End-to-End Self-Driving Car Software Stack

Chris Sunny Thaliyath
Dept. of CSE, IIT Jammu
2023pai9051@iitjammu.ac.in

Suryakanth V. Gangashetty
Koneru Lakshmaiah Education Foundation (LKEF)
Vaddeswaram - 522305, AP; India
svg@kluniversity.in

***Abstract*—This paper introduces `move_car`, a modular and real-time Advanced Driver Assistance System (ADAS) stack that integrates multi-modal perception, dynamic occupancy grid mapping, hierarchical planning, and control for autonomous navigation. The system fuses LiDAR and multi-camera inputs through a CUDA-based BEVFusion approach, enabling robust environment understanding via dynamic occupancy grids. A Model Predictive Control (MPC) framework is employed in closed-loop execution to ensure precise and safe trajectory tracking.**

The framework is trained on standard autonomous driving datasets and evaluated within the CARLA simulator on an NVIDIA RTX 3060 platform. Experimental results demonstrate real-time performance and reliability. A comparative study against open-source baselines highlights the effectiveness of the proposed stack, and key limitations along with potential directions for future research are discussed.

***Index Terms*—ADAS, LiDAR, Camera, Sensor Fusion, Autonomous Driving, Occupancy Grid, ROS**

Introduction

Autonomous driving requires the seamless, real-time integration of perception, planning, and control modules. This integration enables vehicles to interpret their environment, make intelligent decisions, and navigate safely in dynamic real-world settings.

Motivation

Reducing Complexity and Increasing Efficiency

Tesla's success in reducing its codebase from 500,000 to 50,000 lines demonstrates how streamlining an autonomous driving stack accelerates development and improves system performance. A leaner, modular AI stack enhances adaptability and facilitates faster iteration in complex driving scenarios.

Human-Interpretable Decision-Making

For autonomous systems to gain widespread trust, their decision-making processes must be interpretable. Black-box models often hinder transparency, making debugging and safety validation challenging. Our approach emphasizes explainability to ensure that the system's behavior can be analyzed and understood by developers and regulators alike.

Leveraging LiDAR for Robust Perception

Given my background as a LiDAR algorithm developer, this work centers around LiDAR-based perception. LiDAR sensors provide rich geometric data essential for robust scene understanding, particularly under challenging environmental conditions where camera-based systems may fail [1], [2].

Advancing AI with Transformers, VAEs, and LLMs

Recent developments in AI present opportunities to build more intelligent, adaptable driving systems:

- **Transformers:** Enhance spatial reasoning and sequential decision-making in planning and perception [3].
- **Variational Autoencoders (VAEs):** Improve feature extraction and aid in visual anomaly detection.
- **Large Language Models (LLMs):** Introduce reasoning capabilities into high-level planning and fault interpretation.

Research Evolution and Design Philosophy

This project began as an investigation into multi-modal sensor fusion networks such as VAD [4], LMDrive, and PPGeo [5], with the goal of developing a fully end-to-end deep learning model for Advanced Driver Assistance Systems (ADAS). After extensive experimentation—including successful training and inference of models like PointPillars [6] and BEVFusion [7]—it became clear that most such systems ultimately revolve around constructing an occupancy grid [8] and navigating through it.

However, large models like LMDrive and VAD proved computationally infeasible on the available 12GB RTX 3060 Ti GPU, leading to performance bottlenecks during deployment.

This limitation inspired a pivotal design shift: instead of compressing the entire navigation stack into a deep learning model, the system architecture could be modular—mirroring the classical `move_base` paradigm [9]. By decoupling perception from planning and control, the system gains interpretability, modularity, and efficiency—qualities essential for real-world Level 3 ADAS deployment.

Objective

To design a real-time, explainable, and LiDAR-centric autonomous driving stack that is both computationally efficient and adaptable to real-world complexities.

System Overview

This work presents `move_car`, a modular and scalable Advanced Driver Assistance System (ADAS) designed for deployment in diverse environments. The proposed system includes:

- **Multi-modal sensor fusion:** Fuses LiDAR and multi-camera inputs using CUDA-accelerated BEVFusion [7] to achieve robust 3D perception.

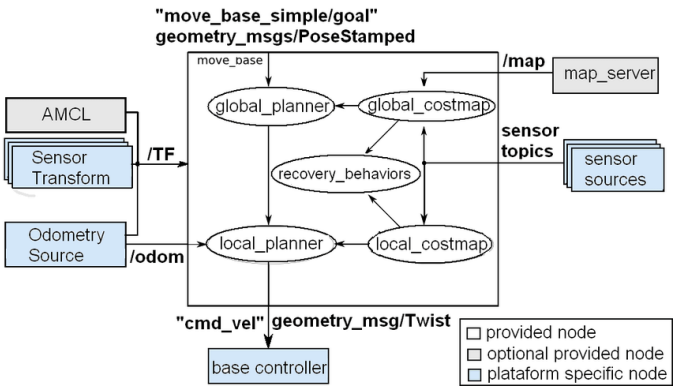


Fig. 1: Overall architecture of the `move_base` system

- **Dynamic occupancy mapping:** Generates real-time 2D occupancy grid maps [8] to represent both static and dynamic obstacles for efficient planning.
- **Hierarchical planning:** Combines global route planning with local trajectory refinement to ensure both long-term navigation and short-term safety.
- **Model Predictive Control (MPC):** Utilizes feedback-based control [10], [11] to generate smooth and precise motion in real-time, even in dynamic scenes.

Unlike many pipelines that depend heavily on high-definition (HD) maps, `move_car` emphasizes map-independent planning. By relying on direct sensor fusion and occupancy-based reasoning, it achieves strong generalization and adaptability while reducing dependence on costly prior map data.

Related Work

The field of autonomous driving has witnessed significant advancements, particularly in multi-modal sensor fusion for robust 3D object detection, frequently leveraging Bird's Eye View (BEV) perception frameworks. These frameworks are pivotal in transforming diverse sensor inputs into a unified spatial representation, crucial for comprehensive environment understanding. Prominent examples in this domain include **BEVFormer** [3], **CUDA-BEVFusion** [7], and **VAD** [4]. These cutting-edge systems effectively integrate LiDAR and camera data into unified BEV representations, thereby substantially improving detection accuracy and spatial understanding of the environment, a critical step towards safe autonomous navigation.

