among these, 17 were effective braking events that successfully prevented potential collisions, while 24 were ineffective, resulting in unnecessary stops (false positives). Out of the 215 vehicles that proceeded to enter the roundabout, 18 experienced collisions (false negatives).

These findings provide key insights into perception-based control for roundabout hazard detection. First, unsafe entries resulting in collisions (the *Go-Collide* cases) were caused by false negatives, suggesting that KITTI-like calibrated sensors alone may be insufficient for comprehensive risk detection. Second, safe but unnecessary braking events highlight the occurrence of false positives, which can negatively affect traffic efficiency.

Both types of perception errors should be carefully addressed, which is only possible through realistic simulation environments such as the one presented in this work.



(a) step[n]: approaching (b) step[n+x]: entering

Fig. 10: Perception-based decision-making at roundabout

One of the key advantages of the proposed integrated KITTI-RounD CARLA scenario is illustrated in Fig. 10. On the left (Fig. 10a), the ego-vehicle decides to enter the roundabout as its left RGB camera does not detect the inbound vehicle. On the right (Fig. 10b), the vehicle is already inside the roundabout when the same left RGB camera detects the hazard, but unfortunately, too late to prevent a collision. This delayed hazard detection was caused by the limited camera field of view, exacerbated by the vehicle's steering away from the approaching risk, thus moving the danger outside the observation zone, as depicted in Fig. 9.

We consider this scenario a valuable benefit of our methodology, as such perception-driven decision errors would not appear in simulation environments using either unrealistic motion planning or idealized (omniscient) sensor perception.

VII. Conclusion and Future Work

In this paper, we presented a methodology for creating realistic, perception-ready simulation scenarios in CARLA by integrating naturalistic RounD traffic trajectories with KITTI-calibrated sensor configurations. Our roundabout-focused case study demonstrated that incorporating both realistic motion planning and sensor-based perception constraints can significantly impact autonomous vehicle (AV) decision-making outcomes. The resulting RounD-KITTI CARLA scenario has been released as open-source to support the broader research community.

For future work, we plan to pursue the following directions:

- **Scenario extension:** Incorporating Vulnerable Road Users (VRUs) and diversifying urban landscapes to enhance the realism and complexity of the simulated environment.
- **Control strategy optimization:** Refining comfort-based, AI-driven roundabout control strategies while explicitly accounting for perception uncertainties, as introduced in [8].
- **Toolset generalization:** Expanding the adaptability of the toolset to enable seamless integration with other real-world and synthetic traffic datasets, ensuring broader applicability across diverse research scenarios.

VIII. Acknowledgements

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References

[1] L. Codeca, R. Frank, and T. Engel, "Luxembourg sumo traffic (lust) scenario: 24 hours of mobility for vehicular networking research," pp. 1–8, 2015.
[2] L. Codeca and J. Härri, "Towards multimodal mobility simulation of c-its: The monaco sumo traffic scenario," vol. In 2015 ieee vehicular networking conference (vnc), pp. 97–100, 2017.
[3] A. Geiger, P. Lenz, C. Stiller, and R. Urtasun, "Vision meets robotics: The kitti dataset," *The International Journal of Robotics Research*, vol. 32, no. 11, pp. 1231–1237, 2013.
[4] H. Caesar, V. Bankiti, A. H. Lang, S. Vora, V. E. Liong, Q. Xu, A. Krishnan, Y. Pan, G. Baldan, and O. Beijbom, "nuscenes: A multimodal dataset for autonomous driving," in *CVPR*, 2020.
[5] J.-E. Deschaud, "Kitti-carla: a kitti-like dataset generated by carla simulator," 08 2021.
[6] R. Krajewski, T. Moers, J. Bock, L. Vater, and L. Eckstein, "The round dataset: A drone dataset of road user trajectories at roundabouts in germany," pp. 97–100, 2021.
[7] G. M. Hoffmann, C. J. Tomlin, M. Montemerlo, and S. Thrun, "2007 american control conference," pp. 2296–2301, 2007.
[8] S. Moradi, A. Nadar, and J. Härri, "Comfort-based ai-driven roundabout control for automated vehicles," *8th International Conference on Models and Technologies for Intelligent Transportation Systems*, june 14-16, 2023, EURECOM, France.