AGV Collision Avoidance System

Lightweight Models for Real-Time Applications

Team #2 Presentation | November 21, 2025

LM-RtA Workshop

Agenda

Proposed System Architecture - 6-layer modular design

Layer Details - Approaches, trade-offs, and analysis for each layer

Implementation Strategy - Incremental development approach

Data Collection - Infrastructure and simulation environment

Timeline - Milestones and deliverables

Next Steps - Immediate actions

Proposed System Architecture

5-Layer Modular Design

Layer 1: Sensor Layer

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Layer 2: Perception Layer

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Layer 3: World Model

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Layer 4: Decision Layer

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Layer 5: Control Layer

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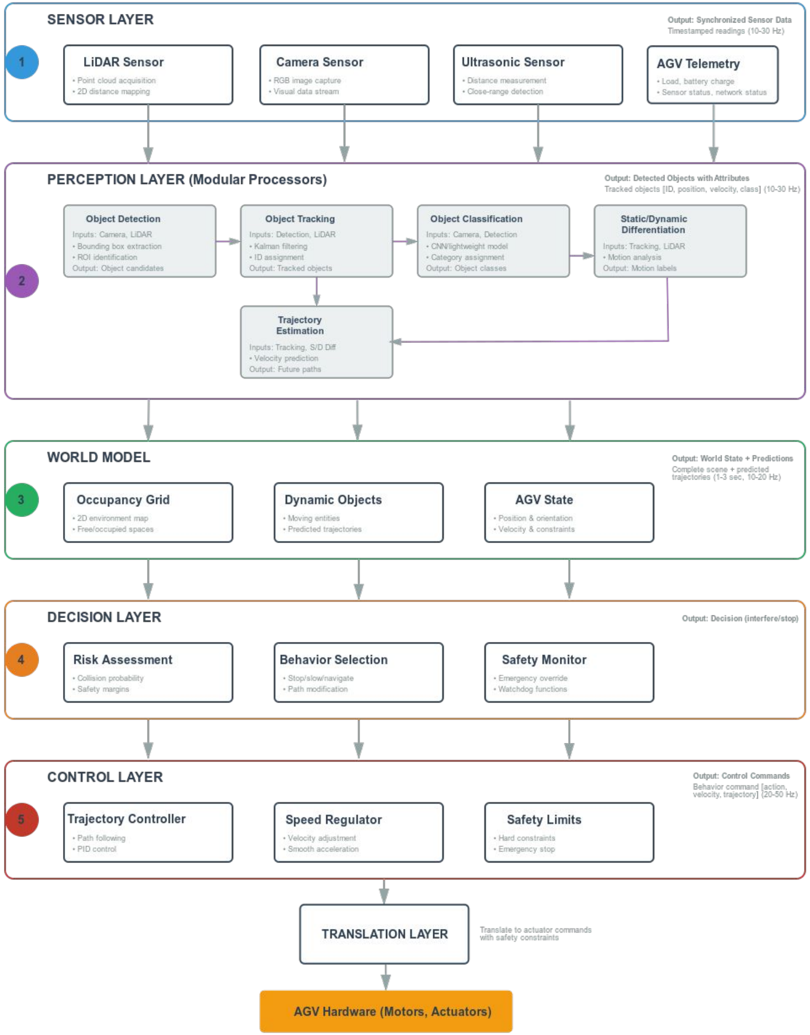
Layer 6: Translation Layer

Principles: Modular design, real-time constraints, bottom-up processing



This approach allows:

- **Test hypotheses systematically**: Each layer can be evaluated independently
- **Isolate variables**: If performance is poor, you know which component to improve
- **Compare methods**: We can swap out the modules and compare 3 different approaches with controlled experiments
- **Ablation studies**: Remove components to see their contribution
- **Lightweight Models**: uses lightweight models at each stage
- **Easy deployment**: Only “Sensors” and “Translation” layers will be substituted
- **Explainability**: AGVs must comply with ISO 3691-4 standards:
  - "Why did the AGV stop?" - With modules, you can trace the decision

Layer 1 Deep Dive: Approach Analysis

Sensor Integration Strategy

Selected Approach: Multi-Sensor Integration

LiDAR (primary) + Camera (classification) + Ultrasonic (safety)

