

AccidentSim: Generating Physically Realistic Vehicle Collision Videos from Real-World Accident Reports

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Abstract

Collecting real-world vehicle accident videos for autonomous driving research is challenging due to their rarity and complexity. While existing driving video generation methods may produce visually realistic videos, they often fail to deliver physically realistic simulations because they lack the capability to generate accurate post-collision trajectories. In this paper, we introduce AccidentSim, a novel framework that generates physically realistic vehicle collision videos by extracting and utilizing the physical clues and contextual information available in real-world vehicle accident reports. Specifically, AccidentSim leverages a reliable physical simulator to replicate post-collision vehicle trajectories from the physical and contextual information in the accident reports and to build a vehicle collision trajectory dataset. This dataset is then used to fine-tune a language model, enabling it to respond to user prompts and predict physically consistent post-collision trajectories across various driving scenarios based on user descriptions. Finally, we employ Neural Radiance Fields (NeRF) to render high-quality backgrounds, merging them with the foreground vehicles that exhibit physically realistic trajectories to generate vehicle collision videos. Experimental results demonstrate that the videos produced by AccidentSim excel in both visual and physical authenticity. See our project page at <https://accidentsim.github.io/>.

1. Introduction

The research and development in autonomous driving heavily relies on diverse training data to enhance performance across a variety of scenarios. However, existing autonomous driving datasets [3, 6, 13, 30, 42] predominantly cover normal driving situations, with a significant lack of data on anomalous events, such as vehicle collisions. The primary reason for this scarcity is that collecting such data is extremely challenging and costly. This limitation constrains the ability of relevant deep learning models to effectively

learn responses to such critical events. This phenomenon is referred to as the Curse of Rarity (CoR) [21], where the occurrence rate of safety-critical events in high-dimensional spaces is occasional. As a result, existing datasets often fail to adequately capture these rare but critical events. This scarcity hinders deep learning models from effectively learning to handle unexpected safety-critical scenarios, ultimately limiting the safety performance of autonomous driving systems. Given this context, driving video generation presents a promising alternative, offering the flexibility to create a wide range of driving scenarios, particularly those involving vehicle collisions, while addressing the challenges associated with data collection.

However, existing video generation approaches for driving scenarios [4, 12, 18, 22, 24, 27, 33, 39–41, 49] provide only partial solutions. These methods still face notable limitations, particularly in vehicle collision scenarios, primarily due to their inability to incorporate crucial physical constraints. For example, they fail to utilize physical elements such as vehicle momentum and impulse during collisions, which are essential for accurately reconstructing real-world vehicle collision scenarios. As a result, while the generated collision scenarios may appear visually realistic, they often fail to capture the underlying physical characteristics of actual vehicle collisions, i.e., they are not physically realistic.

To address the aforementioned problems, we propose AccidentSim, which offers a new research perspective for generating physically realistic vehicle collision videos by utilizing the rich physical clues readily available in real-world accident reports. Specifically, AccidentSim first extracts key physical parameters, such as vehicle speed, collision angle, vehicle mass and so on, from real-world accident reports to prepare the necessary physical cues for generating collision scenarios. The extracted physical cues are subsequently input into a physical simulator, e.g., CARLA simulator [9], which impose corresponding physical constraints that ensure that generated collision scenario exhibit physically realistic post-collision vehicle movements. Additionally, by recording collision trajectories within the physical simulator, we further utilize them to fine-tune a large