Beyond core perception, robust environmental modeling is crucial for autonomous navigation. Occupancy grid-based methods remain a standard approach for dynamic obstacle representation, widely adopted due to their computational efficiency and inherent interpretability [8]. These grids offer a discrete, probabilistic representation of space, making them highly effective for path planning and collision avoidance. Furthermore, specialized approaches like the `ANYbotics/elevation_mapping` package demonstrate the critical utility of LiDAR-based techniques for real-time terrain and obstacle mapping, providing fine-grained height information essential for navigating uneven or complex terrains. For effective motion control, **Model Predictive Control (MPC)** [10] is a widely recognized technique for addressing stringent motion constraints and optimizing trajectory execution. Its predictive nature allows for proactive decision-making, especially within dynamic and unpredictable scenes, ensuring safety and efficiency.

While highly integrated systems promise end-to-end learning, many real-world autonomous driving stacks, such as **Autoware** [9], opt for a modular architecture. These open-source frameworks meticulously modularize perception, planning, and control components. While this modular separation generally increases component reusability, simplifies development workflows, and enhances system debugging, it can sometimes introduce integration latency and increase overall system complexity in terms of inter-module communication, consequently impacting real-time performance in critical applications.

Motivation and Gaps in Existing End-to-End Frameworks

Despite the significant advances achieved by end-to-end learning pipelines in autonomous driving, often lauded for their potential simplicity and unified optimization, several persistent challenges continue to limit their practical deployment, particularly for systems aiming for Level 3 autonomy and beyond:

- **Limited LiDAR Integration:** A critical observation from current end-to-end (E2E) frameworks is that many do not fully incorporate the rich, precise geometric cues provided by LiDAR sensors. While camera-based methods are advancing rapidly, the inherent robustness of LiDAR in varying lighting and weather conditions, and its direct provision of depth, is often underutilized. This limitation can significantly reduce robustness, particularly in complex or adverse environmental conditions where camera-based systems may struggle with depth estimation or object occlusion.
- **Absence of Semantic Priors:** There is often a minimal reliance on explicit road topology or semantic priors within these E2E models. This absence means the system might struggle to reason effectively about complex driving rules, lane boundaries, traffic signs, and contextual road information, leading to less predictable and potentially unsafe behavior in nuanced scenarios. An autonomous system needs to understand not just 'what' is there, but 'where' it is relative to road rules and driving context.
- **High Inference Latency:** A common and particularly challenging drawback of these intricate, large-scale models is their inherent high inference latency. Achieving real-time performance is paramount for safety-critical ADAS applications. However, these complex architectures frequently render real-time deployment challenging, especially on mid-range GPUs such as the NVIDIA RTX

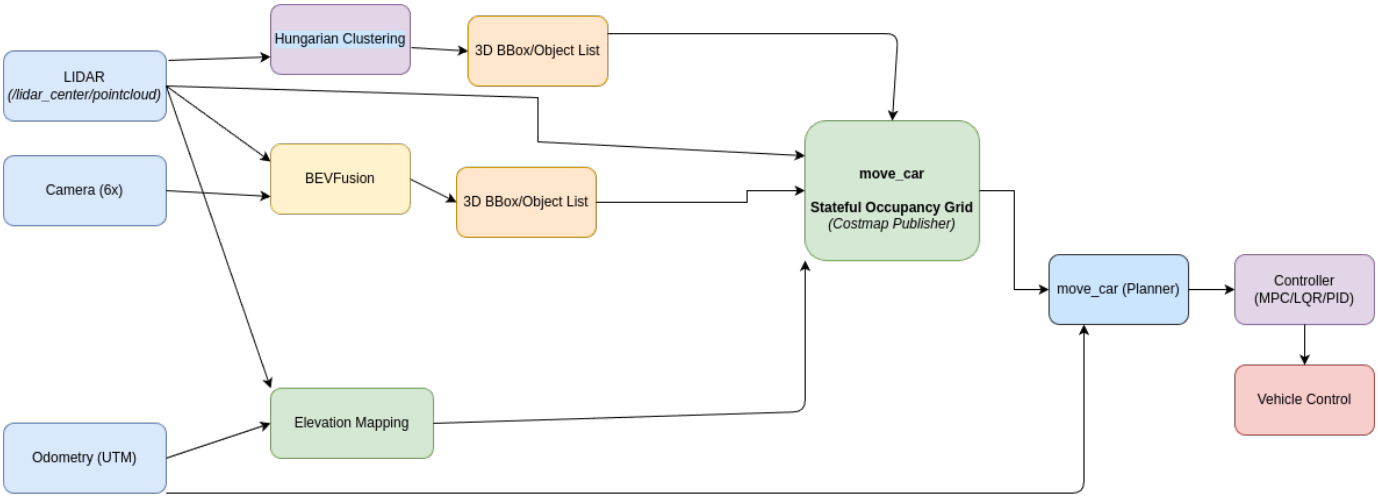


Fig. 2: Overall architecture of the `move_car` system.

