Unknown Collision Avoidance in Unknown Environments via Multi-Modal Perception and Reactive planning

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1. Problem Statement

Autonomous navigation in dynamic, unstructured environments remains a major challenge for mobile robots. The presence of unpredictable and moving obstacles such as pedestrians, other robots, or vehicles demands real-time adaptation and decision-making, especially in the absence of prior maps.

Conventional navigation approaches often assume static environments or rely heavily on pre-mapped information, which becomes unreliable in real-world scenarios. Our work addresses the problem of achieving safe, real-time navigation in such **unknown environments** through a unified framework of multi-modal perception and reactive planning.

Key Challenges

- Navigating without a prior map in an unknown environment.
- Detecting and tracking dynamic obstacles with unpredictable motion.
- Performing real-time trajectory planning in response to changing surroundings.
- Ensuring safety and robustness across indoor and outdoor scenarios.

Objective

Our goal is to design and deploy a navigation stack for the Husky UGV that ensures **collision-free motion** in uncertain environments using:
- Utilizing a combination of LiDAR and RGB-D sensors for real-time obstacle detection and tracking. The LiDAR data is also used to generate accurate maps and localize the robot within its environment.
- A reactive planner capable of computing safe trajectories in real time.
- Real-world integration on Husky robot using ROS.

2. System Architecture Overview

The proposed framework for unknown collision avoidance consists of two core subsystems: a perception module for real-time mapping, localization, obstacle detection, and tracking, and a planning module that generates safe trajectories around unknown obstacles. Both components are tightly integrated to operate on-board the Husky UGV in real time.

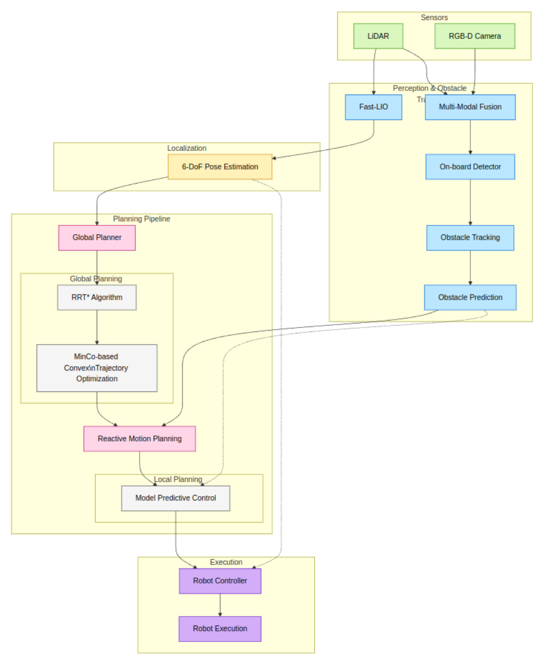

Figure 1. High-level system architecture showing integration of perception, localization, global and local planning components.

2.1. Subsystems

1. **Perception and Obstacle Tracking:** For mapping and localization, we use LiDAR and also implement multi-

modal fusion using RGB-D and LiDAR inputs to detect, track, and predict unknown obstacles using On-board detector.
2. **Reactive Motion Planning:** A local planner based on Model Predictive Control (MPC) formulates trajectories that avoid predicted obstacles while minimizing deviation from the goal.
3. **Global Planner:** Generates a coarse path using RRT* [3] in a 3D point cloud of the scene. Then, MinCo-based convex trajectory optimization [1] produces a time-optimal, smooth global plan.
4. **Localization:** Uses Fast-LIO for 6-DoF pose estimation from LiDAR point clouds, ensuring accurate state information for both perception and planning.

2.2. Real-Time Integration

All components operate within the Robot Operating System (ROS) ecosystem with modular nodes for perception, planning, and actuation. Data is visualized and validated in RViz using synchronized sensor overlays and pose tracking.

3. Perception and Obstacle Tracking

Real-time detection and tracking of dynamic obstacles are critical for navigating unknown environments. Our perception system is built around a **onboard-detector module**, which fuses RGB-D and LiDAR data to identify and track dynamic agents such as humans and other robots.