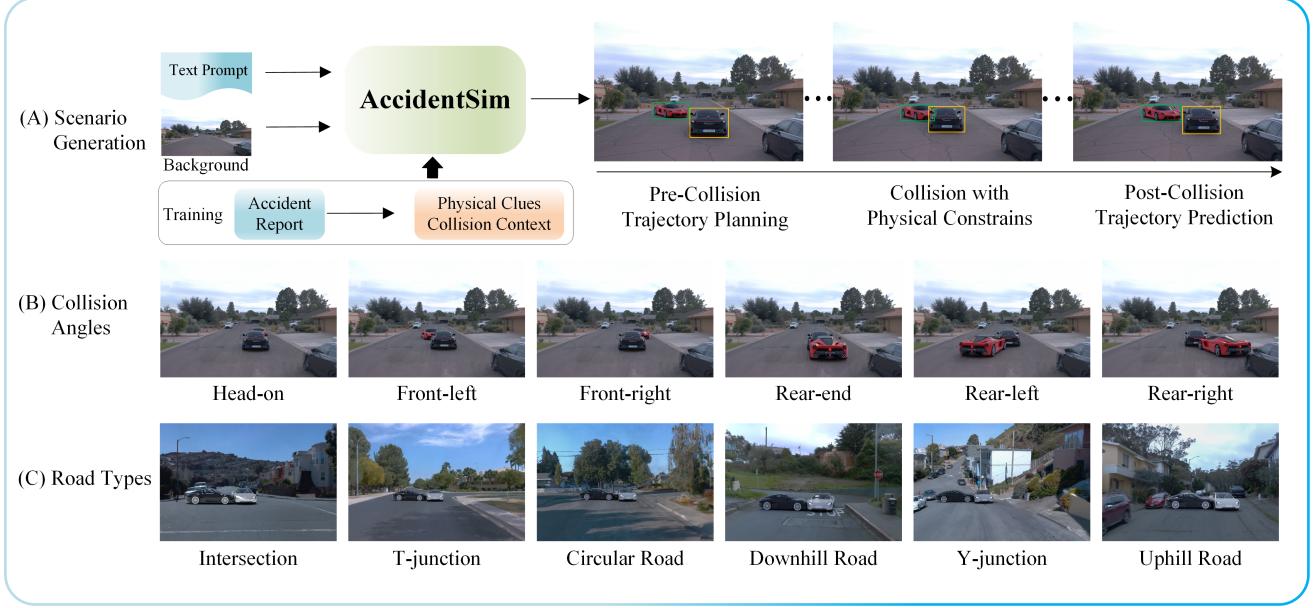


Figure 1. AccidentSim can generate physically realistic vehicle accident videos by incorporating the physical clues and contextual information extracted from real-world accident reports. (A) The physical clues of the collision are extracted from accident reports to create a vehicle collision trajectory dataset in CARLA. This dataset is used to fine-tune a language model within AccidentSim, enabling it to generate physically realistic vehicle collision trajectories directly from user prompts. The extracted contextual information from the accident reports is then utilized to build the accident scenario by integrating the generated collision trajectories. (B) AccidentSim can produce physically realistic post-collision trajectories from various angles, e.g., head-on collision, front-left collision, rear-right collision, etc. (C) AccidentSim can generate collision trajectories for different road types, such as intersections, T-junctions, circular roads, and so on.

language model, e.g., LLaMA-3.1-8B [10], within AccidentSim. This enables AccidentSim to directly respond to user prompts for generating specific, physically realistic vehicle collision trajectories based on user-provided accident descriptions.

In essence, our proposed AccidentSim framework is grounded in physical realism. It incorporates physical clues extracted from accident reports and imposes corresponding physical constraints to ensure that the generated videos accurately reflect the characteristics of real-world vehicle collisions. Consequently, AccidentSim bridges the gap between the generated and the real-world driving scenarios. By generating a diverse array of collision videos, AccidentSim is promising in effectively addressing the shortage of collision scenarios in existing datasets. The main contributions of our work are summarized as follows:

- We propose the AccidentSim framework, which extracts physical clues and contextual information from real-world accident reports to generate physically realistic vehicle collision videos.
- We leverage a large language model for trajectory planning and prediction in vehicle collision, using essential physical clues extracted from accident reports, to ensure that the generated trajectories adhere to real-world physical constraints.

- We validate AccidentSim’s capability to adapt vehicle collision trajectories across various road types and multiple collision angles, demonstrating its generalization and applicability to a wide range of conditions.

2. Related Work

End-to-end models for autonomous driving perform poorly in extreme conditions, such as collision scenarios, primarily due to a lack of data for such events. Therefore, data from scenarios involving collisions plays a crucial role in enhancing the robustness of these models. To address this issue, existing approaches for acquiring and generating accident scenarios can be broadly categorized into two main strategies: real-world data collection and driving scenario generation.

Early research focused primarily on constructing real-world accident datasets. For instance, the CADP dataset provides spatio-temporal annotations of CCTV accident videos, offering valuable support for traffic accident prediction and vehicle collision detection tasks [29]. The DADA-seg dataset includes pixel-level annotations of accident scenarios, aiding models in handling extreme driving scenarios [43]. The CCD dataset further enriches accident scenario semantics by providing diverse environmental annotations

and analyses of accident causes [2]. Despite the value these real-world datasets offer in capturing collision scenarios, they face challenges such as high acquisition and annotation costs, leading to limited dataset sizes and scenario diversity.

To address the difficulty of obtaining real-world accident data, recent studies have explored various scenario generation approaches, which can be categorized into three main directions. First, language-guided traffic generation methods like CTG++ [47] and LCTGen [31] leverage large language models to control traffic simulation through natural language instructions. Second, several works focus specifically on safety-critical scenarios: CAT [45] proposes a closed-loop adversarial training framework to create challenging scenarios, while STRIVE [28] generates difficult but solvable scenarios by optimizing in the latent space of a learned traffic model. NeuroNCAP [23] advances this direction by introducing a NeRF-based simulator that simulates safety-critical scenarios through viewpoint movement for testing autonomous driving systems. Third, in the realm of video generation, methods like DriveDiffusion [20], DriveDreamer [33], and S-NeRF [37] have achieved significant progress in generating realistic driving videos, while Panacea [36], MagicDrive [12], and Drive-WM [34] have focused on improving scenario control capabilities. However, these existing methods still face limitations in simulating accurate vehicle dynamics during and after collisions, making it challenging to create realistic crash scenarios.