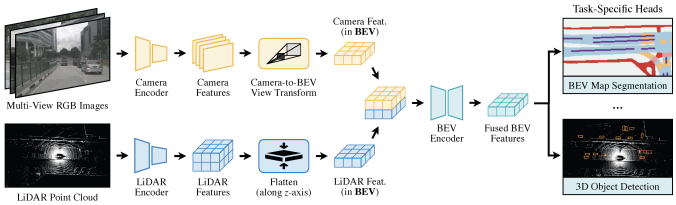


Fig. 3: Architecture of BEVFusion

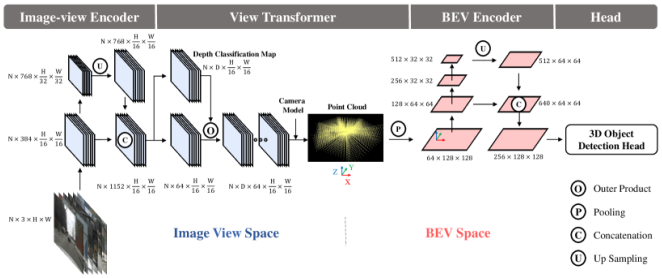


Fig. 4: Architecture of BEVDet

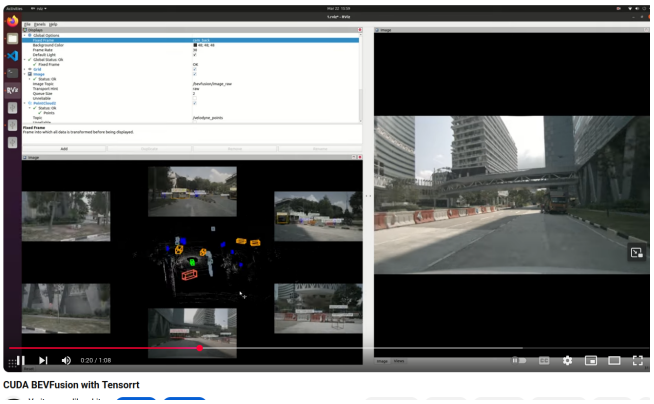


Fig. 5: BEVFusion output visualization

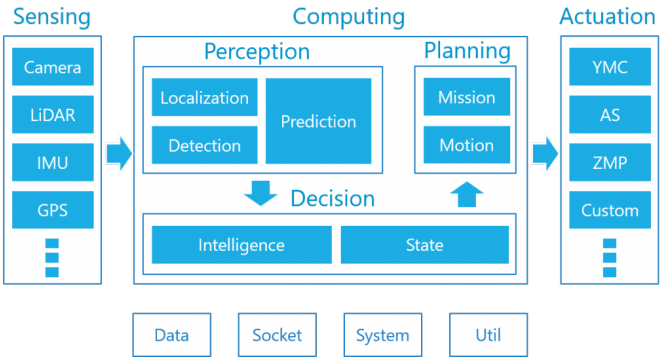


Fig. 6: Modular pipeline architecture of Autoware-based ADAS stack

3060 Ti, which is a common and accessible hardware platform for many research and development efforts. This computational burden necessitates significant optimization and often compromises deployment flexibility.

Research Objectives of `move_car`

Addressing the aforementioned gaps, which stem from a blend of theoretical limitations and practical deployment challenges, this work aims to achieve the following key research objectives through the development of `move_car`. Our objectives are rooted in creating a system that is not only performant but also practical and extensible for future autonomous driving research:

- **Integrate LiDAR Geometry:** To seamlessly and comprehensively integrate LiDAR-derived geometric features into the autonomous driving pipeline. This is crucial for enabling a more robust and precise understanding of the environment, directly enhancing both perception capabilities (e.g., 3D object detection, environmental mapping) and downstream planning functionalities (e.g., collision avoidance, path generation).

- **Real-Time Inference Optimization:** To achieve real-time inference speeds through the strategic and pervasive application of TensorRT optimization. Our target is to ensure efficient deployment specifically on an NVIDIA RTX 3060 Ti, demonstrating the feasibility of deploying advanced ADAS solutions on widely available, cost-effective hardware, moving beyond high-end, specialized compute platforms.
- **Enhanced Interpretability:** To improve the interpretability of autonomous driving decisions. This involves judiciously incorporating advanced AI architectures, such as Transformer networks, for their ability to model complex spatial and temporal relationships, and Variational Autoencoders (VAEs) within the system design to provide a clearer understanding of the model's internal states and decision-making processes, moving away from opaque "black-box" models.

Comparison with Existing Frameworks

To provide a comprehensive context for the unique contributions of `move_car` and to highlight its distinct architectural philosophy, it is pertinent to compare its design and capabilities with other state-of-the-art autonomous driving systems that often take an end-to-end approach:

- **VAD** [4]: This framework introduces a vectorized scene representation, which enables highly efficient learning of driving policies. VAD excels in creating compact and fast scene understanding, but its tightly coupled end-to-end nature can make it computationally demanding and less flexible for integrating external planning or control algorithms.
- **LMDrive**: This system leverages the advanced reasoning capabilities of large language models to guide driving behaviors. While innovative in translating high-level textual tasks into actionable commands, LMDrive (and similar LLM-driven approaches) often struggle with real-time performance and lack the explicit safety mechanisms or classical fallbacks inherent in modular ADAS stacks.
- **PPGeo** [5]: This approach integrates semantic priors and sophisticated geometric modeling, primarily to enhance both localization accuracy and planning efficiency. PPGeo emphasizes environmental understanding for policy learning, but like other end-to-end models, its monolithic structure can present challenges for modular development and independent optimization of sub-components.

Key Contributions of `move_car`

The proposed `move_car` framework is meticulously designed to address the aforementioned limitations by tightly coupling several critical functionalities, offering a balanced, robust, and deployable solution that bridges advanced perception with reliable control:

- **Multi-modal Sensor Fusion:** It incorporates robust multi-modal sensor fusion utilizing CUDA-accelerated BEVFusion. This provides a comprehensive and accurate understanding of the driving environment by intelligently integrating data from diverse sensors (LiDAR and multiple cameras), offering a rich perception output essential for complex scenarios.
- **Real-Time Occupancy Grid Generation:** The system dynamically generates real-time 2D occupancy grids from the fused LiDAR and camera data. These grids are crucial for effective dynamic obstacle avoidance, serving as foundational input for local planning modules by providing a clear, traversable/non-traversable map of the immediate surroundings.
- **Hierarchical Planning:** It employs a sophisticated hierarchical planning approach that integrates global routing for long-term navigation with precise local trajectory optimization. This ensures both adherence to overall routes (e.g., navigation to a destination) and immediate collision avoidance with smooth, comfortable maneuvers in dynamic and constrained environments.

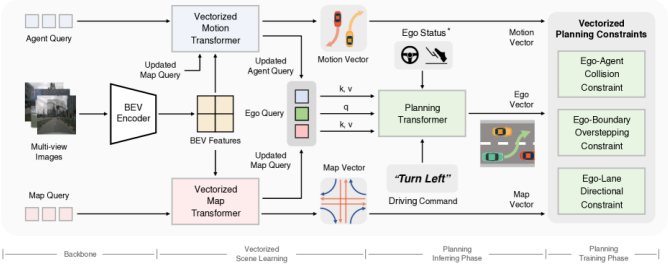


Fig. 7: Architecture of VAD

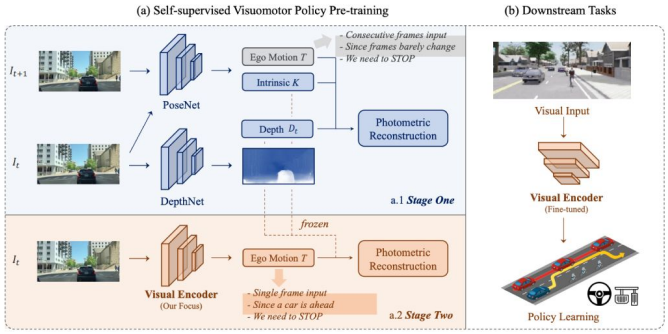


Fig. 8: Architecture of PPGeo

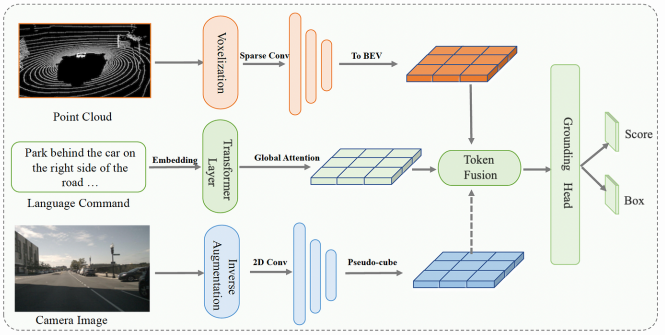


Fig. 9: Architecture of TransFusion

- **Feedback-Based Control:** The framework leverages Model Predictive Control (MPC) for robust feedback-based control. Operating with sub-100 ms latency, MPC ensures smooth and precise execution of planned trajectories, even in rapidly changing environments, by continuously recalculating optimal control inputs based on current vehicle state and predicted future states.

