Robotic Design for Strategic Adversarial Games

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Abstract

Worldwide, over 10,000 high school robotics teams compete in a fast-paced, annual competition using teleoperated robots. Our goal is to demonstrate that a fully autonomous robot can compete at this same level. Autonomous performance in dynamic, adversarial environments remains a major challenge in robotics, requiring systems that can continuously interpret the environment and respond in real time. This project aims to develop a fully autonomous system that integrates multi-sensor perception, real-time state estimation, and a strategic decision-making model to determine how to respond to an opponent. By translating advanced robotics into a familiar and engaging context, we aim to inspire the next generation of engineers.

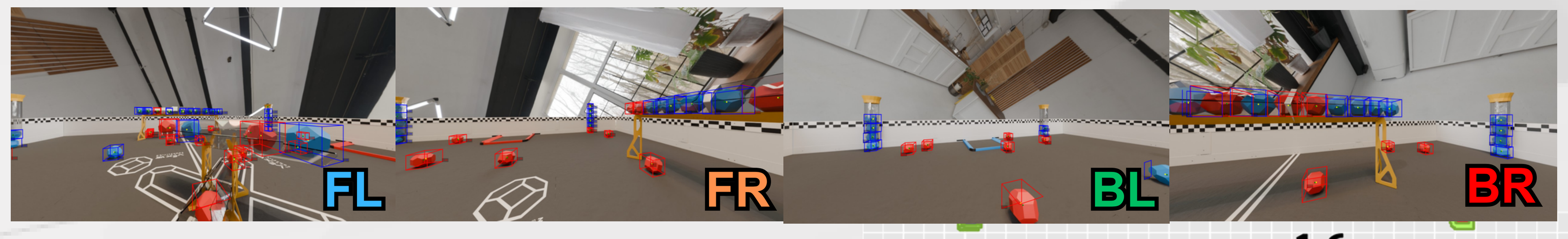
Vision + Object Detection

Real-World Camera View (Post-Processed)

Unified Neural Network for Robot Vision and Object Detection

- **Input**: 4-camera sensor array, **Output:** Positions of all game objects
- ~30M parameters, trained on 4 L40S (24h)
- Dataset: 200k synthetic scenes generated with Blender

Synthetic Data Example



Evaluation Parameters

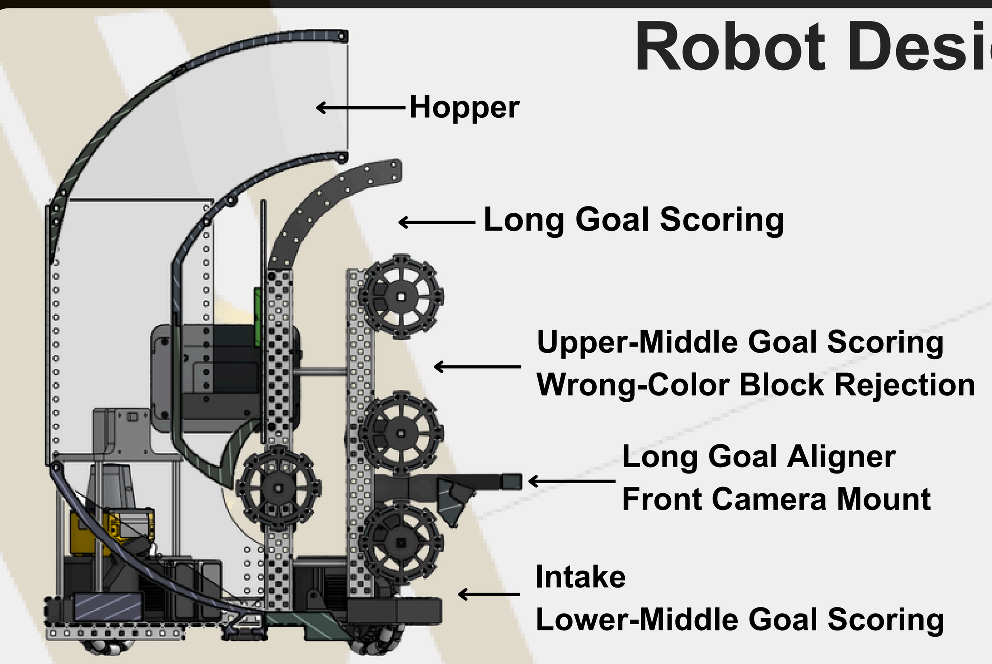
- Using greedy matching[1] technique
- Classification: Precision, Recall
- Localization: L2 Mean

