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A Comparative Review of Autonomous Driving Simulation Platforms: Carla, AirSim, and Gazebo

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Abstract. The rapid evolution of autonomous driving has made high-fidelity simulation essential for validating safety-critical algorithms. Since real-world testing is cost-prohibitive and risky—especially for edge cases—developers rely heavily on virtual environments. This study provides a comparative review of three primary open-source platforms: Carla, AirSim, and Gazebo. Instead of a general overview, we evaluate these tools based on architecture, visual fidelity, physics accuracy, and ecosystem support. The analysis highlights clear trade-offs: Carla is the most effective for urban traffic scenarios due to its rich asset library; AirSim excels in perception tasks by leveraging high-end game engines for photorealism; and Gazebo remains the standard for robotics control due to its precise physics capabilities. The findings offer a practical selection guide, emphasizing that the choice of simulator must depend on the specific subsystem under test, such as end-to-end learning versus vehicle dynamics. Finally, the paper discusses current computational limitations and identifies digital twins as the key future trend for bridging the gap between simulation and reality.

Keywords: Autonomous Driving, Simulation Platforms, Carla, AirSim, Gazebo, Virtual Testing

1. Introduction

Artificial intelligence and computer vision are developing quickly, making autonomous driving a central topic in transportation research. Despite significant progress, deploying and validating these algorithms in real-world environments faces substantial challenges. Physical testing incurs high costs and prolonged development cycles. Moreover, safety remains a critical concern, particularly when testing under adverse weather conditions or rare, extreme traffic situations known as "corner cases." To mitigate these risks, high-fidelity simulation platforms have become essential. They enable researchers to combine virtual environments with real-world physical modeling, allowing for extensive testing without physical risks or temporal constraints.

While numerous tools exist, selecting the appropriate platform is challenging. The three most prominent open-source platforms—Carla, AirSim, and Gazebo—rely on different underlying engines (Unreal Engine, Unity, or OGRE), resulting in distinct performance characteristics in visual rendering and physical dynamics. Existing literature often focuses on single-platform applications rather than holistic comparisons. This paper addresses this gap by systematically comparing these three platforms across multiple dimensions, including system design, sensor simulation capabilities,

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and application scenarios. The objective is to provide practical guidance for researchers in selecting the most suitable tools, thereby enhancing the efficiency of autonomous driving system development.

2. Overview of mainstream simulation platforms

2.1. Carla: an open urban driving simulator

Carla is a specialized tool designed specifically for autonomous driving research. Developed by Intel and the Computer Vision Center, its primary focus is simulating complex urban traffic environments. The system utilizes a server-client architecture: the server manages the simulation environment and calculates physics, while the client interacts with the simulator through APIs to control agents and retrieve sensor data. This decoupling allows for flexible control over the simulation. Carla leverages Unreal Engine 4 to provide high-quality assets, including buildings, pedestrians, and roads. A key feature is its specialized sensor suite, which mimics data streams from real autonomous vehicles, such as lidars, cameras, and GNSS [1].



Figure 1. Various weather conditions (e.g., clear day, rain, wet roads, sunset) simulated in Carla [1]

As illustrated in Figure 1, Carla supports dynamic weather changes. This capability allows researchers to test perception algorithms under varying environmental conditions, such as rain or low light, ensuring robustness in diverse real-world scenarios.

2.2. Airsim: high-fidelity simulation for vehicles and drones

While Carla is primarily designed for urban driving scenarios, AirSim provides broader vehicle support. Created by Microsoft, this platform supports both self-driving cars and unmanned aerial vehicles (UAVs). A distinguishing feature of AirSim is its support for "hardware-in-the-loop" simulations, allowing researchers to connect real flight controllers to the simulation. AirSim works with both Unreal Engine and Unity, focusing heavily on photorealistic rendering. This high visual quality is critical for collecting synthetic data used to train computer vision systems [2].