Key Considerations

- Synchronization timing
- Data rate management
- Calibration

Known Limitations

- LiDAR: reflective surfaces
- Camera: lighting
- Ultrasonic: range

Further Analysis

- Sensor placement
- Failure handling
- Data formats

Layer 2 Deep Dive: Approach Analysis

Static/Dynamic Obstacle Differentiation

Phase 1: Baseline

Velocity-threshold: Position changes

Clustering: DBSCAN/K-means

•Simple tracking

Phase 2: Enhanced

YOLO/MobileNet: Detection

•Semantic segmentation

•Kalman filtering

Pros & Cons

Baseline: Fast, simple, low cost
Enhanced: High accuracy

Analysis Needed

•Velocity thresholds

•Model quantization

•Occlusion handling

PROBLEM STATEMEN

- Indoor AGVs require reliable real-time differentiation between **static** and **dynamic** obstacles under **sensor noise**, **ego-motion**, **partial occlusion** and unpredictable human/object movement.
- Conventional velocity-threshold or clustering-only methods often fail in dense environments or under low-speed motion.

HIGH LIGHTS AND INTERPRETATION

- **In the context of Barrier Lyapunov Function (BLF) control, differentiation is handled by converting the complex dynamics of a moving obstacle into a simplified, yet safe, augmented static representation.**

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  - X. Ye, Z. Deng, Y. Shi, and W. Shen, ''Toward energy-efficient routing of multiple AGVs with multi-agent reinforcement learning,'' *Sensors*, vol. 23, no. 12, p. 5615, Jun. 2023.
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  - P. Theodorou, K. Tsiligkos, and A. Meliones, ''Multi-sensor data fusion solutions for blind and visually impaired: Research and commercial navigation applications for indoor and outdoor spaces,'' *Sensors*, vol. 23, no. 12, p. 5411, Jun. 2023.
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  - D. J. Yeong, G. Velasco-Hernandez, J. Barry, and J. Walsh, ''Sensor and sensor fusion technology in autonomous vehicles: A review,'' *Sensors*, vol. 21, no. 6, p. 2140, Mar. 2021.
  - Y. Wang and H. Fang, ''Estimation of LAI with the LiDAR technology: A review,'' *Remote Sens.*, vol. 12, no. 20, p. 3457, Oct. 2020.

HIGH LIGHTS AND INTERPRETATION

- **This approach identifies dynamic obstacles by tracking their state changes over time using sensors and statistical filtering.**
- **Differentiation relies on measurable, time-dependent change. If an object's state vector (position, velocity) is tracked and predicted using sequential measurements and Kalman filtering, it is confirmed as dynamic and requires appropriate speed obstacle modeling.**

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- M. Jayaratne, D. de Silva, and D. Alahakoon, ''Unsupervised machine learning based scalable fusion for active perception,'' IEEE Trans. Autom. Sci. Eng., vol. 16, no. 4, pp. 1653–1663, Oct. 2019.
- H. Yin, Y. Lin, J. Yan, Q. Meng, K. Festl, L. Schichler, and D. Watzenig, ''AGV path planning using curiosity-driven deep reinforcement learning,'' in Proc. IEEE 19th Int. Conf. Autom. Sci. Eng. (CASE), Aug. 2023, pp. 1–6.

PROPOSED SOLUTION'S

1. Multi-Sensor Feature Fusion and Semantic Segmentation (GG-DRL Framework)
2. Point Cloud Recognition via Categorization (Bag of Graphs - BoG Method)
3. Motion Tracking and Predictive Modeling (Kalman Filtering Method)
4. Control Simplification for Moving Obstacles (Equivalent Safe Distance Method)

Approach 1:

MULTI-SENSOR FEATURE FUSION AND SEMANTIC SEGMENTATION (GG-DRL FRAMEWORK)

1. **Sensor Data Acquisition :** The AGV is equipped with LiDAR and a front-mounted camera,. The camera captures visual images, while the LiDAR generates point cloud data over time steps. Provides concurrent spatial (LiDAR) and visual (Camera) input necessary for both location and identity recognition.

2. **Visual Feature Processing & Classification:** A Siamese Deep Convolutional Neural Network (DCNN) architecture processes the images and includes a scene classification module. This module performs pixel-wise segmentation to classify scene content by specific labels: dynamic carts (red), static obstacles (blue), and target points (green). This is the direct differentiation step. The DCNN is trained to recognize the identity of the object (e.g., an AGV/cart vs. a rail track/wall) and label it semantically as either static or dynamic. This categorization guides subsequent avoidance strategies.

