Integrated Vision-Physics-Reinforcement Learning Framework for Dynamic Industrial Robot Navigation

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1 Project Description

Recent work by Issa et al., 2021 has shown that industrial mobile robots face critical navigation challenges in dynamic environments where traditional methods often fail to adapt to real-time changes, leading to inefficiencies and potential collisions. Our framework addresses this challenge through a novel three-way integration of machine learning approaches: CNN-based perception for boundary detection and object recognition, reinforcement learning (PPO-based) for navigation control, and a unique physics-informed neural network (PINN) for wheel dynamics modeling. This integration enables real-time adaptation to unpredictable obstacles while maintaining physical constraint compliance through multi-modal sensor fusion (LiDAR, camera, IMU).

While recent advances by Tsuruta and Morioka, 2024 and Taheri and Hosseini, 2024 have shown progress in combining reinforcement learning and image segmentation, our key innovation lies in the addition of a dedicated learning network for wheel-level dynamics. Our framework introduces a third learning component that optimizes wheel-specific parameters (turning thresholds, acceleration/deceleration rates) based on environmental feedback. This layered learning architecture enables bidirectional information exchange between perception (CNN), decision-making (RL), and physical control (PINN) layers, allowing the robot to discover optimal wheel behavior thresholds for different scenarios while maintaining safe and efficient navigation in industrial environments.

The framework is initially developed and validated in a simulation environment, focusing on perfecting the three-way integration of learning components before potential real-world deployment. This simulation-first approach allows for comprehensive testing of the wheel dynamics learning system, where the robot can safely learn appropriate thresholds for different scenarios, including challenging situations that might cause hesitation or jitter in traditional systems.

Recent work by X. Wang, 2025 and Qu et al., 2021 has demonstrated significant improvements in environmental perception for mobile robots through multi-modal sensor fusion. Our key innovation, as compared to recent work by Tsuruta and Morioka, 2024 and Taheri and Hosseini, 2024, is a layered learning framework where three components interact bidirectionally:

- **Perception Layer**: CNN processes images for boundary detection and object recognition
- **Dynamics Layer**: PINN models individual wheel behaviors (turns, acceleration, deceleration)
- **Decision Layer**: PPO-based RL optimizes both high-level navigation

and low-level wheel control

1.1 Framework Overview

Our framework uniquely introduces a three-way integration:

1. Real-time adaptation to unpredictable obstacle movements using CNN-based boundary detection
2. Physical constraint compliance through PINN-modeled wheel dynamics
3. Multi-modal sensor fusion (LiDAR, camera, IMU) for robust environmental perception
4. Novel wheel-level learning for fine-grained motion control

Recent advances in multi-modal sensor fusion Qu et al., 2021; X. Wang, 2025 have demonstrated significant improvements in environmental perception for mobile robots.

1.2 Technical Framework

- **Simulation Environment Integration**:
  - Custom environment inheriting from gym.Env
  - Evaluation of multiple simulation platforms:
    * ROS2-Gazebo: Traditional robotics simulation
    * Unity: Modern gaming engine with ROS2 plugin support
    * MuJoCo: Physics-accurate simulation capabilities
  - Multi-threaded sensor processing pipeline
- **Reward Structure**:
  - $r_{boundary} = +1.0$ for maintaining safe distances
  - $r_{object} = +2.0$ for successful target detection
  - $r_{dynamics} = -0.5$ for excessive wheel jitter
  - $r_{collision} = -5.0$ for boundary violations
  - **Note**: Reward structure will be subject to change
- **Feedback Loop**:
  - CNN $\rightarrow$ RL: Boundary positions and object locations
  - PINN $\rightarrow$ RL: Predicted wheel states and dynamics
  - RL $\rightarrow$ PINN: Action commands for validation
  - PINN $\rightarrow$ CNN: Motion-compensated image processing

Previous studies by Liu et al., 2017 and Ma et al., 2020 have proven the effectiveness of CNN-based vision models for obstacle detection and avoidance in various robotic applications.

2 Available Datasets

2.1 Modified KITTI Vision Dataset

- **Type**: Domain-adapted road scenes
- **Samples**: 2,801 frames (1242x375 px)
- **Features**: Industrial object overlays via StyleGAN2
- **Access**: http://www.cvlibs.net/datasets/kitti/
- **Adaptation**: Custom industrial annotations

2.2 BotanicGarden Dataset

- **Type**: High-quality robot navigation dataset
- **Environment**: Luxuriant botanic garden (48,000+ m^2)
- **Sensors**: Gray/RGB cameras, 3D LiDARs, IMUs
- **Features**: 33 sequences (17.1km total trajectories)
- **Relevance**: Multi-modal sensor fusion in GNSS-denied environments

2.3 THUD++ Dataset

- **Type**: Dynamic scene understanding
- **Environments**: 13 large-scale dynamic scenarios
- **Data**: 90K+ RGB-D frames with 20M annotations
- **Relevance**: Algorithm testing in dynamic environments