Evaluation Results:
(Performance at varying object distances; P = Precision, R = Recall, L2 = L2 Mean)

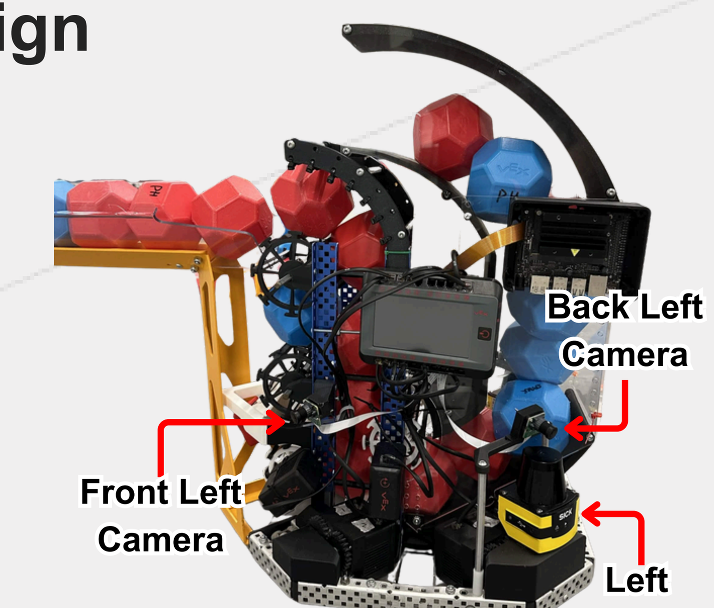
- **0.0–0.8 m → P:** 0.9118 **R:** 0.7487 **L2:** 0.93 cm
- **0.8–1.6 m → P:** 0.9164 **R:** 0.8215 **L2:** 0.91 cm
- **1.6–3.2 m → P:** 0.8813 **R:** 0.8130 **L2:** 0.98 cm
- **3.2–6.4 m → P:** 0.7894 **R:** 0.6115 **L2:** 1.09 cm

1. nuScenes (Caesar et al., 2020)