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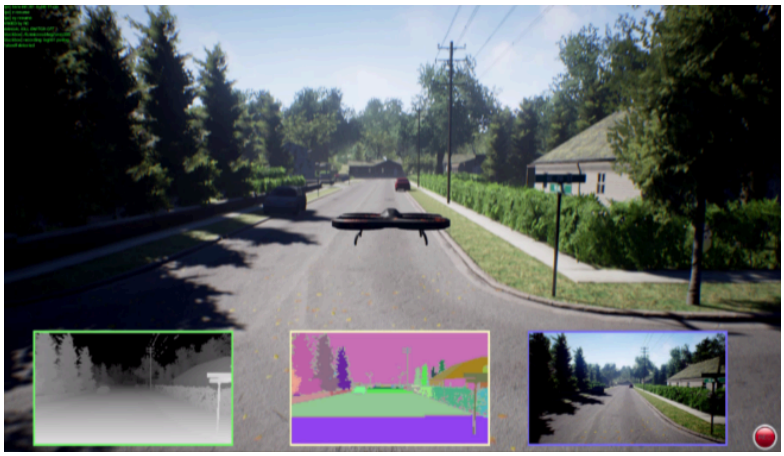

Figure 2. A snapshot from AirSim showing an aerial vehicle with real-time depth and segmentation generation [2]

Figure 2 demonstrates AirSim's ability to generate multi-modal data in real-time. Besides the raw visual feed, it automatically produces perfectly aligned depth maps and semantic segmentation masks (shown in the bottom insets), which are invaluable for supervised training of deep learning models.

2.3. Gazebo: the standard for robotics simulation

Gazebo differs significantly from the previous two platforms. It did not originate as a dedicated autonomous driving simulator but has a long history as the standard tool for general robotics. Its greatest strength lies in its modular design and tight integration with the Robot Operating System (ROS). This integration allows engineers to write control code that can be deployed to physical robots with minimal modification. Gazebo prioritizes versatility and physical accuracy over visual aesthetics. It can simulate diverse mechanisms, from warehouse robots to articulated arms, making it the suitable choice for studying vehicle dynamics and control theory [3].

3. Comparative analysis of key features

3.1. Visual fidelity and rendering engines

The visual quality of a simulation depends on its underlying graphics engine, which is crucial for training perception algorithms. Both Carla and AirSim utilize Unreal Engine 4, a powerful game engine capable of creating realistic lighting, shadows, and textures. As noted by Chance et al., these engines can simulate complex weather phenomena, such as heavy rain or fog, which are essential for training robust vision systems [4]. AirSim is particularly noted for its photorealism and ability to generate detailed semantic segmentation maps. In contrast, Gazebo typically uses the OGRE engine. While OGRE is computationally efficient, the rendered images are generally less detailed and flatter. Consequently, simulators based on game engines (Carla and AirSim) are significantly superior for tasks involving semantic segmentation or object detection, whereas Gazebo's visual output is often insufficient for training advanced deep learning-based perception models [5].

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3.2. Physics engines and dynamics

While visuals are paramount for perception, physical accuracy is vital for control and planning. Gazebo focuses on physical precision, offering users a choice of multiple high-fidelity physics engines, including ODE, Bullet, Simbody, and DART. These engines calculate forces like friction, inertia, and gravity with high precision, making Gazebo ideal for validating vehicle stability and dynamic control algorithms. On the other hand, Carla and AirSim typically rely on PhysX, the built-in physics engine of Unreal Engine. PhysX was originally designed for real-time interactive applications (games), prioritizing speed over scientific accuracy. Although recent updates have improved its precision, it may simplify complex interactions, such as tire-road friction during extreme maneuvers. For research requiring rigorous dynamic validation, Gazebo's dedicated physics solvers are generally preferred [5,6].

3.3. Ecosystem and programming interfaces

Ease of use is often an important consideration in simulator selection. Carla and AirSim are tailored for the modern AI community, offering robust support for Python. This seamless integration with deep learning frameworks like TensorFlow and PyTorch lowers the barrier to entry for AI researchers [1,2]. Gazebo, rooted in traditional robotics, primarily uses C++ and requires a deep understanding of ROS. While highly reliable for roboticists, it presents a steeper learning curve for pure AI developers. Regarding asset availability, Carla provides a comprehensive library of pre-built urban assets (pedestrians, buildings), whereas Gazebo relies more on community-contributed models, which can vary in quality [3]. Table 1 summarizes the key differences discussed above.