Given the limitations of existing methods, this work introduces AccidentSim, a framework designed to generate highly realistic accident video data based on real-world accident reports. By integrating a physical simulation engine, we effectively simulate accident scenarios that closely reflect real-world conditions.

3. Method

As illustrated in Figure 2, the proposed approach leverages a compact version of Llama (i.e., Llama-3.1-8B [10]) to decompose the accident scene into vehicle motion information and view information. The vehicle motion information guides **Foreground Processing** to generate physics-constrained foreground images of the vehicle collision, while the view information directs **Background Processing** to produce realistic background images with consistent lighting. Finally, **Scenario Composition** combines the foreground and background images to create a cohesive driving scenario featuring the collision.

Foreground Processing. As illustrated in the foreground processing block of Figure 2, vehicle motion information from the previous accident description processing in LLaMA undergoes pre-collision trajectory planning (detailed in Section 3.1) to identify the vehicle models, subsequently generating both the pre-collision trajectory and

collision information. These outputs are subsequently processed by AccidentLLM to infer realistic post-collision trajectories (as explained in Section 3.2), ultimately forming complete vehicle trajectories. Once the complete vehicle trajectories are obtained, physics-realistic foreground images depicting the vehicle collision can be rendered.

Background Processing. As illustrated in the background processing block of Figure 2, the background processing pipeline consists of two main phases: viewpoint adjustment and background rendering. In the viewpoint adjustment phase, we first parse the view information into positional and angular shift parameters corresponding to the target viewpoint. These shift parameters are then converted into the appropriate extrinsic transformation matrix and combined with the initial parameters to yield an updated viewpoint configuration. In the background rendering phase, if a novel viewpoint is needed, we apply the scene reconstruction method from ChatSim[35]; otherwise, the original video frame is used as the background. Specifically, ChatSim’s scene reconstruction method incorporates multi-camera alignment and luminance consistency rendering techniques, ensuring that the generated background seamlessly and naturally aligns with the vehicle’s viewpoint.

Scenario Composition. In the final scenario composition stage, we employ alpha channel compositing techniques to finely adjust transparency between the foreground and background images, ultimately generating a visually and physically realistic collision scenario.

3.1. Pre-Collision Trajectory Planning

We present a trajectory planning algorithm designed to generate valid pre-collision trajectories and collision information using vehicle motion information, which includes the dynamics of all involved vehicles and scene map information. The algorithm operates across three primary phases: in the **Initial State Extraction** phase, essential vehicle and collision parameters are extracted to establish the initial state for each vehicle and define the collision target; during **Lane and Path Selection**, the algorithm identifies suitable lanes based on vehicle dynamics and the scene map, forming potential lane combinations to ensure feasible paths for collision trajectory planning; finally, in **Trajectory Generation and Validation**, valid pre-collision trajectories are generated using the selected lane combinations, which are then evaluated against collision criteria to yield a final set of feasible pre-collision trajectories. For more algorithmic details, refer to Section A of the supplementary materials.

Initial State Extraction. In this phase, the algorithm initiates by extracting essential vehicle and collision parameters from the input motion information \mathcal{I} , which includes the dynamics of all vehicles involved in the scenario. Using this data, the algorithm first isolates variables such as the col-