Robot Design

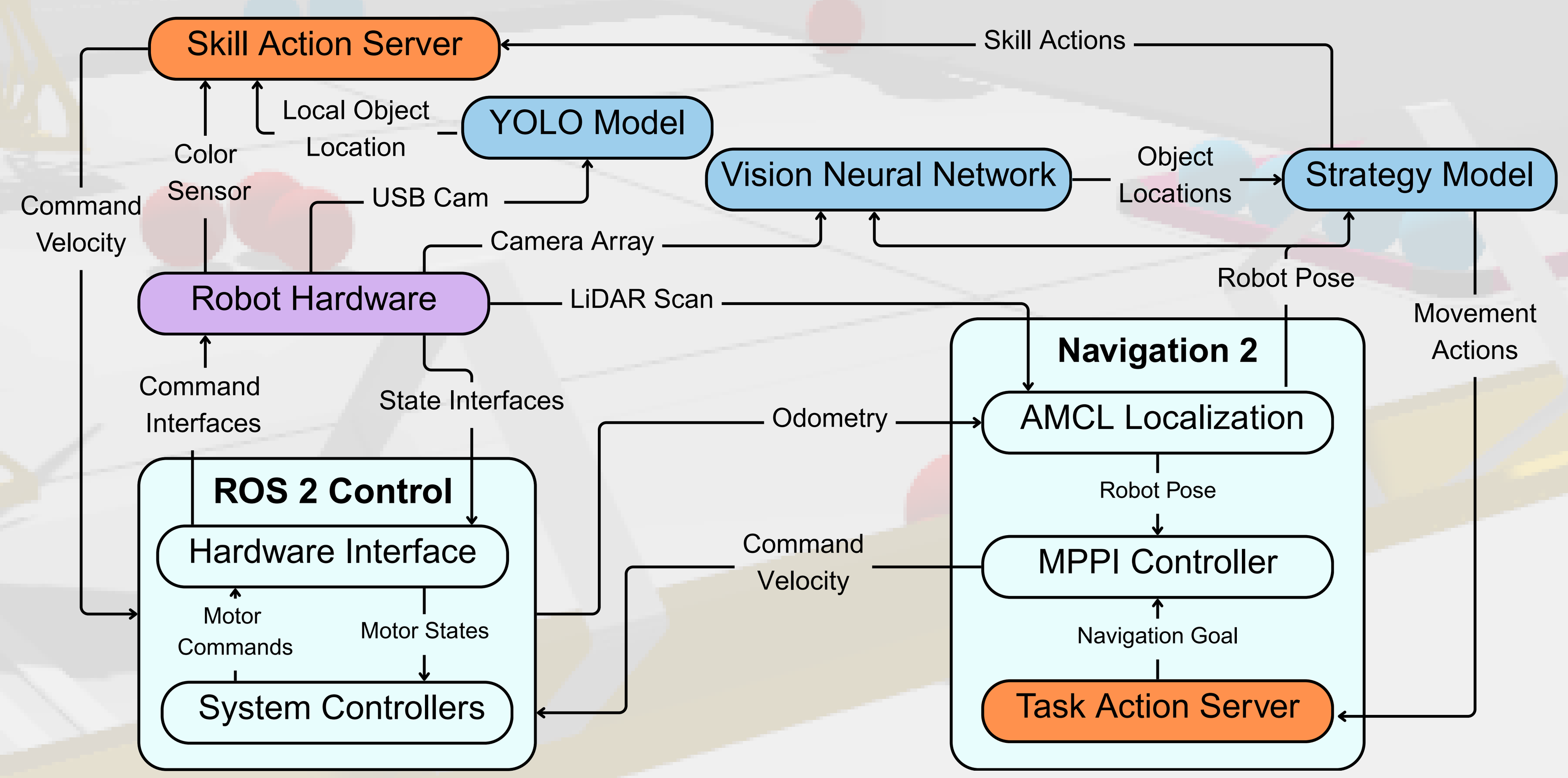


CAD Cross-Section View



Real-World Robot

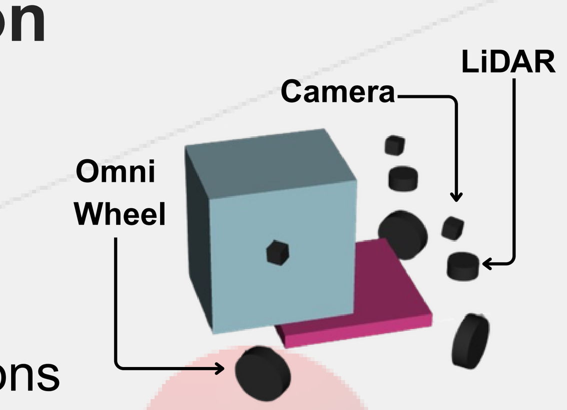
Software Architecture



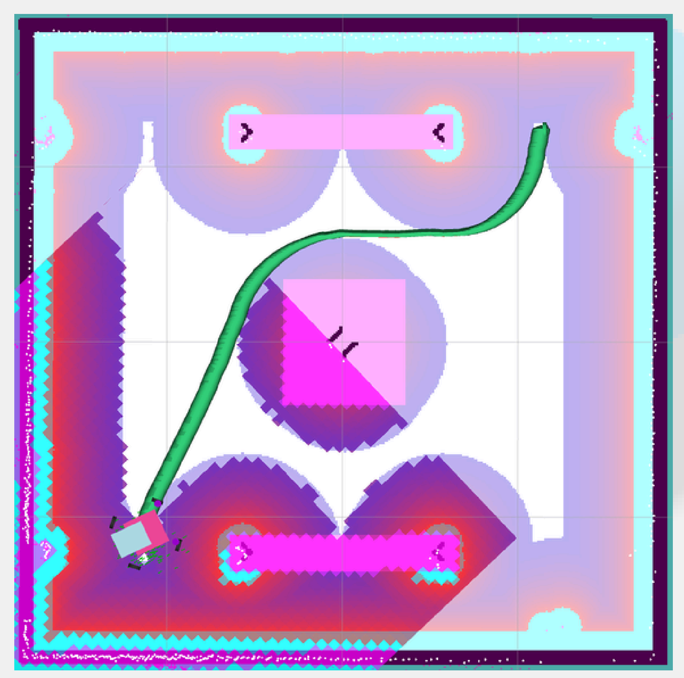
ROS 2 & Simulation

Core ROS 2 Stack

- Navigation 2 (Nav2)
  - Adaptive Monte-Carlo Localizer
  - Model Predictive Path Integral Controller
  - BehaviorTrees for regulating robot decisions
- ROS 2 Control
  - Omni Wheel Drive Controller used to control the robot base
  - Forward Velocity Commanders for each intake motor
  - Hardware interface for communicating with the VEX V5 Brain