Table 1. Comparison of mainstream autonomous driving simulators

Feature	Carla	AirSim	Gazebo
Primary Engine	Unreal Engine 4	Unreal Engine / Unity	OGRE
Physics Engine	PhysX	PhysX (Fast Physics)	ODE / Bullet / DART
Visual Fidelity	High (Photorealistic)	Very High (Photorealistic)	Medium (Functional)
Primary API	Python / C++	C++ / Python / C#	C++ (ROS)
Best Use Case	Urban AD, Traffic Scenarios	Computer Vision, UAVs	Dynamics, Control, Robotics
Scenario Gen	Built-in Traffic Manager	Script-based	Manual / Plugin-based

4. Applications and selection strategies

4.1. Deep learning and end-to-end training

"End-to-end learning" aims to teach a vehicle to drive by mapping raw sensor inputs directly to control outputs. This approach requires massive amounts of labeled visual data. Carla is particularly well-suited for this task due to its built-in sensor suite and the "CoRL" benchmark for conditional imitation learning, which allows researchers to compare their algorithms against standardized baselines [7]. AirSim is also a strong contender; its ability to generate diverse environments prevents AI models from overfitting to a single track. For pure deep learning research—specifically training perception and control policies from raw pixels—these two platforms are superior to Gazebo because they offer automated data generation tools and higher visual complexity that matches the requirements of neural networks [8].

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4.2. Addressing the Sim-to-Real gap

A major challenge in simulation is the "Sim-to-Real" gap, where models trained in virtual environments fail in the real world due to domain discrepancies. AirSim addresses this through high-fidelity rendering and domain randomization (varying textures and lighting). For instance, Pan et al. demonstrated that reinforcement learning agents trained in realistic environments with domain randomization transfer more successfully to physical vehicles than those trained in lower-fidelity environments [9]. This makes high-fidelity simulators critical for pre-training models before real-world deployment.

4.3. Complex traffic and multi-agent collaboration

Safety testing requires simulating interactions between multiple vehicles, often involving Vehicle-to-Everything (V2X) communication. Carla excels in generating complex traffic flows using its "Traffic Manager" module, enabling the creation of dangerous scenarios—such as a pedestrian suddenly stepping into the street—that are impossible to test safely in real life. Recent datasets like V2X-Sim leverage these capabilities to study collaborative perception [10]. For studying traffic systems and multi-agent safety protocols, Carla offers the most robust environment [11].

In summary, the selection of a simulator should be driven by the specific subsystem under test: AirSim is the optimal choice for perception and vision-based learning; Carla is best suited for traffic scenario planning and decision-making research; and Gazebo remains the gold standard for low-level vehicle dynamics and control validation.

5. Discussion

These platforms are powerful, but they exhibit limitations. One main worry is the computational resource requirements. The high-quality graphics of Carla and AirSim require high-end GPUs. Running a simulation with multiple high-resolution cameras and lidars can significantly slow down the simulation step time, making large-scale training computationally expensive. Additionally, physics engines still struggle with highly complex interactions, such as tire-soil mechanics or hydroplaning in rain.

Looking ahead, the evolution of autonomous driving simulation is aligned with the concept of "Digital Twins" [12]. This involves creating exact, real-time virtual replicas of physical cities or vehicles. Future platforms will likely integrate more closely with high-definition (HD) maps and real-time traffic data, aiming to combine the physical accuracy of robotics simulators with the visual power of game engines. This progress could eventually allow autonomous vehicles to be certified purely through simulation.

6. Conclusion

This paper has compared three leading tools for simulating self-driving cars: Carla, AirSim, and Gazebo. The analysis reveals that each platform serves a distinct purpose. Carla is the premier option for simulating urban traffic and scenarios; AirSim stands out for its visual fidelity, making it critical for training computer vision systems; and Gazebo holds its place as the standard for general robotics and dynamic control. Choosing the correct simulator is a vital step that saves time and resources. Understanding these distinctions prevents developers from utilizing tools ill-suited for their tasks. Despite current limitations in computational load and physics complexity, the integration

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of digital twin technologies promises to further bridge the gap between simulation and reality, paving the way for safer and more efficient autonomous vehicle development.

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