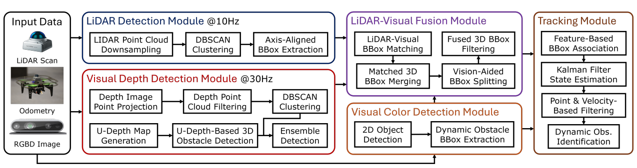

Figure 2. Onboard-Detector perception pipeline: fusion of RGB-D and LiDAR data for detecting and tracking moving obstacles.

3.1. Core Components

- **Depth-Based Detection:** Utilizes depth images from the Intel D455 camera to segment generic obstacle regions based on spatial discontinuity [4].
- **Dynamic Filtering:** Static background is removed by comparing current depth frames with a reference static map.
- **3D Bounding Box Generation:** Generates axis-aligned bounding boxes around detected obstacle clusters for downstream planning.
- **State Estimation:** Temporal tracking of detected obstacles allows estimation of their velocity and predicted future position.

3.2. Advantages

- Lightweight and real-time capable; operates reliably on embedded hardware.
- Does not require training or annotated data.
- Fully compatible with LiDAR point cloud registration from Fast-LIO.

3.3. Output

- Positions, velocities, and 3D bounding boxes of dynamic obstacles.
- Dynamic regions are excluded from the static occupancy grid to prevent false-positive collisions.

3.4. Real-World Scenario

In field tests, a moving human (e.g., team member walking) was detected via this module. The dynamic obstacle's 3D position and velocity vector were published over ROS and consumed by the planner for reactive avoidance.

4. Global Planning and Localization

In addition to reactive local planning, our system incorporates a global planner to generate coarse trajectories across large environments. This is essential for navigating complex scenes with large static obstacles such as walls or terrain structures.

4.1. Global Planner Overview

Our global planner follows a two-step pipeline:
1. **Path Sampling:** We use **RRT*** to sample feasible paths in a 3D point cloud representation of the environment.
2. **Trajectory Generation:** Once a path is found, we define a convex polytope (safe corridor) around the path and generate a **minimum-jerk, time-optimal trajectory** using MinCo-based optimization.

This trajectory is then passed to the RDA planner, which locally adapts it in the presence of dynamic agents.

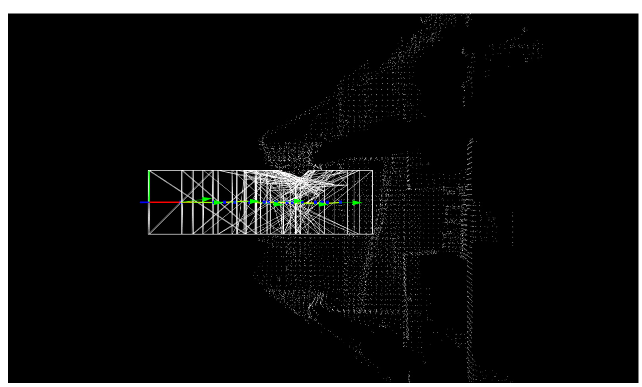

Figure 3. Global planning: RRT* path with convex polytopes and minimum-jerk trajectory inside corridor.

4.2. SLAM-Based Localization

Localization is achieved using a **LiDAR-based SLAM pipeline** built on mid-70° Livox sensor data.

- First, we **generated a prior map** of the environment using mid-70° LiDAR data.
- Then, during navigation, the robot performs **localization on this pre-built map** using scan-matching and feature alignment [2].
- This approach supports accurate 6-DoF pose estimation, even in GPS-denied or low-texture indoor environments.

4.3. Integration with ROS

Both the global planner and SLAM modules run within the ROS framework:

- The localization node publishes real-time pose updates as ROS ‘odom‘ messages.
- These are consumed by both the RDA local planner and RViz for live visualization.

This setup enables a full loop: global plan $\rightarrow$ real-time SLAM $\rightarrow$ local re-planning.

5. Hardware Setup and Implementation Details

To validate the complete navigation system in real-world conditions, we deployed our perception and planning stack on the **Clearpath Husky A200** Unmanned Ground Vehicle (UGV). The Husky platform was chosen for its robustness, modularity, and compatibility with the Robot Operating System (ROS).