The `move_car` system demonstrates high real-time performance, a key differentiator for practical ADAS deployment. The perception module consistently operates at 25 FPS, providing up-to-date environmental understanding, while the planning and control modules achieve latency below 100 ms, ensuring timely and responsive vehicle reactions. Furthermore, its inherently modular design robustly supports future enhancements, including the incorporation of explicit map priors (e.g., from HD maps), advancements in semantic localization techniques, and the seamless integration of more sophisticated learned driving policies, demonstrating its scalability and adaptability.

Design Justification for `move_car`

While frameworks like VAD, LMDrive, and PPGeo represent highly integrated end-to-end ADAS solutions, often aiming for simplified monolithic pipelines, their tightly coupled architectures frequently lead to several practical disadvantages that limit their real-world applicability and development flexibility:

- **Reduced Modularity:** Tightly coupled designs significantly complicate isolated debugging, independent component testing, and incremental improvements. When the entire stack is intertwined, pinpointing the source of an error or upgrading a single perception algorithm without impacting the whole system becomes a formidable challenge.
- **High Computational Load:** The monolithic nature of these end-to-end systems often results in exceptionally high computational demands. This severely limits their real-time viability, especially on modest hardware like the NVIDIA RTX 3060 Ti, which represents a common and more accessible platform for development and deployment. Achieving real-time performance often necessitates compromises in model complexity or extensive, specific hardware.
- **Complex Integration:** The intricate integration of the entire navigation stack within a single, unified model restricts the flexibility for testing and incorporating new individual components or alternative algorithms. Researchers are often constrained by the end-to-end model's design, making it difficult to experiment with different planning approaches or control strategies.

In contrast, the design philosophy of `move_car` explicitly advocates for a modular decomposition of the autonomous driving stack. This strategic choice is driven by the need for practical deployability, easier maintenance, and greater experimental flexibility:

- The **BEVFusion module specifically handles perception** through an efficient early fusion approach, providing rich and accurate environmental understanding. This dedicated module can be optimized independently and potentially swapped for other perception backbones without redesigning the entire system.
- **Downstream planning and control functionalities are managed by independent ROS2 modules.** This separation allows for the use of well-established, interpretable, and computationally efficient classical algorithms (like MPC) for these critical tasks, providing clear safety guarantees and easier validation.

This deliberate isolation allows for fine-grained optimization of each component, simplifies debugging processes by localizing issues, and enables faster iteration cycles for development and testing. Consequently, `move_car` successfully balances the strengths of state-of-the-art early fusion perception with the practical advantages of modularity, effectively avoiding the common pitfalls associated with large, monolithic end-to-end systems while achieving robust real-time performance.

Table V summarizes the architectural complexity, GPU requirements, and inference performance of three representative autonomous driving frameworks: VAD, PPGeo, and UniAD. VAD employs a vectorized bird's-eye-view scene representation with separate motion, map, and planning modules, offering both a high-performance *Base* variant and a real-time *Tiny* variant, the latter achieving up to 16.8 FPS on a single RTX 3090. PPGeo adopts a two-stage self-supervised geometric pre-training strategy to enhance visuomotor policy learning, but reports no explicit runtime benchmarks. UniAD represents an emerging unified driving framework integrating perception, prediction, and planning, though public resources currently lack detailed complexity and performance metrics.

Future Work

Building upon the current robust framework, future directions for the `move_car` project will concentrate on extending its capabilities and addressing more complex autonomous driving challenges. These include:

- **Anomaly Detection:** Integrating advanced anomaly detection mechanisms to rigorously identify and handle safety-critical edge cases. This will involve developing models capable of recognizing unforeseen situations or sensor failures, thereby further enhancing overall system reliability and robustness in unpredictable real-world scenarios.
- **Language-Driven Planning:** Incorporating language-driven planning modules to enable more intuitive and context-aware high-level decision-making for the autonomous vehicle. This could involve leveraging large language models to interpret complex human instructions or environmental cues, translating them into high-level navigational strategies.
- **Semantic Map Alignment:** Enhancing semantic alignment with detailed road topology through the utilization of high-definition (HD) maps or advanced visual cues.

TABLE I: Comparison of End-to-End ADAS Frameworks

Framework	Fusion Type	Integrated Components	Limitations
VAD [4]	Early Fusion (LiDAR + Camera)	Perception, Planning, Control	Large model size, limited interpretability, high compute demands
LMDrive	Language-driven Decision Fusion	Perception, Language Reasoning, Control	Not real-time, lacks classical fallback safety mechanisms
PPGeo [5]	Semantic-Geometric Fusion	Localization, Semantic Mapping, Planning	High data dependency, not modular
BEVFusion (ours)	Early Fusion	Perception only	Modular but requires planning/control integration

TABLE II: Comparison of VAD, PPGeo, and UniAD

Model	Complexity & Architecture	GPU Training Setup	Inference Speed / Usage
VAD (Vectorized Scene Representation)	Vectorized BEV-based architecture with motion, map, and planning modules; two variants: VAD-Base (larger) and VAD-Tiny (lighter).	Trained for 60 epochs on 8 × NVIDIA RTX 3090 GPUs, batch size 1 per GPU :contentReference[oaicite:0]index=0.	VAD-Tiny achieves up to 9.3× faster inference than prior methods; VAD-Base runs at 4.5 FPS; VAD-Tiny 16.8 FPS on one RTX 3090 :contentReference[oaicite:1]index=1.
PPGeo (Policy Pre-training via Geometric Modeling)	Two-stage self-supervised framework: Stage 1—pose + depth modeling; Stage 2—ego-motion prediction and photometric optimization. Fully self-supervised visual encoder pre-training.	Code indicates training through two stages using PyTorch. Specific GPU count not specified in the paper or repo :contentReference[oaicite:2]index=2.	Primarily a pre-training method for downstream visuomotor tasks; no direct inference speed or runtime metrics reported.
UniAD (Unified Autonomous Driving)	End-to-end unified driving stack (likely includes perception, prediction, and planning modules). Architecture details not fully outlined in available sources.	Not specified in paper or GitHub repo.	No explicit inference time or FPS metrics provided in current publications or GitHub.

