MECH 460 Team Design 2024: Vision-based Intelligent Robotic System based on NVIDIA Jetson

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ABSTRACT

The development of autonomous parallel parking is a major challenge in robotics and computer vision. This project uses the Quanser QCar platform to implement and compare traditional computer vision (CV) and convolutional neural networks (CNN) methods in both virtual and physical environments. The system achieves parking space detection accuracy of 90% using CNN methods and 70% using CV methods, with successful parking execution in controlled environments. Our implementation demonstrates the viability of vision-based autonomous parking while providing a comparative analysis of the efficiency, adaptability, and trade-offs between traditional algorithms and deep learning methodologies.

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Purpose

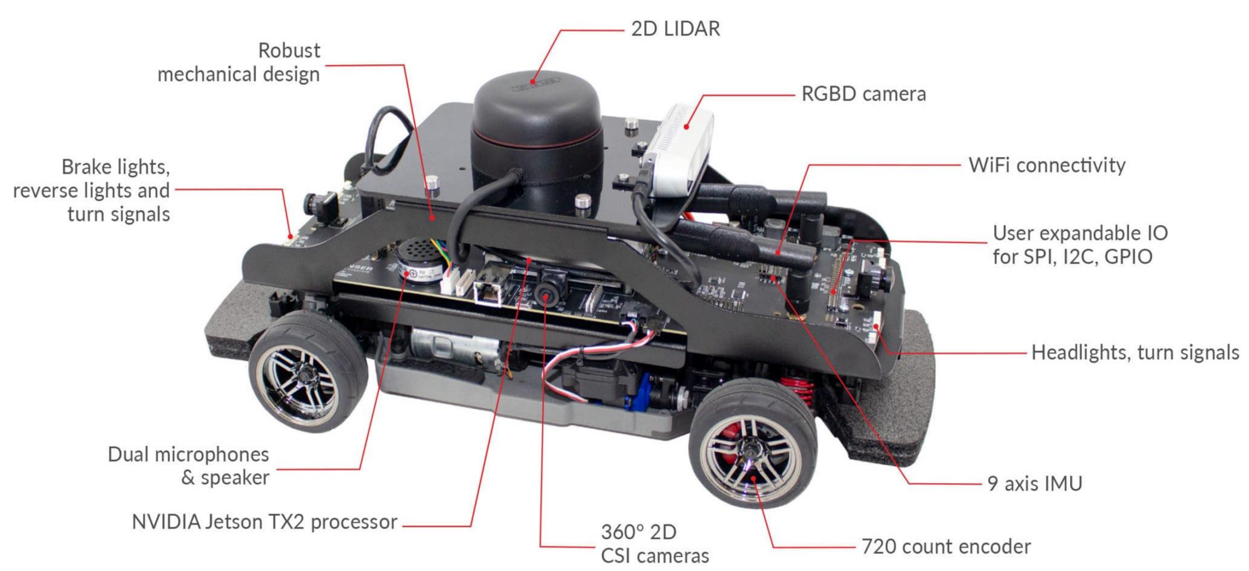
The QCar serves as a learning tool, enabling students to explore robotics and autonomous systems through hands-on experience. It bridges theoretical learning with practical application, fostering multidisciplinary skills in computer vision, control systems, and machine learning.

QCar –Specifications

The Quanser QCar platform integrates multiple sensing modalities:

- 4x CSI cameras (160° FOV) providing 360° coverage
- Intel RealSense D435 RGB-D camera
- Jetson TX2 processing unit
- Custom motor control system
- ROS-based software architecture for modular development

Testing environments include both simulation and physical settings, allowing rapid testing and validation of algorithms before deployment.



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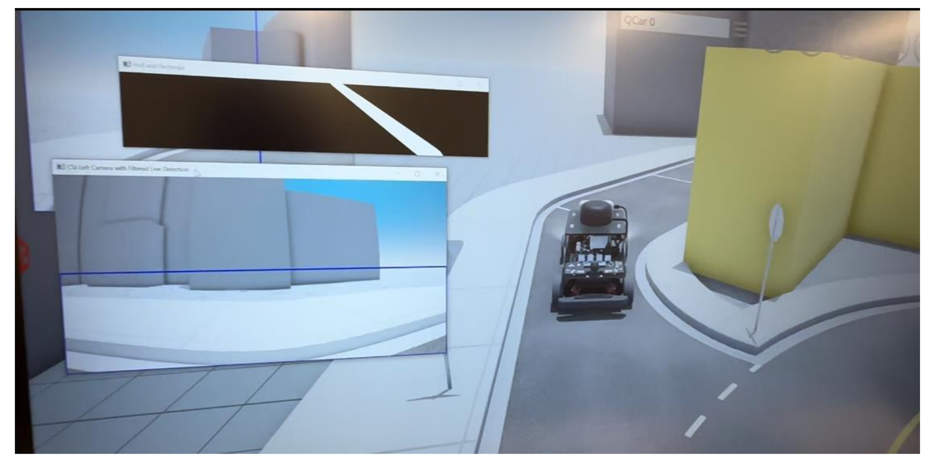
Traditional CV Method & Convolutional Neural Network Method

Computer Vision Method

Purpose: The purpose of the CV approach is to detect parking lines and align the vehicle parking by analyzing the **entry point**, and **parking lines.**

Parking-line Analysis:
The parking line was found using an image pipeline where various line sizes, angles and image cropping was don't to isolate the parking line of the left CSI camera.