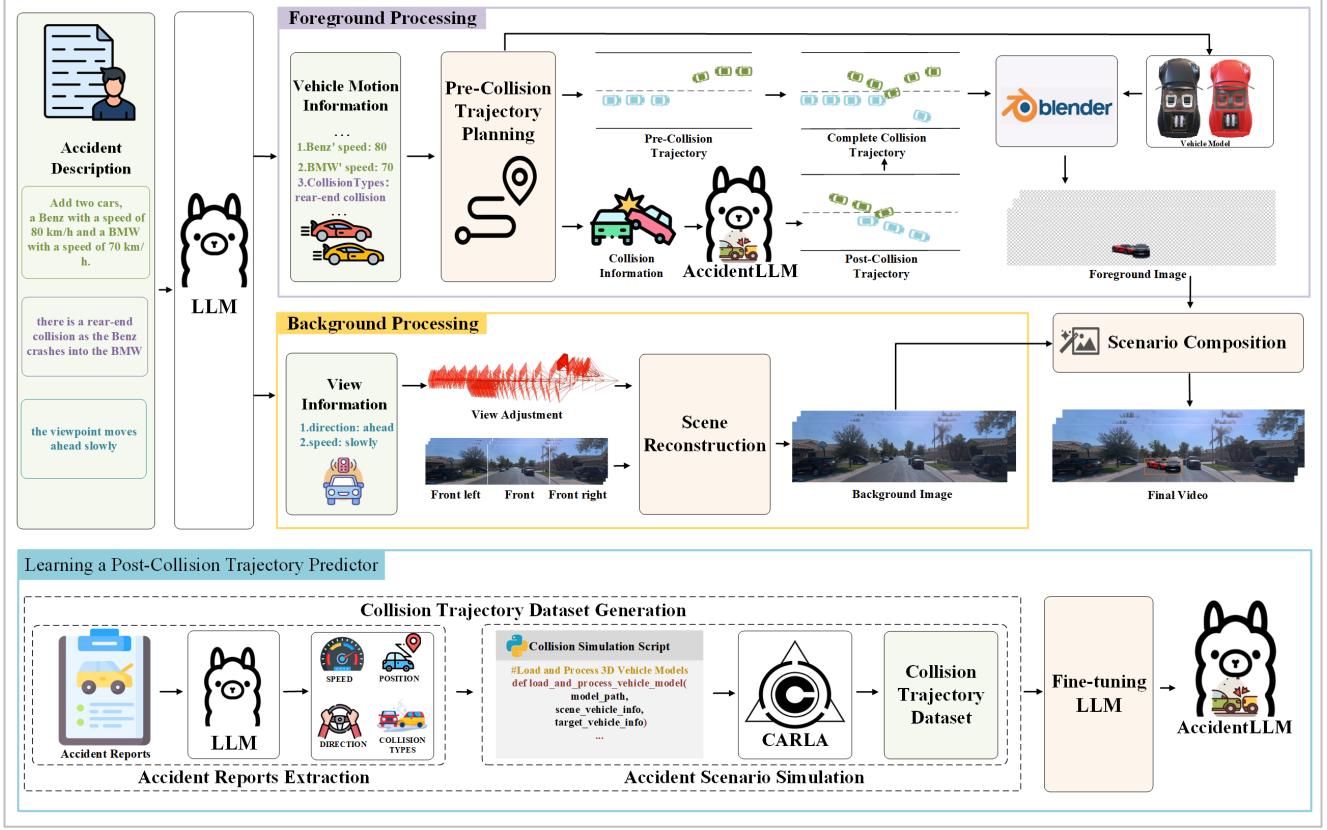


Figure 2. Architecture of AccidentSim. We propose AccidentSim, a framework for generating physically realistic collision scenarios. To achieve this, we extract physical physical clues, such as vehicle speeds and collision types, as well as contextual information, like road types, from accident reports. The extracted information is then utilized in CARLA to generate corresponding collision trajectories, which form a dataset. This dataset is subsequently used to fine-tune the LLaMA model, enabling it to adapt to various road types and ultimately forming AccidentLLaMA. Building on this foundation, AccidentSim can leverage user-provided accident descriptions to conduct pre-collision trajectory planning, generating both the pre-collision trajectory and relevant collision information, such as vehicle speeds, collision angles, and more. The collision information is then processed by AccidentLLaMA, which produces physically realistic post-collision trajectories, resulting in a complete collision trajectory. These realistic collision trajectories facilitate the creation of comprehensive collision scenarios.

lision point \mathcal{C} , vehicle count n , distances D , velocities V , accelerations A , and orientation angles θ . This extraction process establishes a comprehensive view of each vehicle's current state and potential collision zones. The algorithm then determines the starting points P_0 for each vehicle by factoring in directional and dynamic properties.

Lane and Path Selection. This phase focuses on selecting suitable lanes within the scene map \mathcal{M} to enable feasible trajectory planning. The algorithm begins by parsing the scene map to identify available lanes L , ensuring that each candidate lane is assessed for compatibility with the vehicle's current orientation θ and collision constraints \mathcal{C} . A subset of valid lanes \mathcal{L} is then assembled, containing only those that meet the criteria defined by vehicle orientation and other relevant dynamics. After identifying valid lanes, the algorithm generates various lane combinations \mathcal{G} by analyzing lane connectivity and spatial feasibility in relation

to the parameters n, D, V, A , and θ .