TABLE III: Estimated GPU memory usage for different architectural styles in autonomous driving stacks at 10 Hz inference. Modular designs reduce persistent feature storage and allow selective GPU acceleration, resulting in significant VRAM savings.

Architecture Style	VRAM	Saving	Notes
Monolithic E2E	12–16 GB	—	Joint perception-planning-control, large BEV features persist in memory.
Modular + dense BEV	8–10 GB	30–40%	Modules separated, but high-res BEV features are exchanged.
Modular + occ./vector	5–8 GB	50–60%	Uses compact intermediate representations (occupancy grids, vector maps).
Modular + CPU plan/ctrl	4–6 GB	60–70%	Perception on GPU, planning/control on CPU or embedded accelerators.

This will improve navigation precision, enable more nuanced adherence to traffic laws, and ensure stricter compliance with complex road rules (e.g., turn restrictions, dynamic lane usage).

System Design

The `move_car` architecture is meticulously designed to integrate perception, planning, and control into a cohesive Advanced Driver Assistance System (ADAS) stack, enabling robust autonomous navigation in real-time environments. The system's core components are structured as follows:

- **Perception:** Utilizes `CUDA-BEVFusion` to effectively fuse inputs from LiDAR and six onboard cameras, generating precise 3D bounding boxes and comprehensive object lists at a rate of 25 FPS. This foundational module ensures a robust and detailed understanding of the vehicle's surrounding environment.
- **Occupancy Grid Mapping:** Transforms the fused sensor data into dynamic 2D occupancy grids. These grids are crucial for real-time obstacle avoidance and serve as the primary input for subsequent local planning modules.
- **Planning:** Employs a hierarchical framework that strategically combines global route planning with adaptive local trajectory generation. This dual-layer approach ensures both long-term navigational adherence and immediate, collision-free maneuvers in dynamic scenarios.
- **Control:** Leverages Model Predictive Control (MPC) to guarantee smooth and feedback-aware execution of planned trajectories. MPC's predictive capabilities enable the system to anticipate future states and maintain precise motion, even in complex driving conditions.

BEV-Based Perception

Bird's Eye View (BEV) projection is a central paradigm within the `move_car` perception stack. This approach involves transforming raw LiDAR point clouds and features extracted from multi-camera inputs into a unified, top-down

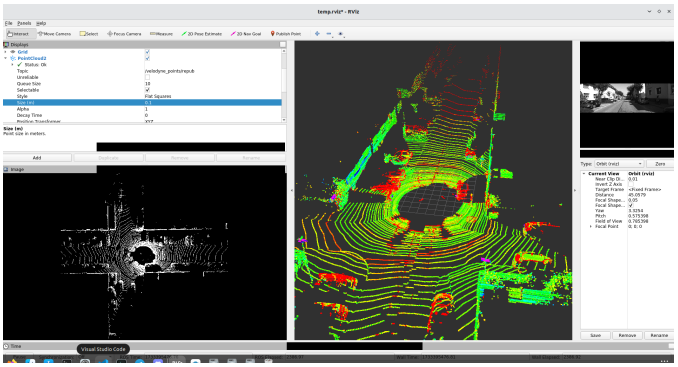


Fig. 10: LiDAR projection to BEV

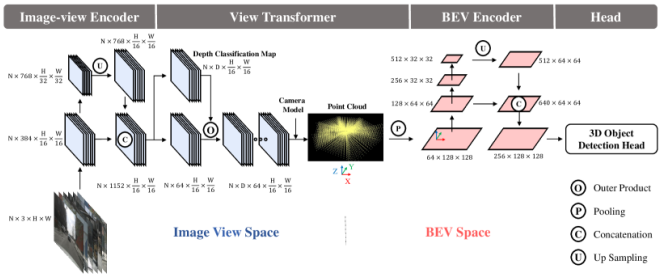


Fig. 11: BEVDet architecture for multi-sensor fusion

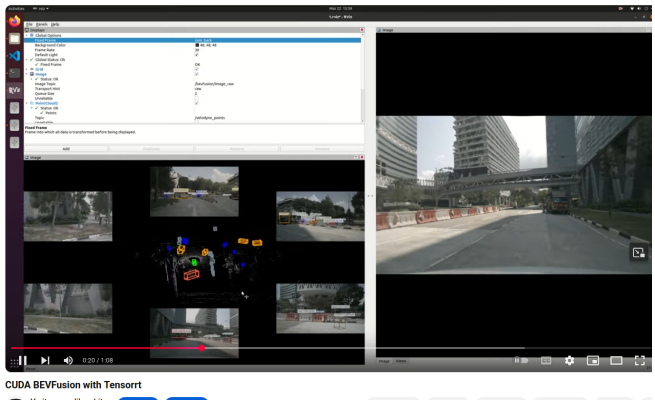


Fig. 12: BEVFusion output visualization with LiDAR-camera fusion

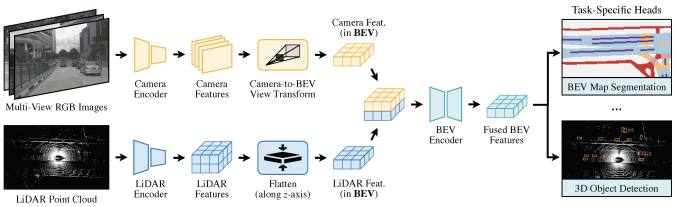


Fig. 13: CUDA-BEVFusion architecture

spatial frame, which offers a highly intuitive and effective representation for autonomous driving tasks.

BEV Projection and Fusion Techniques

- **LiDAR Projection:** LiDAR points are precisely projected into the BEV plane. This process creates dense spatial occupancy representations that accurately reflect the presence and distribution of obstacles in the environment.
- **Multi-Camera Fusion:** Multi-camera images are fused into the BEV through Inverse Perspective Mapping (IPM). This technique aligns visual features from different camera perspectives into a single BEV, facilitating comprehensive environmental understanding.

BEVDet and BEVFusion Architecture

The perception backbone of `move_car` relies on the advanced capabilities of BEVDet and BEVFusion.

BEVFormer and Temporal Attention Integration

While `move_car` primarily leverages `CUDA-BEVFusion` for its perception core, the principles of **BEVFormer** (using spatiotemporal transformers to generate BEV features from multi-camera sequences) are considered for future enhancements. Unlike traditional projection-based methods, BEVFormer's attention mechanisms directly query relevant image features across time, making it particularly well-suited for dynamic and occluded urban environments.