3. **Temporal Data Processing & Fusion:** Long Short-Term Memory (LSTM) networks are used to process the LiDAR point cloud data over time steps, extracting distance and angle information. This is integrated with camera features and the AGV's own state information. Incorporates temporal consistency. While the visual module provides the semantic label, the LSTM processing of time-series LiDAR data confirms if the identified object exhibits motion (dynamic) or remains fixed (static), reinforcing the initial visual classification for accurate environmental modeling.

HIGH LIGHTS AND INTERPRETATION

- **This technique achieves explicit, semantic differentiation by fusing visual and spatial information using deep learning networks.**
- **This technique is considered the most complete differentiation step because it provides a direct, labeled classification (static/dynamic) as a foundational output of the environmental perception system, crucial for decision-making in the Deep Reinforcement Learning (DRL) stage.**

- L. Jia, P. Cheng, Z. Zhang, L. Ji, and C. Xu, ''Integrated development of rail transit and energies in China: Development paths and strategies,'' Chin. J. Eng. Sci., vol. 24, no. 3, p. 173, 2022.
- M. Yang, Y. Bian, L. Ma, G. Liu, and H. Zhang, ''Research on traffic control algorithm based on multi-AGV path planning,'' in Proc. IEEE Int. Conf. Syst., Man, Cybern. (SMC), Oct. 2021, pp. 697–702.
- A. Y. Pratama, M. R. Ariyadi, M. N. Tamara, D. S. Purnomo, N. A. Ramadhan, and B. Pramujati, ''Design of path planning system for multi-agent AGV using A* algorithm,'' in Proc. Int. Electron. Symp. (IES), Aug. 2023, pp. 335–341.
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Approach 2:

POINT CLOUD RECOGNITION VIA CATEGORIZATION (BAG OF GRAPHS - BOG METHOD)

1. **Categorization Goal:** The system aims for obstacle categorization/recognition, helping implement "more precise static/dynamic differentiation; e.g. standing human will not be categorized as static". Categories include {Tree, Car, Pole, Pedestrian, Cyclist}. Establishes that identifying the object type is the core method for inferring its dynamic potential.
2. **Point Cloud Segmentation & Feature Extraction:** Object candidates are segmented, and the Bag of Graphs (BoG) methodology is applied directly to point clouds. Local features (like local convex hull volume, characteristic radius, etc.) are calculated around key points. The physical characteristics extracted from the shape inform the classification engine about what the object is.
3. **Classification:** Local patterns are defined as graphs of clustered key points. The frequency of these patterns is compared to classify the object's shape into predefined semantic categories. The classification output (e.g., classifying an object as 'Pedestrian' vs. 'Tree') automatically determines whether the object must be treated as dynamic (requiring constant tracking and motion prediction) or static (requiring only fixed avoidance).

HIGH LIGHTS AND INTERPRETATION

- **This method differentiates obstacles by identifying their physical category from limited 3D point cloud data, inherently separating static objects (like infrastructure) from potentially dynamic agents (like people or vehicles).**
- **Differentiation is achieved indirectly through semantic classification. The system does not explicitly track velocity to confirm if a "Pedestrian" is currently moving, but rather categorizes the object type, requiring the AGV to assume and plan for the potential dynamic behavior inherent to that category.**

- T. N. Tien and K.-V. Nguyen, ''Updated weight graph for dynamic path planning of multi-AGVs in healthcare environments,'' in Proc. Int. Conf. Adv. Technol. Commun. (ATC), Oct. 2022, pp. 130–135.
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Approach 3:

MOTION TRACKING AND PREDICTIVE MODELING (KALMAN FILTERING METHOD)