Robot URDF for Simulation

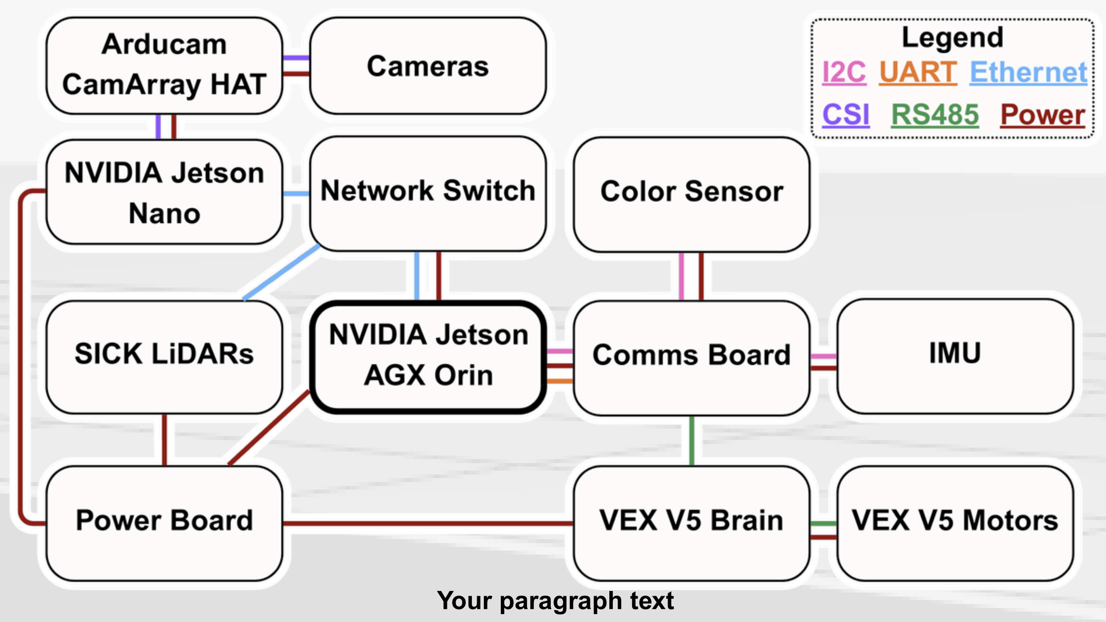


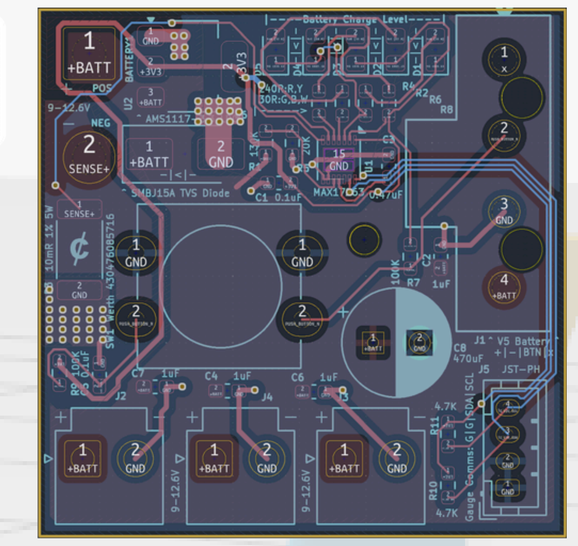
Visualizing the Nav2 MPPI Controller Path in Rviz

Developing in Simulation

- Built URDF robot model and tested core functionality in Gazebo Sim before deploying on hardware
- Able to play the full game in simulation
  - Services for controlling various field and game elements
  - Identified shortcomings in simulation and created a plugin to improve it

Electronics





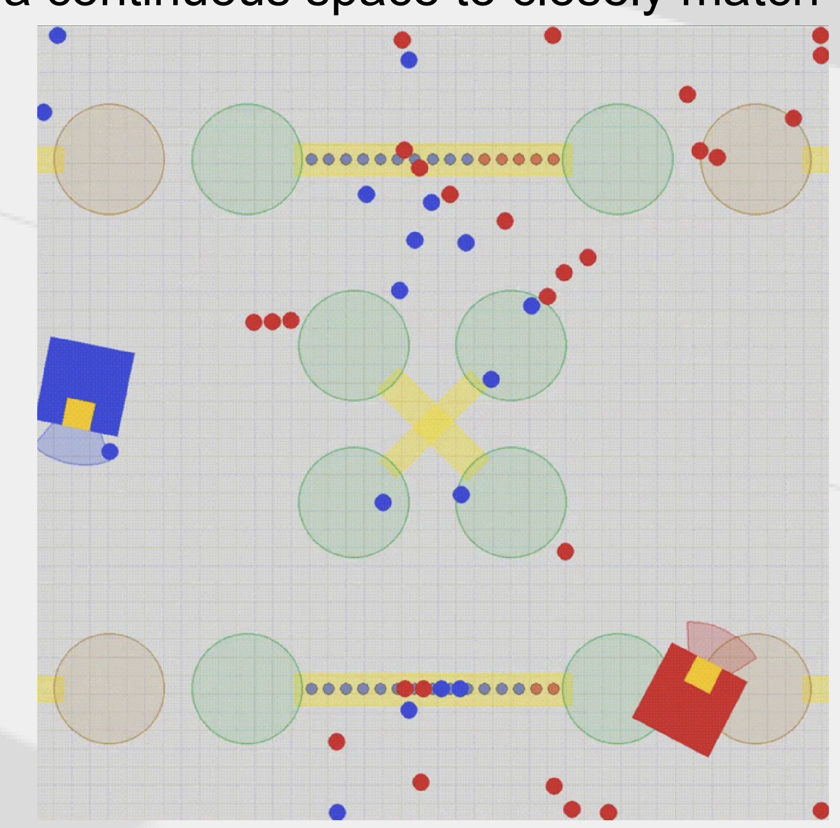
PCB Layout of Power Board

- NVIDIA Jetson AGX Orin runs the ROS 2 system and AI models
- Comms board adapts Jetson to I²C sensors and RS-485 actuators
- Power board distributes 12V to Jetson, LiDARS and VEX hardware
- Camera images are synchronized with CamArray and sent over Ethernet