Trajectory Generation and Validation. The final phase involves generating and validating trajectories based on the preselected lane combinations. For each lane combination G_i in \mathcal{G} , the algorithm checks whether it meets specific collision criteria using the collision parameters \mathcal{C} . Upon identifying a valid lane combination G_s that satisfies these conditions, it proceeds to generate the trajectory paths \mathcal{T} . This process incorporates the starting points P_0 and valid lane combination G_s to form trajectories that are both dynamically feasible and collision-aware. Each trajectory is then evaluated to ensure it conforms to the safety criteria established for pre-collision scenarios. The validated set of trajectories \mathcal{T} and the associated imminent collision information \mathcal{S} are then outputted as the final result, representing a selection of feasible paths for preemptive collision management.

3.2. Learning a Post-Collision Trajectory Predictor

Given the validated trajectories \mathcal{T} and the associated imminent collision information \mathcal{S} , a predictor is required to be capable of generating physics-realistic post-collision trajectories. To achieve this, we propose a framework that leverages physical insights extracted from accident reports to train a specialized version of LLaMA [10]. The trained model, termed *AccidentLLM*, can respond to user prompts and predict contextually appropriate post-collision trajectories adaptable to various road conditions, based on the provided descriptions.

As shown in “Learning a Post-Collision Trajectory Predictor” block of Figure 2, the proposed framework is structured into three stages: (1) **Accident Report Extraction** (see Section 3.2.1), where collision-specific information is extracted from accident reports; (2) **Accident Scenario Simulation** (see Section 3.2.2), which generates physics-constrained post-collision trajectories; and (3) **Fine-tuning AccidentLLM** (see Section 3.2.3), where the extracted attributes and simulated scenarios are used to tailor the model for accurate trajectory prediction.

3.2.1. Accident Report Extraction

Traffic accident reports provide crucial data to support collision simulations, encompassing pre-accident environmental conditions, collision dynamics, and post-accident outcomes. The SoVAR [14] employs a template-based approach in conjunction with language models to extract key information from accident reports. However, due to the inherent diversity in the descriptions of accident reports, a single-template approach is inadequate for adapting to the various types of accident scenarios. To address these challenges, we employ a Llama model [10] with a few-shot learning strategy to automatically extract essential information from accident reports, including pre-accident environmental conditions, road features, and driver behaviors; in-collision details such as vehicle positioning, speed, and collision type; and post-accident data, including emergency responses. This information enhances the realism of accident simulations in CARLA, supporting safety analysis and accident prevention in autonomous driving systems.

3.2.2. Accident Scenario Simulation

In the accident simulation phase, we developed a comprehensive scenario reconstruction pipeline to accurately recreate real-world collision scenarios and generate high-quality datasets for model fine-tuning. The process begins by partitioning accident report data into vehicle-specific information, such as velocity and location, and road-related details. Using RoadRunner [7], we construct high-fidelity 3D road models, which are seamlessly integrated into the CARLA simulation environment. CARLA’s advanced vehicle navigation capabilities, combined with the extracted vehicle dynamics and physical parameters such as friction and gravity,

ensure realistic motion and collision behavior. Frictional forces are determined by road slope and surface properties, while gravity influences acceleration and deceleration, particularly on inclined surfaces. As the vehicle approaches the designated collision point, collision sensors capture critical data such as speed, position, and orientation at the moment of impact, and scripts record the post-collision trajectory. This detailed collision trajectory data provides a robust foundation for fine-tuning the LLaMA model [10], significantly enhancing its ability to predict physics-realistic post-collision trajectories.

3.2.3. Fine-tuning LLM

After obtaining the collision dataset from the previous process, we fine-tune the Llama model [10] to specialize in predicting post-collision trajectories, resulting in a model we term AccidentLLM. To achieve efficient fine-tuning, we use the Low-Rank Adaptation (LoRA) method [17], preserving original model parameters while adding trainable low-rank matrices. This supervised fine-tuning optimizes the LLM for precise collision trajectory prediction in complex scenarios.

To enhance the accuracy of the trajectory prediction, we utilize an l_1 loss function to quantify the discrepancy between the predicted and actual trajectories. This loss is computed by calculating the absolute difference between the predicted and true values of the vehicle’s position and rotational angles across each time step. The trajectory matching loss is formulated as:

$$L_{\text{traj}} = \frac{1}{N} \sum_{i=1}^N \left(\sum_{j=x,y,z} |p_{j,i} - y_{j,i}| + \sum_{k=x,y,z} |\theta_{k,i} - \theta_{k,i}^*| \right) \quad (1)$$

where $p_{j,i}$ denotes the predicted position at time step i , and $y_{j,i}$ represents the corresponding ground truth position. Similarly, $\theta_{k,i}$ refers to the predicted rotational angle about axis k , and $\theta_{k,i}^*$ represents the ground truth rotational angle. N is the total number of time steps in the trajectory. This formulation integrates both spatial and rotational dynamics, ensuring that the predicted trajectories closely align with the actual physical behavior observed in real-world collision scenarios.