1. **Motion Measurement:** The AGV obtains relative coordinates of obstacles via LiDAR. The absolute position of obstacles is obtained in the global map using the map differencing method. Motion parameters are calculated according to the change in the position of obstacles at different moments. Any object that shows a consistent, measurable change in its position relative to the global map over sequential time steps is differentiated as a dynamic obstacle.
2. **State Prediction:** The Kalman filtering algorithm is chosen for prediction of the dynamic motion parameters (position and velocity) of obstacles. The Kalman filter explicitly estimates dynamic motion parameters (like v_x, v_y), confirming that the object is not static and providing the data required for dynamic avoidance strategies (like the improved Speed Barrier Method).
3. **Zonal Handling:** A triple area (Safety zone, Obstacle avoidance layer, Emergency obstacle avoidance layer) is set up around the AGV. Kalman filtering is updated iteratively in the outermost "safety zone" to obtain accurate prediction results. This zonal system formalizes the treatment of dynamic obstacles: an object is differentiated as dynamic and continuously tracked in the outer zone before becoming an active avoidance priority in the inner zone.

Layer 3: World Model

Unified Environment Representation

Unified Representation + Fusion

Sensor Fusion

Data Level: Direct fusion

Feature Level: Combined features

Decision Level: Weighted fusion

Avoid timestamp-based fusion

Phase 1 Implementation

2D occupancy grid + feature-level fusion

Phase 2: Probabilistic mapping

Layer 3 Deep Dive: Approach Analysis

Unified World Model & Sensor Fusion

Fusion Strategy Comparison

Data-Level: Direct sensor combination

Feature-Level: Combine features ✓ Phase 1

Phase 1: Basic

2D grid: Spatial representation

Dynamic tracking: Track objects

Motion models: Linear velocity

Phase 2: Advanced

Probabilistic: Handle uncertainty

Semantic: Object classes

Trajectory: Predict paths

Key Challenges

Avoid timestamp fusion | Map frequency | Conflict resolution

Layer 3 Deep Dive: Approach Analysis

Unified World Model & Sensor Fusion

Multi-Sensor Fusion Localization for Forklift AGV Based on Adaptive Weight Extended Kalman Filter (2025)

- **EKF-based multi-sensor fusion**.
- **Odometry** → **prediction**, **LiDAR** → **correction**.
- **Adaptive weighting** adjusts sensor influence in real time.
- **Suppresses odometry drift** and improves localization stability.

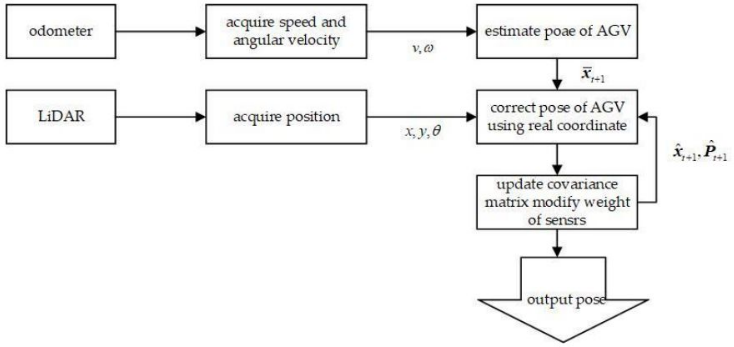


Figure 4. General framework of EKF fusion localization system.

Layer 3 Deep Dive: Approach Analysis

Unified World Model & Sensor Fusion

Challenges Associated with Sensors and Data Fusion for AGV-Driven Smart Manufacturing (2021)

data from AGV sensors + IoT/AS subsystems for higher positioning accuracy.

Dynamic fusion configuration adapts to available sensors and tasks. **Uses ontology models** to unify heterogeneous sensor data for M2M communication.

Integrates multi-source streams to improve navigation, cooperation, and system awareness.

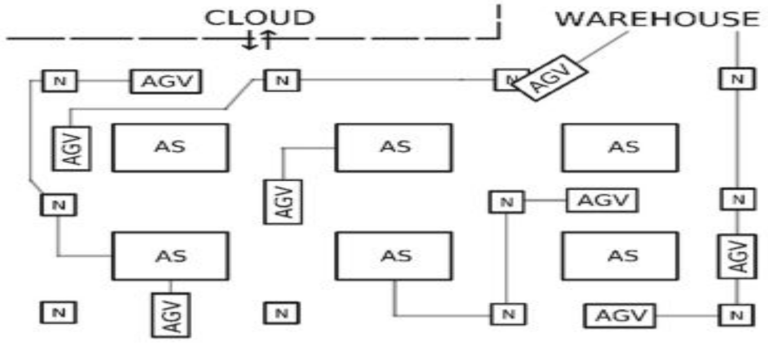


Fig. 1. Autonomous guided vehicles in manufacturing environment (N - NFC module).