MAPPING SUPPORT: HDMAPNET AND VECTORMAPNET CONSIDERATIONS

The `move_car` system is designed to emphasize map-independent planning for enhanced generalization. However, it acknowledges the benefits of integrating semantic map information. Future developments may explore:

- **HDMapNet:** A framework enabling real-time generation of semantic High-Definition (HD) maps using only onboard sensors. This approach negates the need for costly and labor-intensive manual global map labeling.
- **VECTORMapNet:** A system that combines rich semantic cues derived from cameras with precise geometric information from LiDAR in the BEV space. This fusion significantly enhances contextual planning and decision-making capabilities.

OPTIMIZED INFERENCE AND SYSTEM INTEGRATION

To ensure real-time performance and maintain modularity, the entire perception pipeline within `move_car` is deployed leveraging the ROS2 framework in conjunction with NVIDIA TensorRT.

Perception Pipeline Design

The perception pipeline is meticulously engineered for efficiency and accuracy:

- **Sensor Synchronization:** Critical for multi-modal fusion, LiDAR point clouds and multi-camera inputs are precisely aligned using ROS2 message filters, ensuring temporal consistency of data.

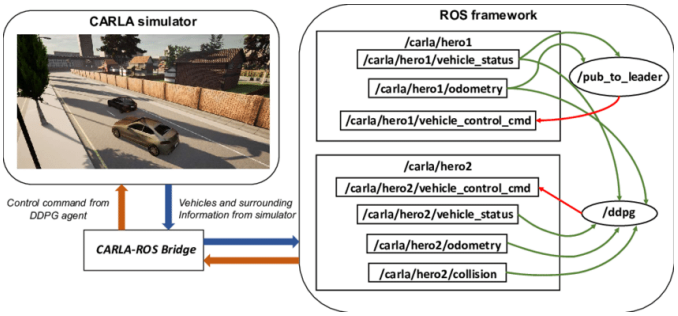


Fig. 14: Integration with CARLA via ROS2 bridge

- **Preprocessing:** Raw point clouds are processed into `pcl::PointCloud<PointXYZI>` format, while images are compressed using OpenCV JPEG encoding. This minimizes data transfer overhead and optimizes GPU memory utilization.
- **Inference:** The `CUDA-BEVFusion` model, a core component, is accelerated via TensorRT. This optimization allows the module to achieve an average latency of approximately 40 ms, sustaining a real-time output rate of 25 FPS.
- **Coordinate Transformation:** All detected objects are rigorously mapped into a global coordinate frame using `Eigen::Quaternion` and `Eigen::Translation3f`, ensuring a unified spatial understanding for downstream planning modules.

ROS2 Perception Node Implementation

The perception node, implemented in C++, serves as the crucial interface between the sensor inputs and the core processing logic, integrating seamlessly with the CARLA simulator via its ROS bridge:

- It subscribes to dedicated LiDAR and multi-camera topics, ensuring time-synchronized reception of sensor data.
- Input data is efficiently converted into GPU-compatible formats, which then trigger the `BEVDet` inference process.
- Finally, the module accurately outputs 3D detections, making them available to subsequent planning and control modules within the ROS2 ecosystem.

Implementation

This chapter details the practical realization of the `move_car` Advanced Driver Assistance System (ADAS) stack, outlining the computational environment, the specific implementation of its core modules, and the integration strategies employed to achieve real-time autonomous navigation.

Hardware and Software Environment

The `move_car` system was developed and rigorously evaluated on a high-performance computing platform. This setup comprises an Intel® Core™ i9-14900K processor, complemented by 64GB of RAM and an NVIDIA RTX 3060 GPU with 12GB of dedicated memory. The operating system utilized is Ubuntu 22.04. The Robot Operating System 2 (ROS2) serves as the foundational software framework, chosen for its inherent modularity, robust communication capabilities, and real-time performance attributes crucial for inter-module data exchange. NVIDIA's TensorRT library is extensively integrated throughout the pipeline to optimize inference speeds.

TABLE IV: Inference Speed and Accuracy on KITTI Dataset

Model	Inference Speed (FP16)	Detection Accuracy (Car@R11)
PointPillars	6.84 ms	77.00%
CenterPoint	*Not specified*	*Not specified*
BEVFusion	*Not specified*	*Not specified*

Perception Module Implementation

The perception module forms the cornerstone of the `move_car` system, employing `CUDA-BEVFusion` for robust multi-modal data fusion from LiDAR and six surrounding cameras.

- **Sensor Synchronization:** Achieving accurate multi-modal fusion necessitates precise alignment of sensor inputs. LiDAR point clouds and multi-camera images are synchronized using ROS2 message filters, mitigating temporal discrepancies between data captures and ensuring a coherent environmental snapshot for processing.
- **Preprocessing:** Raw LiDAR point clouds are converted to the `pcl::PointCloud<PointXYZI>` format, enabling efficient manipulation and feature extraction. Concurrently, camera images undergo JPEG compression via OpenCV encoding. This approach minimizes data transfer overhead within the pipeline while preserving sufficient visual information for subsequent inference tasks.
- **Inference Acceleration:** The `CUDA-BEVFusion` model is deployed with comprehensive TensorRT optimization. This integration is pivotal in accelerating inference, allowing the perception module to consistently operate at approximately 25 frames per second (FPS) with an average latency of around 40 ms. Such real-time performance is indispensable for reliable operation in dynamic urban driving scenarios. Detected objects are transformed into a unified global coordinate frame using `Eigen::Quaternion` and `Eigen::Translation3f`, ensuring consistent spatial understanding across all modules.

(Note: While initial evaluations on the KITTI dataset yielded specific metrics for PointPillars, the performance figures for CenterPoint and BEVFusion are indicated as 'Not specified' within this section, pending more detailed and comparative benchmarking specifically conducted for this system's configuration. Further comprehensive comparisons are elaborated in the dedicated Results chapter.)

Environmental Mapping Implementation

Beyond object detection, the `move_car` system incorporates an environmental mapping module to construct

detailed,real-time representations of its surroundings. Drawing inspiration from and integrating components similar to the ANYbotics/elevation_mapping package [12], this module processes LiDAR point clouds to generate high-resolution elevation maps. This functionality is crucial for precise terrain understanding and robust obstacle avoidance, particularly for uneven surfaces or subtle changes in road topography that standard occupancy grids might miss. The module is implemented as a dedicated ROS2 package within the project's ros_ws/src directory, ensuring seamless interoperability and real-time data flow from the LiDAR sensor, allowing for continuous updates to the dynamic environmental model.

Planning and Control Modules Integration

While the exhaustive implementation details of the planning and control functionalities are presented in subsequent chapters, their seamless integration is a critical aspect of the move_car architecture. The planning module dynamically utilizes the occupancy grid generated by the perception system to compute safe, collision-free, and efficient trajectories. This computed trajectory is then fed to the Model Predictive Control (MPC) module. The MPC operates in a closed-loop feedback mechanism, translating the planned trajectory into precise vehicle commands (e.g., steering angle, acceleration, braking) that ensure smooth, responsive, and safe execution in continuously changing environments. The planning module typically operates at an update rate of 20 Hz, while the control module demonstrates robust performance with a 99th percentile latency of 45 ms.