4. Experiments

To evaluate the performance of our proposed method, we refer to the method in SoVAR [14] and conduct a series of experiments on the publicly available Waymo Open Dataset [30]. For a more detailed component analysis, we utilize real-world accident report dataset to evaluate the performance of each component through metrics such as Attribute Extraction Accuracy, Scenario Reconstruction Rate (SRR), Collision Trajectory Error, and Physical Consistency Error.

Table 1. Collision Rate (CR): We use the collision rate to evaluate the performance of different scenario generation methods. "PP" is short for "Pre Pretraining," which represents the performance of the ego vehicle in the test scenarios before fine-tuning.

Metric	Algo.	Dual Vehicle Scenarios				Triple Vehicle Scenarios				Multi Vehicle Scenarios				Avg.
		Straight Obstacle	Unprotected Left-turn	Right- turn	Lane Changing	Straight Obstacle	Unprotected Left-turn	Right- turn	Lane Changing	Straight Obstacle	Unprotected Left-turn	Right- turn	Lane Changing	
CR ↓	PP	0.48	0.67	0.46	0.58	0.52	0.59	0.47	0.63	0.43	0.60	0.51	0.68	0.552
	LC	0.12	0.00	0.37	0.51	0.22	0.13	0.40	0.52	0.28	0.25	0.39	0.46	0.304
	AS	0.23	0.05	0.41	0.53	0.31	0.10	0.38	0.45	0.28	0.17	0.35	0.58	0.320
	CS	0.22	0.22	0.19	0.39	0.17	0.26	0.17	0.48	0.12	0.29	0.10	0.48	0.258
	AT	0.14	0.00	0.23	0.30	0.21	0.04	0.28	0.21	0.23	0.02	0.31	0.18	0.179
	ChatScene	0.03	0.10	0.01	0.11	0.09	0.21	0.06	0.24	0.05	0.16	0.09	0.19	0.112
	AccidentSim	0.05	0.08	0.01	0.09	0.07	0.11	0.13	0.12	0.02	0.07	0.10	0.03	0.073

For collision avoidance tasks, we evaluate performance using the collision rate.

4.1. Datasets

Waymo Open Dataset. We utilized the Waymo Open Dataset [30] to generate the reconstructed videos for our non-reference scenario quality evaluation. The Waymo Open Dataset contains data from 1,150 driving scenarios across a range of urban and suburban areas in multiple U.S. cities, including San Francisco, Mountain View, and Phoenix. Each scenario is recorded for 20 seconds and includes synchronized data from five LiDAR sensors and five high-resolution pinhole cameras. The dataset encompasses approximately 6.4 hours of driving data, including around 12 million LiDAR box annotations for 3D boundaries and 12 million camera box annotations for 2D images. The geographic diversity and high-quality annotations of the Waymo Open Dataset serve as a robust foundation for modeling and validating complex driving scenarios, thereby enhancing the authenticity and quality of AccidentSim in real-world environments.

Real-world Accident Reports. To evaluate the performance of each component in our framework, we utilized real-world accident reports to generate realistic vehicle trajectories in accident scenarios. The real-world accident data are sourced from the National Motor Vehicle Accident Causes Investigation Database, maintained by the National Highway Traffic Safety Administration (NHTSA) [26]. NHTSA follows the Model Minimum Uniform Crash Criteria (MMUCC) guidelines [25], delineating key factors contributing to vehicle crashes. To collect the required accident reports, we segment NHTSA police reports based on crash type and randomly select a sample from each category. This approach ensures a comprehensive representation of diverse environmental conditions, including various road types, and different crash classifications.

4.2. Evaluation Metrics

Collision Rate. To evaluate the effectiveness of our generated collision scenarios in collision avoidance training, we adopted the Collision Rate (CR) as the primary evaluation metric. The CR metric measures whether the autonomous

vehicles trained with our collision scenarios can successfully avoid accidents by assessing the frequency of collisions during trajectory execution. Specifically, we utilized CR to validate that vehicles trained in our generated scenarios learn better collision avoidance capabilities. A lower CR value after training indicates that our collision scenarios effectively help autonomous vehicles learn to navigate safely in dangerous situations, thus demonstrating the value of our scenario generation method in improving collision avoidance performance.

Scenario Reconstruction Rate. To evaluate the performance of pre-collision trajectory planning, we adopted the methodology outlined in SoVAR [14], using the Scenario Reconstruction Rate (SRR) as the primary evaluation metric. The SRR metric measures the efficiency of scenario reconstruction by assessing the similarity between generated and real-world trajectories.