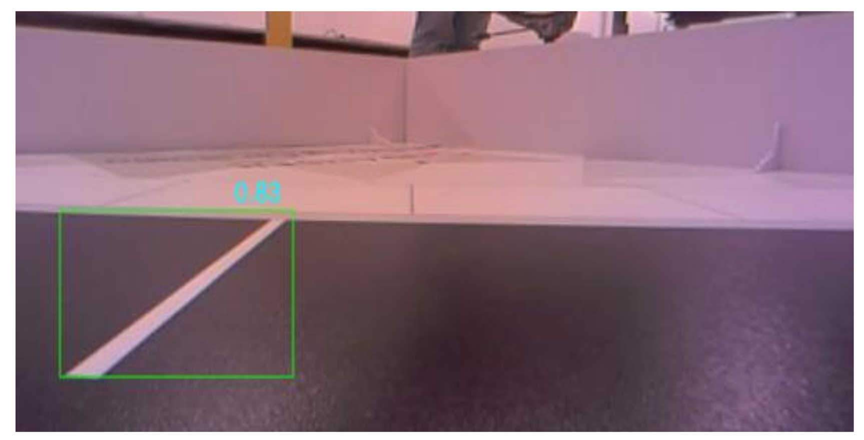
Image Collection → Grayscale → Smoothing → Region of interest → Line Isolation → Cropping



Entry Point Analysis:
The car uses curb following to calculate the distance between the curb and the car to line it up perfectly once the parking lines are detected.

Convolutional Neural Network (CNN)

The deep learning approach utilizes the MobileNet V2 architecture, specifically optimized for embedded deployment on the Jetson TX2 platform. The network was trained on a diverse dataset of 1500 manually annotated parking space images, augmented through rotation, brightness variation, and noise injection to improve robustness. Training employed a 70-20-10 split for training, validation, and testing respectively, The model was then optimized using TensorRT to optimize inference time on our platform. While the computational overhead exceeds the traditional CV approach, the CNN method demonstrates superior detection accuracy and robustness to environmental variations.



Data collection (1500 images) → Mobile Net v2 (Training) → Real-time (Detection >90%)

Motion Control

The parking execution system implements a state-based control architecture ensuring reliable and precise maneuvering. Initial manual approach transitions to autonomous control upon entering the parking region, where lane-following algorithms guide the vehicle until space detection is confirmed. Position alignment optimizes the vehicle's approach angle before initiating the reverse parking sequence. The complete parking sequence executes within 15 seconds, balancing efficiency with precise control.

Initiate Parking Maneuver → Move forward until line is detected, stop → Move forward until line is not detected → Moves forward for a set amount of time → Moves backward while steering left → Moves backward while steering right → Move forward and align

Software Used:

Quanser Interactive Labs	Python CV	Pytorch
Virtually using the Cityscape Lite landscape	Image processing and OpenCV libraries	Single Shot MultiBox Detector

Live Demo:

Comparison of both methods

The CNN method is a more reliable and accurate approach to achieve the technical specifications of the project scope. The model demonstrates adaptability to various lighting conditions and can park within 5 cm from center of parking area. The CNN method is equipped with transfer learning which require less training data and minimal human intervention because pre-trained models can classify and predict over datasets accurately.

Economic Analysis

Educators at Queens require a similar car that costs less and can be used as a learning tool. It must have the same sensor suite as the QCar. A bill of materials containing components and their approximate prices is shown below:

Part #	Description	Qty.	Unit Cost
1	Jetson Nano	1	$400
2	LD 19 D300 (LiDAR)	1	$150
3	YDLIDAR OS30A 3D Depth Camera	1	$200
4	CSI Camera	4	$20
5	IMU	1	$50
6	Drive Motor	1	$25
7	Motor Encoder	1	$60
8	Communication Interface	1	$100
9	Chassis	1	$220
10	Servo Motor	1	$30
11	Power System	1	$200
12	Miscellaneous Expenses	1	$200
	Total		$1,715

The total of $1,715 is reasonable compared to the $20,000 price of the QCar.

Future Recommendations

Path planning algorithms can be enhanced through integration of dynamic obstacle avoidance and improved trajectory optimization. Extended environmental testing under varied conditions will validate system robustness, while implementation of full autonomy capabilities will eliminate the need for initial manual positioning. Integration of LIDAR sensing would provide redundancy and enhanced safety through multi-modal perception.

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