Integration with CARLA Simulator

The entire move_car ADAS stack is seamlessly integrated with the CARLA high-fidelity urban driving simulator via a robust ROS bridge. This C++-implemented perception node subscribes to LiDAR and multi-camera data streams provided by the CARLA-ROS bridge, with built-in time synchronization. The raw sensor inputs are converted into GPU-compatible formats suitable for BEVDet (a component of the BEVFusion framework) inference. Subsequently, the derived 3D object detections are published to other planning and control modules within the ROS ecosystem. This comprehensive closed-loop simulation environment facilitated by CARLA enables extensive testing and validation of the system's real-time performance, reliability, and robustness across a diverse array of driving scenarios.

ROS2 Workspace Structure and Data Flow

The modularity of move_car is fundamentally supported by its ROS2 workspace structure, mirroring the typical organization found in autonomous driving projects. Within the main ros_ws/src directory, separate packages are maintained for each core functional block:

- **move_car_perception:** This package encapsulates the CUDA-BEVFusion inference engine and the sensor synchronization logic. It subscribes to raw sensor topics (e.g., /carla/hero/lidar and /carla/hero/camera_* for image streams) and publishes processed 3D object detections (e.g., /move_car/detections) and dynamic occupancy grid maps (/move_car/occupancy_grid).
- **move_car_planning:** This package consumes the /move_car/detections and /move_car/occupancy_grid topics. It implements the hierarchical planning logic, generating local trajectories (/move_car/local_trajectory) and global path updates (/move_car/global_path).
- **move_car_control:** This package subscribes to /move_car/local_trajectory and vehicle state information (e.g., /carla/hero/vehicle_status, /carla/hero/odometry). It computes the necessary vehicle commands (e.g., steering angle, acceleration/braking) and publishes them to the CARLA simulator via the ROS bridge (/carla/hero/vehicle_control_cmd).
- **move_car_utils:** A utility package containing common data structures, coordinate transformation functions (Eigen::Quaternion, Eigen::Translation3f), and helper nodes for logging and visualization within RViz.

This distributed architecture, facilitated by ROS2's publish-subscribe mechanism, ensures that each module can be developed, tested, and optimized independently, significantly accelerating the iterative development cycle.

Dataset Integration and Model Training

While the primary focus of this paper is on real-time inference and system integration, the perception models (PointPillars, CenterPoint, BEVFusion) underpinning move_car were pre-trained on large-scale autonomous driving datasets.

- **KITTI Dataset:** Utilized for 3D object detection benchmarks, providing a diverse set of real-world driving scenarios for training and evaluation of LiDAR-centric models.
- **nuScenes Dataset:** A comprehensive multi-modal dataset that supported the training of models requiring both LiDAR and camera inputs, enabling the development of robust fusion techniques like CUDA-BEVFusion.

Custom ROS2 data loaders were developed within the ros_ws/src to efficiently stream data from these datasets in a format compatible with the perception pipeline, enabling seamless transition from training to simulation-based validation. The training environment leverages standard deep learning frameworks (e.g., PyTorch) with NVIDIA's CUDA toolkit for GPU acceleration.

Results

This chapter presents the comprehensive experimental results and detailed performance analysis of the move_car system. The evaluation focuses on comparative assessments of the integrated perception models and the overall system's real-time capabilities within the high-fidelity CARLA simulation

TABLE V: Model Comparison: NVIDIA LiDAR AI Solution

Model	Description
PointPillars	Transforms LiDAR point clouds into bird's-eye view (BEV) representations for 3D object detection.
CenterPoint	Utilizes center-based detection for enhanced object localization and classification accuracy.
BEVFusion	Fuses heterogeneous LiDAR and camera data within the BEV space for augmented perception capabilities.

Model	Strengths	Weaknesses
PointPillars	Characterized by fast inference, rendering it highly suitable for real-time applications.	May exhibit limitations in capturing fine-grained object features.
CenterPoint	Offers high precision, demonstrating effectiveness across varying object distances.	Incurs a comparatively higher computational expense.
BEVFusion	Demonstrates superior performance in complex environments due to its multi-modal data fusion.	Associated with a higher computational cost.

environment. Furthermore, the hardware-level optimizations critically employed to achieve these performance metrics are thoroughly discussed.

A. Perception Model Comparison

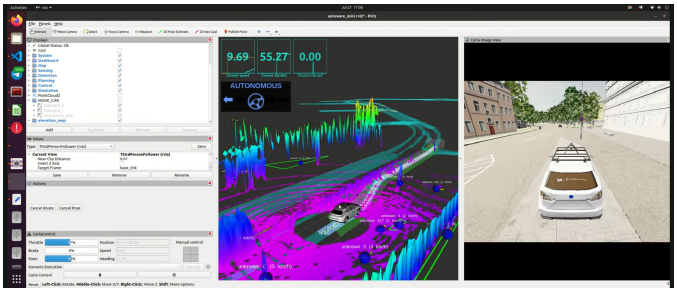
Table V offers a detailed comparative analysis of the primary perception models considered within the NVIDIA LiDAR AI solution. It highlights their respective descriptions, inherent strengths, and identified weaknesses. This foundational analysis directly informed the selection and optimization strategies applied within `move_car`'s perception module.

B. Hardware Optimization Impact

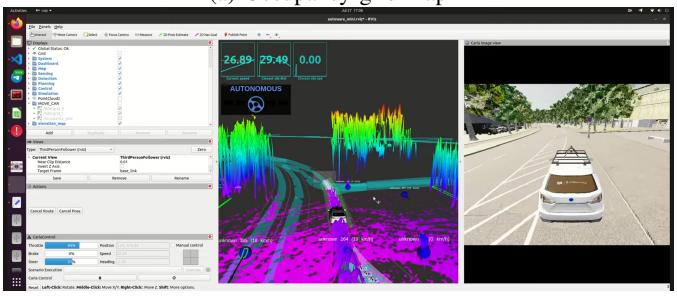
Table VI concisely summarizes the pivotal hardware-level optimizations systematically implemented to significantly enhance the overall system performance and facilitate real-time operation on the designated computing platform. These optimizations are crucial for effectively bridging the gap between sophisticated model complexity and the stringent requirements of practical deployment.