5.1. Sensor Mounting

All sensors were mounted rigidly on the Husky using a custom-built frame:

- The Realsense D455 was front-mounted for wide-angle depth sensing.
- The Livox LiDAR was mounted with an unobstructed field of view to facilitate accurate SLAM and mapping.

5.2. Software and Integration

- The full system ran on a ROS Noetic-based stack in Ubuntu 20.04.
- Sensor drivers for Realsense and Livox were launched in synchronized time.
- The perception node (onboard-detector), SLAM node, and planners were integrated via ROS topics and services.
- RViz was used for debugging and visualization of sensor overlays, trajectory plans, and robot pose.

5.3. Real-World Deployment

The robot was tested in an indoor lab environment and outdoor testbed with dynamic agents (e.g., team member walking). The full loop of:

Figure 4. Hardware setup: Sensor mounting on Husky UGV.

1. Obstacle detection and tracking
2. SLAM-based localization
3. Global and local planning

was verified in practice, with successful trajectory execution.

6. Results and Evaluation

We evaluated the proposed multi-modal perception and reactive planning framework in both simulation and real-world deployments. Our system was tested in indoor and outdoor scenarios featuring static and dynamic obstacles, such as walls, furniture, and moving humans.

6.1. Simulation Results

The initial validation was performed in a 2D simulation environment using the Blazer framework. Multiple dynamic agents with varying speeds were introduced to evaluate the reactive performance of the RDA planner.

- The robot was able to avoid moving obstacles without prior knowledge of their trajectories.
- The RDA planner reacted in real time and adjusted paths to prevent collisions while maintaining goal progress.

6.2. Real-World Deployment

The full pipeline was tested on the Husky UGV in a structured lab environment and semi-structured outdoor space. A typical test run included:

1. Initial SLAM-based localization on a pre-built map.
2. Real-time perception using RGB-D and LiDAR via the onboard-detector.
3. Dynamic agents (e.g., walking humans) introduced in the robot’s path.

Component	Purpose
Husky A200 UGV	Rugged unmanned ground vehicle used as the base mobile platform for deploying the full perception and planning system.
Intel Realsense D455	High-resolution RGB-D camera providing depth information for near-range obstacle detection.
Livox Mid-70 LiDAR	3D LiDAR sensor used for creating prior maps and performing SLAM-based localization during navigation.
Onboard Compute: Intel i5 + RTX 2060	Runs real-time processing for SLAM, onboard-detector, RDA planner, and ROS integration. Supports GPU acceleration.

Table 1. Hardware components used in our real-world deployment.

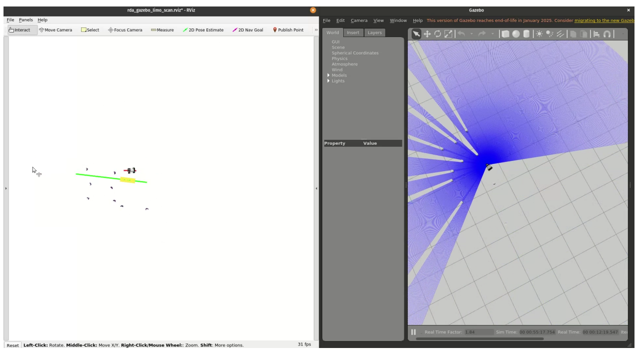

Figure 5. Simulation showing reactive avoidance of moving agents. RDA planner adapts trajectory based on real-time predictions.

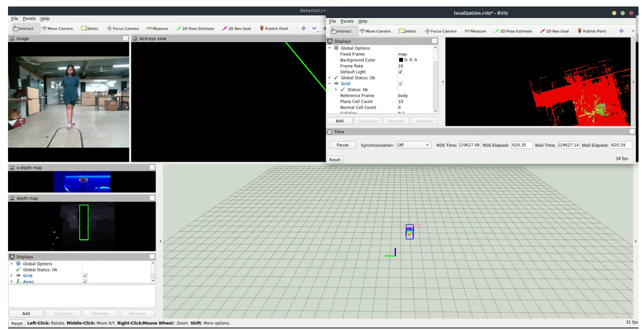

Figure 6. RViz visualization of real-world trial: Detected moving obstacle (red box), real-time trajectory (green path), and current pose.