Layer 3 Deep Dive: Approach Analysis

Unified World Model & Sensor Fusion

Research on Multi-AGV Rail Transportation Path Planning and Dynamic Obstacle Avoidance Based on Multi-Sensor Environmental Perception and Deep Reinforcement Learning (2025)

Multi-sensor feature fusion algorithm combines data from all onboard sensors (e.g., LiDAR, vision, proximity).

Extracts features from each sensor stream and merges them into a unified perception model.

Fused features enable detection of dynamic AGVs, static obstacles, and targets.

Provides a complete environment map used by the DRL module for safer path planning and obstacle avoidance.

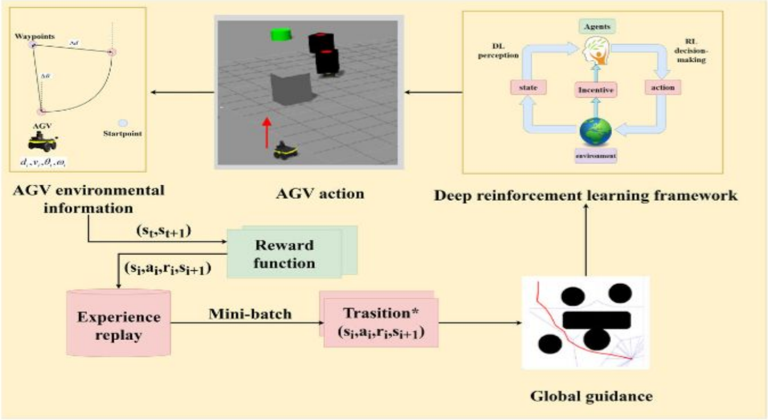


FIGURE 12. A multi-AGV path planning framework based on deep reinforcement learning under global guidance.

Team Lead: Asif Huda | Focus: Environmental representation

Layer 3 Deep Dive: Approach Analysis

Unified World Model & Sensor Fusion

Enhancing Automated Guided Vehicle Navigation with Multi-Sensor Fusion and Algorithmic Optimization (2024)

- **Fuses 2D-LiDAR with vision (YOLO + MobileNet)** to add semantic obstacle classification.
- **Combines LiDAR geometry with vision-based object labels** for richer, more reliable perception.
- **Uses dual-laser LiDAR extrinsic calibration** to merge data from multiple LiDARs into one coherent frame.
- **Fusion enhances obstacle detection accuracy and supports faster, more stable relocalization.**

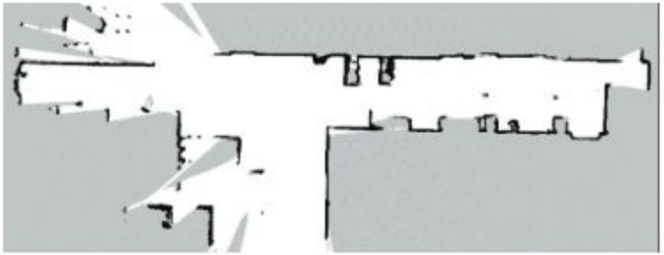


Fig. 6: Fusion Grid Map

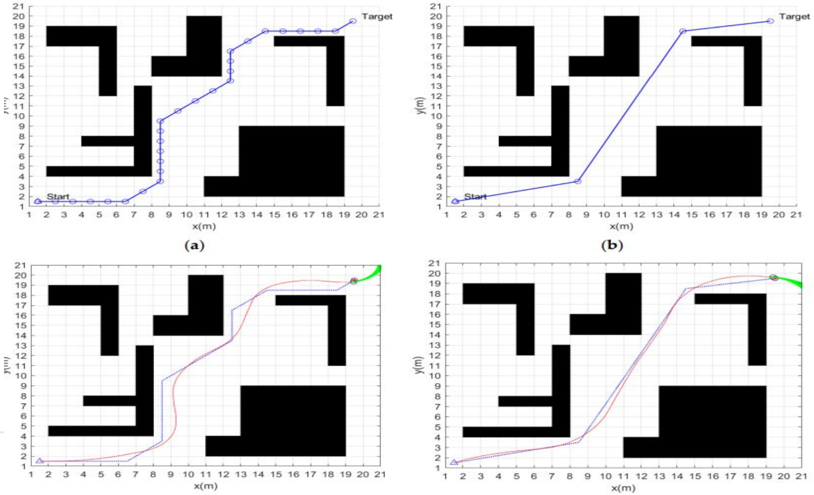
Team Lead: Asif Huda | Focus: Environmental representation