2.4 Open Images Dataset V4

- **Type**: 9.2M images with unified annotations
- **Features**: 15.4M bounding boxes for 600 object classes
- **Samples**: 30.1M image-level labels for 19.8k concepts
- **Access**: https://doi.org/10.1007/s11263-020-01316-z
- **Relevance**: Large-scale dataset for training CNN perception

2.5 AdobeIndoorNav Dataset

- **Type**: Real-world indoor navigation
- **Features**: 3D scene reconstructions, 2D obstacle maps
- **Sensors**: RGB-D camera, 360° panoramic camera
- **Relevance**: CNN-based perception training

3 Relevant Papers

3.1 Double DQN with R-CNN Issa et al., 2021

- **Authors**: Issa, R.B. et al.
- **Contribution**: Cooperative fusion of supervised and reinforcement learning using Faster R-CNN for obstacle identification in autonomous navigation
- **Access**: https://doi.org/10.3390/S21041468

3.2 LiDAR-CNN Fusion Schneider and Stemmer, 2024

- **Authors**: Schneider, D.; Stemmer, M.R.
- **Contribution**: CNN-based multi-object detection and segmentation in 3D LiDAR data for safe and efficient robot navigation in dynamic industrial environments
- **Access**: https://www.preprints.org/manuscript/202410.0496/v1

3.3 RL Navigation Research Z. Wang et al., 2024

- **Authors**: Wang, Z. et al.
- **Contribution**: Combined Deep Q Network and PPO approach for optimized path planning with real-time feedback and adaptive capabilities
- **Access**: https://arxiv.org/abs/2407.02539

3.4 Enhanced PPO Navigation Taheri and Hosseini, 2024

- **Authors**: Taheri, H.; Hosseini, S.H.
- **Contribution**: Enhanced neural network structure and reward function design for safe mobile robot navigation using LiDAR sensor data
- **Access**: https://arxiv.org/abs/2405.16266

3.5 ROS-Based Navigation Tsuruta and Morioka, 2024

- **Authors**: Tsuruta, R.; Morioka, K.
- **Contribution**: ROS-based autonomous navigation system combining RL and semantic segmentation, validated through real-world experiments
- **Access**: https://doi.org/10.1109/sii58957.2024.10417188

3.6 DRL Object Detection Simenthy and Mathana, 2024

- **Authors**: Simenthy, J.R.; Mathana, J.M.
- **Contribution**: Enhanced object recognition accuracy and efficiency in complex scenarios using DRL-based algorithms
- **Access**: https://doi.org/10.1109/adics58448.2024.10533558

3.7 Mobile Robot Perception X. Wang, 2025

- **Authors**: Wang, X.
- **Publisher**: Applied and Computational Engineering
- **Year**: 2025
- **Type**: Journal
- **Contribution**: Multimodal sensor fusion approach
- **Access**: https://doi.org/10.54254/2755-2721/2025.20215

3.8 CNN-Based Obstacle Avoidance Liu et al., 2017

- **Authors**: Liu, C. et al.
- **Publisher**: MATEC Web of Conferences
- **Year**: 2017
- **Type**: Conference
- **Contribution**: Vision-based obstacle avoidance system for mobile robots using CNN architecture
- **Access**: https://doi.org/10.1051/matecconf/201713900007

3.9 Multi-Sensor Fusion Methods Qu et al., 2021

- **Authors**: Qu, Y. et al.
- **Publisher**: Sensors
- **Year**: 2021
- **Type**: Journal
- **Contribution**: Comprehensive framework for indoor navigation using multi-sensor fusion techniques
- **Access**: https://doi.org/10.3390/s21051605

3.10 USV Obstacle Detection Ma et al., 2020

- **Authors**: Ma, L. et al.
- **Publisher**: Mathematical Biosciences and Engineering

- **Year**: 2020
- **Type**: Journal
- **Contribution**: Convolutional neural network implementation for marine vehicle obstacle detection
- **Access**: https://doi.org/10.3934/mbe.2020045

4 Additional Technical Details

4.1 Implementation Architecture

- **Simulation Environment**:
  - Industrial environment with dynamic obstacles
  - Flexible sensor configuration:
    * LiDAR integration (configurable beam count and rate)
    * RGB-D camera support (adjustable resolution)
    * IMU for state estimation
  - Platform selection criteria:
    * Physics accuracy requirements
    * ROS2 integration capabilities
    * Training data generation support
- **Neural Architectures**:
  - CNN: Modified ResNet-18 with custom boundary detection heads
  - PINN: Physics-constrained autoencoder for wheel dynamics
  - RL: PPO with separate policy/value networks

The integration of multiple sensors follows the established methods outlined by Qu et al., 2021 for reliable navigation in complex environments.

4.2 Technical Novelty

While Z. Wang et al., 2024 and Schneider and Stemmer, 2024 have made significant advances in perception and navigation respectively, our framework introduces three key innovations:

1. **Wheel-Level Learning**: Individual wheel dynamics modeling through PINN, enabling fine-grained motion control absent in current literature

2. **Three-Way Integration**: Bidirectional information flow between CNN, PINN, and RL, creating a truly adaptive system

3. **Dynamic Threshold Learning**: Automatic discovery of optimal wheel parameters (turn rates, acceleration limits) through RL feedback

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