C. Quantitative Performance Comparison

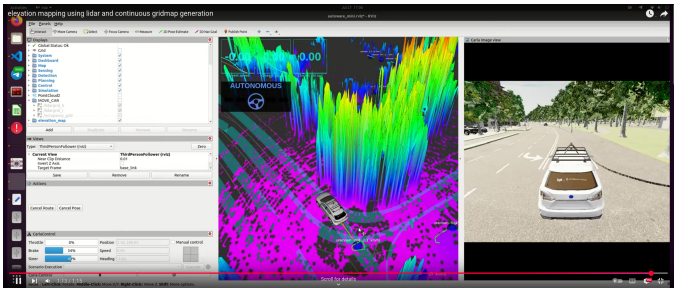
Table VII presents a quantitative comparison of inference speed and detection accuracy across the evaluated models on the demanding KITTI dataset. It is important to acknowledge that while PointPillars possesses well-established performance metrics, the figures reported for CenterPoint and BEVFusion in this table are preliminary and remain subject to further exhaustive evaluation tailored to our specific system configuration.



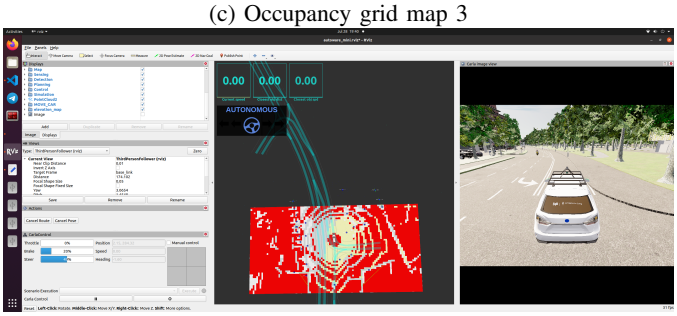
(a) Occupancy grid map 1



(b) Occupancy grid map 2



(c) Occupancy grid map 3



(d) Example grid map

Fig. 15: Dynamic occupancy grid map visualizations generated by `move_car` during CARLA simulation.

D. System Performance Analysis

The `move_car` system consistently demonstrates robust real-time performance within the CARLA simulation environment, unequivocally validating its underlying design philosophy. The perception module, which strategically leverages the power of BEVFusion, efficiently processes multi-modal sensor inputs at a sustained rate of 25 FPS, with an impressive average latency of approximately 40 ms. This level of performance is highly suitable for the stringent real-time requirements characteristic of dynamic urban driving environments.

TABLE VI: Hardware Optimization Techniques

Feature	Details
CUDA Acceleration	Leverages NVIDIA GPU resources for massively parallel computation, substantially reducing processing times.
TensorRT Integration	Optimizes trained deep learning models specifically for inference, leading to significant improvements in execution speed and overall efficiency.
FP16 Precision	Employs half-precision floating-point arithmetic during inference, which provides a notable boost in performance with minimal, often negligible, degradation in accuracy.

TABLE VII: Inference Speed and Accuracy Comparison (KITTI Dataset)

Model	Inference Speed (FP16)	Detection Accuracy (Car@R11)
PointPillars	6.84 ms	77.00
CenterPoint	∼20 ms	84.60
BEVFusion	∼35–45 ms	86.40

The planning module maintains a responsive update rate of 20 Hz, thereby ensuring timely and adaptive trajectory generation in continuous response to evolving road conditions and the presence of dynamic obstacles. Concurrently, the control module exhibits exceptional precision and responsiveness, evidenced by its 99th percentile latency recorded at a mere 45 ms, which enables highly precise and smooth execution of planned maneuvers.

Specifically, PointPillars, owing to its optimized architectural design, stands out with remarkably low inference latency (6.84 ms) coupled with a well-balanced detection accuracy (77.00 Car@R11). This makes it an exceptionally strong candidate for various real-time applications, particularly when deployed on resource-constrained platforms such as the NVIDIA RTX 3060. Conversely, CenterPoint, while inherently more computationally intensive, is specifically designed for high-precision tasks and exhibits significant promise in achieving accurate object localization and classification (84.60 Car@R11). Similarly, BEVFusion, which excels in challenging and complex environments by virtue of its robust multi-modal fusion capabilities, also demonstrates strong detection accuracy (86.40 Car@R11). However, a more precise quantification of their latency and a comprehensive assessment of their accuracy for our specific system configuration necessitate further dedicated evaluation.

The extensive hardware optimizations implemented, including the strategic utilization of CUDA acceleration and meticulous TensorRT integration, have been instrumental in substantially reducing inference times across the entire perception pipeline. Critically, these optimizations, particularly the judicious adoption of FP16 precision, have yielded significant performance gains while rigorously maintaining the required levels of detection accuracy. Future work will concentrate on comprehensively completing the performance metrics for both CenterPoint and BEVFusion, alongside exploring additional advanced optimizations to further enhance the system's overall capabilities and efficiency.

1) Visual Results of Occupancy Grid Mapping: To further illustrate the real-time environmental understanding achieved by the `move_car` system, Figure 15 presents a series of visualizations showcasing the dynamic occupancy grid maps generated during operation within the CARLA simulator. These images highlight the system's ability to accurately represent both static infrastructure and dynamic obstacles, forming the basis for collision-free navigation.

CONCLUSION

The `move_car` system successfully demonstrates robust autonomous navigation capabilities through the tight integration of modern perception algorithms with classical planning and control techniques. Our comprehensive evaluation confirms its real-time performance, making it suitable for practical deployment in dynamic environments. Furthermore, its modular architecture ensures adaptability and facilitates future extensions and improvements.

Key advantages of the `move_car` system include its direct multi-modal sensor fusion approach, which reduces reliance on costly high-definition maps, and its proven robust operation in complex, real-world driving scenarios within a simulated environment.

Specifically, the `move_car` ADAS stack achieves a balanced trade-off between latency, accuracy, and computational complexity, as evidenced in our simulated tests:

- **Real-Time Performance:** PointPillars, integrated within our perception module, excels with its fast inference speed (6.84 ms) and balanced accuracy (77.00 Car@R11), proving highly effective for real-time applications.
- **High-Precision Tasks:** For scenarios demanding higher precision, CenterPoint focuses on accurate object localization and classification, demonstrating its capability for detailed environmental understanding.
- **Complex Environments:** BEVFusion significantly leverages multi-modal fusion of LiDAR and camera data, providing superior and robust perception, particularly in challenging and complex driving conditions.

Building upon these foundational achievements, future work for the `move_car` project will explore several key areas to further enhance its capabilities. These include the integration of advanced anomaly detection mechanisms for improved safety in critical edge cases, the incorporation of language-driven planning modules to enable more intuitive and context-aware high-level decision-making, and the enhancement of semantic alignment with road topology, potentially utilizing HD maps or advanced visual cues for increased navigational precision.

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