Attribute Extraction Accuracy. The accuracy of attribute extraction from accident reports, as outlined in SoVAR, is critical for evaluating the precision of the Pre-Collision Trajectory Planning module. This metric directly reflects the model's ability to effectively represent features extracted from accident reports, which is crucial for accurately implementing trajectory prediction. Specifically, it measures the accuracy of extracting relevant attributes from the reports, such as road network attributes (e.g., road type, number of lanes), and dynamic entities (e.g., driving behavior, collision types). High accuracy indicates the model's effectiveness in capturing and utilizing key information, which is essential for generating realistic and accurate collision simulations.

Trajectory Prediction Error. To evaluate the performance of AccidentSim in predicting post-collision vehicle trajectories, we employed the L2 error as the primary metric. This metric calculates the L2 error between the expected and actual trajectories at each time step. A lower L2 error indicates that the predicted post-collision trajectory is more accurate and stable, highlighting the effectiveness of our approach.

Physical Consistency Error. During vehicle collisions, maintaining physical consistency with real-world dynamics is essential. In this regard, we compared the momen-

Table 2. Information Extraction Accuracy: We compare AccidentSim with SoVAR and AC3R regarding their accuracy in extracting road networks, traffic guidance, and dynamic object information [14] from accident reports.

Attributes	Road Network and Traffic Guidance [14]			Dynamic Objects [14]		
	LaneNum ↑	SpeedLimit ↑	CollisionLocation ↑	DrivingActions ↑	CrashType ↑	ParticipantsNumber ↑
SoVAR [14]	93.33%	100.00%	96.00%	76.33%	90.67%	100.00%
SoVAR_N [14]	76.00%	91.33%	95.33%	55.00%	90.00%	100.00%
AC3R [19]	70.67%	82.67%	78.67%	43.67%	11.67%	94.67%
Ours	98.00%	100.00%	98.00%	93.00%	88.00%	100.00%

Table 3. Post-Collision Trajectory Prediction: The accuracy of post-collision trajectory in terms of L2 (m) of AccidentSim compared to AutoVFX across different accident scenarios.

Accident Scenarios	Method	Trajectory Prediction Error				Physical Consistency Error			
		L2 (m)				Impulse		Momentum	
		1s	2s	3s	Average ↓	MAE ↓	RMSE ↓	MAE ↓	RMSE ↓
Straight Obstacle	AutoVFX	1.21	1.90	2.42	1.84	2.89	2.91	2.77	2.65
	AccidentSim	1.00	1.45	2.01	1.49	2.02	1.98	2.12	2.21
Unprotected Left-turn	AutoVFX	1.02	1.43	1.82	1.42	1.93	1.87	1.76	1.84
	AccidentSim	1.22	1.67	2.31	1.73	2.31	2.40	2.87	2.54
Right turn	AutoVFX	1.04	2.32	2.76	2.04	3.10	3.02	2.87	2.71
	AccidentSim	0.45	0.83	1.54	0.94	0.89	0.94	0.78	0.87
Lane Changing	AutoVFX	1.45	1.98	2.58	2.00	3.21	3.18	2.89	2.92
	AccidentSim	0.67	1.21	1.95	1.28	1.37	1.48	1.54	1.64

tum and impulse changes in AccidentSim generated trajectories with those observed in CARLA (as ground truth), using metrics such as MSE (Mean Absolute Error) and RMSE (Root Mean Square Error) to evaluate the error between the two. Smaller errors indicate that the AccidentSim generated vehicle trajectories align more closely with real-world physical factors.

4.3. Adversarial Training on Accident Scenarios

The purpose of these experiments is to demonstrate that the accident scenarios generated by AccidentSim help enhance the ego vehicle’s ability to avoid collisions.

Experiment Setting. We conduct our experiments on the Safebench platform [38] with an Nvidia A40 GPU. For scenario generation, we transfer vehicle driving situations from complex accidents reported by NHTSA to the driving scenarios in the Waymo dataset and use the Scenic language [11] to script and simulate accident scenarios in Waymo environments within CARLA. In total, 4000 training scenarios and 1000 testing scenarios are generated. For the classification of accident scenarios, We adopt the accident scenario categorization proposed in ChatScene [44] and extend it to include three-vehicle and multi-vehicle collision scenarios. For training, we employ the SAC algorithm [15] to train the ego vehicle’s control policy. The SAC agent is trained for 500 epochs with a learning rate of 0.0001, and we evaluate its performance every 50 epochs to report the optimal results.

To evaluate the performance of our approach, we con-

duct comparisons with several mainstream scenario generation methods in a simulated environment. The mainstream methods include Learning-to-collide (LC)[8], AdvSim

(AS)[32], Carla Scenario Generator (CS) [5], Adversarial Trajectory Optimization (AT) [46], and ChatScene[44]. These methods cover a range of adversarial-based and knowledge-based techniques, and we assess the effectiveness of our method by comparing collision rates.