Strategy Model

- **Goal**: take in the current state of the game and give out an action to play
- Trained using a simulated game in a continuous space to closely match the real world

Input: field state (robot, ball, goals, and loaders' locations, etc.)
Output: action state (pick-up, score, block, move)



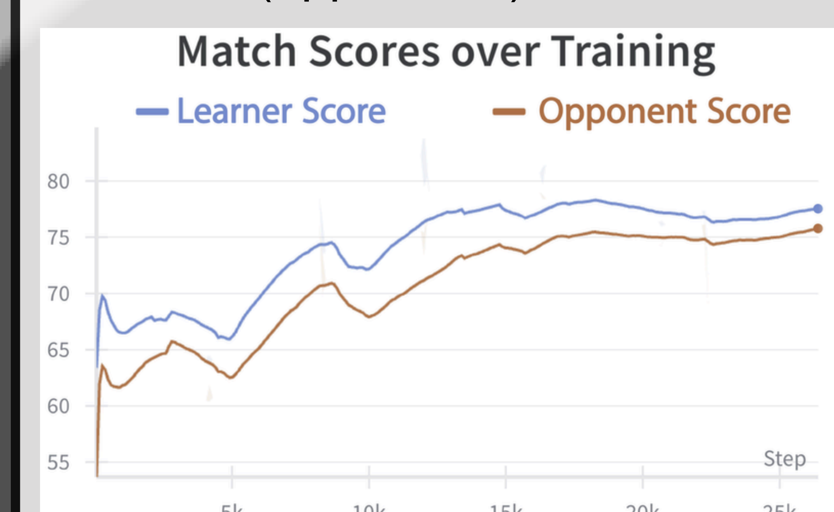
Visualization of Training Environment

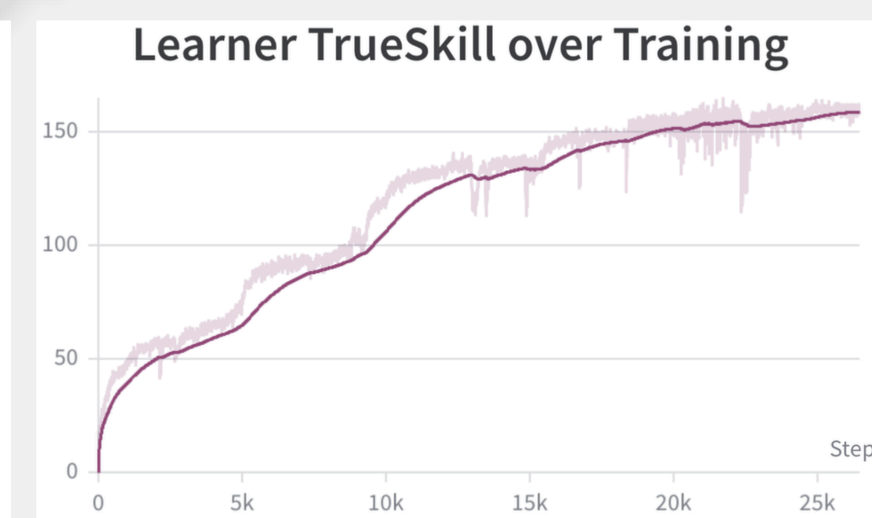
Architecture and Training

Pipeline: ~1.5M parameter MLP model trained with reinforcement learning over 150 hours for ~26M games

Training and Evaluation

- Model snapshots were evaluated and scored with TrueSkill
- The current model (learner) version would play old snapshots of the model (opponents) to evaluate the current model





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