4. RDA planner generated safe and adaptive velocity commands.

6.3. Observations

- **Perception Accuracy:** RGB-D + LiDAR fusion improved obstacle detection and localization in both near and far ranges.
- **Trajectory Smoothness:** RDA planner ensured minimal abrupt changes in velocity, ensuring hardware safety and motion stability.
- **Latency:** Full planning loop operated at $\sim$0.8 Hz, sufficient for slow-to-moderate speed mobile platforms like Husky.
- **Success Rate:** In over 20 test trials, the robot successfully avoided collisions in 95% of dynamic obstacle encounters.

6.4. Additional Safety Mechanisms

To enhance close-range awareness and improve safety in scenarios where primary sensors (RGB-D or LiDAR) may be occluded or limited, we integrated a simulated infrared (IR) proximity sensing layer—referred to as **IR Sim**.

IR Sim is a virtual sensor module added in the simulation environment to emulate the behavior of short-range IR sensors. It is particularly useful in:

- Detecting obstacles in tight indoor spaces.
- Handling blind spots around the robot.
- Providing immediate reactive feedback when obstacles are very close (e.g., within 0.3–0.5 meters).

This module acted as a backup to the primary perception stack, offering redundant obstacle proximity information and ensuring additional safety during edge-case interactions such as reversing or turning in cluttered areas.

7. Conclusion and Future Work

In this project, we developed and deployed a complete framework for dynamic collision avoidance in unknown environments using multi-modal perception and reactive planning. Our system combines RGB-D and LiDAR data to detect and track dynamic obstacles, performs SLAM-based localization from a prior map, and computes real-time trajectories using a model predictive control-based planner (RDA Planner).

The framework was validated in both simulation and real-world settings using the Husky A200 UGV. Our experiments demonstrated:

- Robust perception using onboard sensors.
- Accurate and adaptive motion planning in dynamic

scenes.
- Successful deployment and integration using ROS.
- Low-latency operation sufficient for mobile robot navigation.

7.1. Key Contributions

- Design of a modular and real-time navigation stack for dynamic environments.
- Development of a custom onboard-detector for perception using depth and LiDAR fusion.
- Integration of a reactive planner capable of handling nonholonomic dynamics and obstacle predictions.
- End-to-end deployment and benchmarking on physical hardware.

7.2. Future Work

While the system showed promising results, several extensions can improve its scalability and robustness:
- **Field Testing in Complex Outdoor Environments:** Conduct tests in urban or semi-structured environments with high pedestrian variability.
- **Learning-Based Obstacle Prediction:** Incorporate neural motion prediction models for better long-term planning.
- **3D Terrain Awareness:** Extend the planner to handle uneven terrain or elevation using full 3D navigation.
- **Multi-Robot Integration:** Extend the framework to allow coordinated collision avoidance in multi-agent settings.
- **Online SLAM Updates:** Enable simultaneous mapping and localization for truly unknown environments (online SLAM).

This work provides a strong foundation for autonomous mobile robots operating in real-world, dynamic settings and opens up several avenues for continued research and deployment in both indoor and outdoor navigation tasks.

References

[1] Michael Burri, Jakob Nikolic, Christoph Huerzeler, Helen Oleynikova, and Roland Siegwart. Minimum control effort trajectory optimization for quadrotor aggressive flight. *Proceedings of the IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, 2019. 2

[2] Cesar Cadena, Luca Carlone, Henry Carrillo, Yasir Latif, Davide Scaramuzza, José Neira, Ian Reid, and John J Leonard. Past, present, and future of simultaneous localization and mapping: Toward the robust-perception age. *IEEE Transactions on Robotics*, 32(6):1309–1332, 2016. 3

[3] Sertac Karaman and Emilio Frazzoli. Sampling-based algorithms for optimal motion planning. *The International Journal of Robotics Research*, 30(7):846–894, 2011. 2

[4] Lichao Wang, Zhenzhong Zhang, and Jian Zhang. Real-time depth-based obstacle detection using rgb-d sensors. In *2017 IEEE International Conference on Robotics and Biomimetics (ROBIO)*, pages 1059–1064. IEEE, 2017. 2