Evaluation Results. Table 1 demonstrates that our method effectively enhances the robustness of the ego vehicle. Compared to the ego vehicle without finetuning, our approach reduces the collision rate by 47.9%, showing a significant improvement over other methods in terms of collision reduction. The experimental results highlight that accident scenarios generated from real accident reports help the vehicle avoid collisions, thereby compensating for the limitations of general driving datasets.

4.4. Component Analysis

Pre-Collision Trajectory Planning. We conducted a com-

Table 4. Trajectory Planning Capability: The accuracy of collision trajectory planning of AccidentSim is compared to SoVAR across different road types.

Evaluation indicators	Method	Road Types (Samples)		
		Intersection (140)	T-junction (109)	Straight Road (123)
SRR ↑ [14]	SoVAR [14]	93.3%	72.7%	82.0%
	Ours	95.0%	76.3%	90.2%

parative analysis of different methods in terms of their ac-



Figure 3. The results show that collisions generated by AutoVFX [16] lack gravity constraints, resulting in unrealistic post-collision trajectories. In contrast, AccidentSim, which incorporates physical constraints, produces physically realistic collision effects.

curacy for collision trajectory planning across various generated road scenarios. As mentioned in Paragraph 2 of Section 4.2, we use SRR as the primary evaluation metric. The results, as presented in Table 4, indicate that AccidentSim’s collision planning accuracy consistently surpasses that of SoVAR across a range of randomly selected road configurations, with notable improvements observed at T-junctions and on straight roads. This is attributed to the enhanced trajectory planning and imposed physical constraints of AccidentSim, which allow for greater accuracy and control in complex scenarios. Additionally, as shown in Figure 1, AccidentSim demonstrates superior adaptability to varying scenario conditions, ensuring higher consistency and fidelity in scenario reconstruction. For more accident scenarios generated by AccidentSim, refer to Section D of the supplementary materials.

Attribute Extraction. To assess AccidentSim’s ability to extract data from accident reports, we conducted a comparative evaluation of attribute extraction accuracy from accident reports across AccidentSim, SoVAR [14], and AC3R [19]. As shown in Table 2, the results indicate that AccidentSim achieves the best accuracy in extracting key information, such as lane number and speed limits, compared to SoVAR [14] and AC3R [19]. Additionally, AccidentSim performs similarly to SoVAR [14] in identifying collision locations and extracting information on dynamic objects. This high extraction accuracy ensures the reliability of the subsequent dataset generation, providing a solid foundation for model training.

Post-Collision Trajectory Prediction. To comprehensively validate the accuracy and physical consistency of AccidentSim in post-collision trajectory prediction, we conducted experiments from two perspectives. First, we compared AccidentSim with the AutoVFX[16] and tasked both methods with outputting vehicle motion trajectories for up to three seconds following the collision. The experimental results, as shown in Table 3, indicated that AccidentSim generally outperformed AutoVFX. Furthermore, AccidentSim demonstrated higher stability and accuracy,

especially in accident scenarios such as Straight Obstacle, Right Turn, and Lane Changing. Secondly, we employed the collision models proposed by Hou et al. [48] and Pawlus et al. [1] to assess whether the trajectories generated by AccidentSim adhere to the principle of momentum conservation. By calculating the changes in momentum and impulse before and after the collision, as summarized in Table 3, we compared the results of AccidentSim with those from AutoVFX[16], using CARLA ground truth data as the benchmark. We found that AccidentSim’s trajectories were more consistent with the CARLA ground truth data compared to AutoVFX[16], further validating the accuracy and reliability of the model. Additional visualizations in Figure 3, the results demonstrate that the simulated vehicle collisions by AccidentSim are physically constrained by gravity and follow smoother trajectories more consistent with real-world dynamics. These improvements highlight the accuracy of our approach in modeling realistic collision physics compared to AutoVFX[16].

5. Conclusion

In this paper, we introduce AccidentSim, an innovative framework designed to generate vehicle collision videos that are both visually authentic and physically realistic. By extracting and utilizing physical clues and contextual information from real-world accident reports, AccidentSim effectively addresses the shortage of vehicle collision videos available for training autonomous driving models. Leveraging a language model-driven approach, AccidentSim excels in planning and predicting physically consistent collision trajectories. Using CARLA as a reliable physical simulation engine, AccidentSim ensures realistic vehicle motion in collision scenarios. Experimental results demonstrate that AccidentSim generates vehicle collision videos with high visual quality and physical consistency. In our future work, we aim to enhance AccidentSim by integrating vehicle deformation during collisions and incorporating additional physical clues related to road and weather conditions, thereby improving the realism of the generated videos.

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