Layer 3 Deep Dive: Approach Analysis

Unified World Model & Sensor Fusion

Global Dynamic Path Planning of AGV Based on Fusion of Improved A* Algorithm and Dynamic Window Method (2024)

- **Fuses improved A* (global planning) with Dynamic Window Method (local planning)**.
- **Global–local fusion** ensures optimal long-range paths plus real-time obstacle avoidance.
- **A* provides the global route**, while **DWM adjusts motion locally** around dynamic and unknown obstacles.
- **Fusion enables smooth, safe navigation** while keeping the AGV on the optimal path.



Team Lead: Asif Huda | Focus: Environmental representation

Layer 3 Deep Dive: Approach Analysis

Unified World Model & Sensor Fusion

Summary of the studies

Title	Main Idea	Difficulty	Pros	Cons	Rank
Multi-AGV	DRL and multi sensor fusion	High	70% reduction in collision	High computational demand	1
Multi Sensor fusion	Adaptive EKF fusing LiDAR and odometry	High	high localization accuracy	Odometry accuracy degrades significantly	2
Enhancing AGV navigation	Yolo based object detection and using Map fusion	High	Reduced relocalization time by 35%	High time consumption	3
Global dynamic path plannning	Fusion of improved A* and DWM for fast obstacle avoidance	Medium	A* enables 26% faster path planning	Verification was done in simulation environment	4
Challenge associated	Identifies challenges related to sensor fusion for AGV precise positioning, navigation	-	Highlights asynchronous data stream handling to increase measurement precision	-	

Team Lead: Asif Huda | Focus: Environmental representation

Layer 4: Decision Layer

Risk Assessment & Behavior Selection

Components: Risk Assessment, Behavior, Safety
Goal: Evaluate risk and select safe behavior

Safety Zones

Warning: Pre-emptive detection

Slowdown: Reduce speed

Emergency: Immediate halt

Principle: Activate only when necessary

Initial Implementation

Phase 1: Rule-based with distance thresholds

Later: Deep RL for adaptive decisions

Layer 4 Deep Dive: Approach Analysis

Intelligent Decision-Making & Risk Assessment

Safety Zone Architecture

Warning → Slowdown → Emergency Stop

Phase 1: Rule-Based

Distance thresholds: Fixed zones

Priority system: Conflicts

- **Intelligent activation**
- **Graceful degradation**

Phase 2: Learning-Based

Deep RL: Adaptive

- **Context-aware**
- **Risk prediction**
- **Multi-objective**

Further Analysis: Optimal thresholds, explainability (ISO 3691-4)

Team: Milad Jafari / Sadat Hossain

Layer 5 Deep Dive: Approach Analysis

Trajectory Planning & Control

Phase 1: Baseline

Vector Field Histogram + Lateral Deviation

- Uses only LIDAR/sonar
- Read LIDAR arc in front of the robot
- Detect obstacle-free sectors
- Pick the one closest to the goal direction
- Apply slight lateral deviation to avoid obstacles
- Return to original heading once path is clear

Pros: Simple, fast, reliable

Phase 2: Advanced Planning

Genetic Algorithms for path optimization

Reinforcement Learning for learned obstacle avoidance

Cons: Higher complexity

Key Considerations

Trajectory update frequency, smooth path generation, loop avoidance

Team Lead: Leonardo Schiavo | Focus: Smooth, safe trajectories

Layer 5 Deep Dive: Approach Analysis

Trajectory Planning & Control

Option 2: Dynamic Window Approach

- Samples all admissible linear & angular velocities
- Simulates short trajectories (1–2 seconds)
- Discards those causing collisions
- Scores remaining candidates (goal proximity, clearance, velocity, smoothness)
- Selects the best velocity command

Additional: Sensor Fusion with Kalman Filters (support module, not a planner)

- Improve state estimation by filtering noisy LIDAR/odometry readings
- Provide smoother and more reliable velocity & position estimates
- Enhance the stability and accuracy of whichever planner is used

Key Considerations

Trajectory update frequency, smooth path generation, loop avoidance

Layer 5 Deep Dive: Milestones

Trajectory Planning & Control

Milestone 1 — Baseline Local Planner
Implement VFH-Lite + lateral deviation; test on simulated LIDAR conditions; validate obstacle avoidance and smoothness.

Milestone 2 — Dynamic Window Approach Prototype
Implement DWA in simulation; compare performance with VFH-Lite (speed, smoothness, safety).

Milestone 3 — Sensor Fusion Integration
Add Kalman Filter or simpler filters to smooth LIDAR/odometry data and improve state estimates.

Milestone 4 — Benchmarking & Evaluation
Measure performance: response time, collision rate, trajectory smoothness, goal convergence.

Milestone 5 — Final System Integration
Combine the best-performing approach with the full navigation stack; validate in realistic or simulated industrial scenarios.

Team Lead: Leonardo Schiavo | Focus: Smooth, safe trajectories

Development Philosophy

Iterative Enhancement Strategy

Core Principles

Start Simple: Basic algorithms first

Validate Early: Test each layer

Iterate: Add complexity gradually

Phase 1: Foundation

- Simple clustering
- 2D occupancy grid
- Rule-based decisions

Phase 2: Enhancement

- Deep learning detection
- Probabilistic mapping
- Advanced path planning

Data Requirements & Limitations

Dataset Specifications and Impact on Solution Design

Required Data

- **LiDAR:** Point cloud
- **Camera:** RGB images
- **Ultrasonic:** Close range
- **Telemetry:** Position/velocity

Limitations

- **Synchronization:** Timing
- **Volume:** Large datasets
- **Labeling:** Time-consuming
- **Noise:** Measurement uncertainty

Solution Strategy

Phase 1: Isaac Sim (synthetic data)

Phase 2: Real data via Station

Strategy: Simulation-first → real-world integration

Development Infrastructure

Simulation Environment & Data Collection

NVIDIA Isaac Sim

Primary Development:

- Physics-accurate simulation
- Multi-sensor (LiDAR, cameras)
- Rapid prototyping
- Reproducible test scenarios

Computational Station

Real-World Data:

- Camera data acquisition
- LiDAR data collection
- Real-time processing
- AGV hardware integration

Infrastructure: Simulation to real-world deployment

Technical Infrastructure

Development & Testing Environment

Development Environment

Platform: NVIDIA Isaac Sim

Approach: Simulation first

Transfer: Sim-to-real validation

Computational Station

Status: In development

Capabilities: Camera & LiDAR

Purpose: Real-world data gathering

Data Requirements

Sources: LiDAR point clouds, camera images, telemetry | **Challenges:** Synchronization, noise, edge cases

Proposed Solution Summary

Integrated Approach for AGV Collision Avoidance

Core Solution

5-layer modular architecture with simulation-first development

Key Advantages

Modular: Independent layers

Phased: Working baseline first

Multi-sensor: Robust awareness

Safety-first: Protective zones

Risk Mitigation

Simulation: Validate first

Clear interfaces: Layer comms

•Gradual complexity

•Parallel workstreams

Phase 1 Success (Dec 4th)

Functional baseline in Isaac Sim: multi-sensor acquisition, obstacle detection, world model, collision avoidance

Project Timeline

Key Milestones & Deliverables

Nov 21, 2025	Propose solutions and discuss data requirements
Dec 4, 2025	Initial prototypes, progress showcase, milestone decisions
Jan 9, 2026	Complete system implementation, initial deployment
Jan 23, 2026	Complete system demonstration, results analysis, industrial feedback
Feb 6, 2026	Project evaluation, publication preparation, documentation

Next Steps & Action Items

Preparation for December 4th Milestone

Before December 4th Lab Visit

Isaac Sim Setup | **Phase 1 Baseline**

Integration Testing | **Demonstration**

Technical Tasks

- Finalize data formats
- Setup code repository
- Implement baseline algorithms

Team Coordination

- Weekly sync meetings
- Progress tracking
- Risk assessment

Questions & Discussion

Thank you for your attention

Team Members: Myroslav Mishchuk | Leonardo Schiavo Asif Huda | Milad Jafari | Sadat Hossain