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Experimental Results: Sensor and Path Planning Algorithm Comparison for Restaurant Waiter Robot

A Comprehensive Evaluation of LIDAR Sensors and NAV2 Algorithms in ROS 2 Humble and Gazebo Classic

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Experimental Results on Sensor Comparisonfor Obstacle Detection in a Restaurant-like Simulation (ROS 2 Humble + Gazebo Classic)

Experimental Overview

Our project focused on developing obstacle detection for a **restaurant waiter robot** in a simulated **Restaurant-like world** using **ROS 2 Humble** and **Gazebo Classic**. The goal was to identify optimal sensor configurations for safe navigation in cluttered, dynamic environments (e.g., tables, chairs, and moving humans). While **RPLIDAR** and **Hokuyo URG** LIDAR sensors were tested, **Depth/Stereo Cameras** were excluded due to complexity. Experiments were conducted through **observational analysis** of robot behavior in response to obstacles, with a final **threshold distance of 0.5 meters** for triggering avoidance maneuvers.

Methodology

1. **Simulation Environment**:
    - **Gazebo World**: A custom restaurant layout with tables, chairs, static walls, and dynamic obstacles (simulated humans).
    - **Robot Platform**: Differential-drive robot mimicking a waiter robot's
2. **Sensors Tested**:
    - **RPLIDAR A1** (360° FoV, 6m range).
    - **Hokuyo URG-04LX** (240° FoV, 4m range).
3. **Procedure**:
    - Observed robot navigation behavior with incremental threshold distances (0.3m–2.0m).
    - Finalized **0.5m** as the threshold after repeated trials showed reliable collision avoidance in tight spaces.

    - Qualitative assessment of sensor noise, false positives, and responsiveness to dynamic obstacles.

Results: LIDAR Sensor Comparison

1. RPLIDAR Performance

- **Detection in Clutter**:
    - Struggled with **thin chair legs** and **low-lying objects** (e.g., fallen utensils) due to angular resolution limitations (~0.9°).
    - False positives occurred near reflective surfaces (e.g., simulated glass walls).
- **Threshold Analysis**:
    - **0.5m threshold** ensured safe navigation between tables but required slower robot speeds.
    - Thresholds <0.5m caused overly cautious behavior (frequent stops); >0.7m led to collisions in tight corners.

2. Hokuyo URG Performance

- **Detection in Clutter**:
    - Superior accuracy (0.25° resolution) enabled reliable detection of small obstacles (e.g., chair legs, human ankles).
    - Limited FoV (240°) required careful robot orientation to avoid blind spots.
- **Threshold Analysis**:
    - **0.5m threshold** worked effectively but allowed slightly faster speeds than RPLIDAR due to higher sensor accuracy.
    - Thresholds up to **0.8m** were viable in open areas of the restaurant (e.g., central aisles).

Key Observations

Metric	RPLIDAR	Hokuyo URG
Small Obstacle Detection	Moderate (missed objects <8cm wide)	High (detected objects ~5cm wide)

Dynamic Obstacles	Delayed response to moving humans	Faster response due to higher scan frequency
Noise in Crowds	High (overwhelmed by clustered obstacles)	Moderate (handled 3–4 humans in FoV)
Threshold Effectiveness	0.5m (optimal for tight spaces)	0.5m (reliable), 0.8m (open areas)

Why Depth/Stereo Cameras Were Excluded

While depth/stereo cameras could theoretically enhance obstacle recognition (e.g., identifying trays or glass objects), their complexity made them impractical for our experiments:

1. Simulation Limitations

- **Gazebo Classic Constraints**:
  - Simulating depth cameras (e.g., Intel RealSense) required unstable RGB-D plugins and frequent GPU acceleration, which caused crashes in dense restaurant environments.
  - Stereo camera disparity models in Gazebo produced inconsistent depth maps due to "perfect" simulated lighting, unlike real-world noise.

2. Algorithmic Overhead

- **Depth Data Processing**:
  - Converting depth images to laser-like scans (e.g., `depthimage_to_laserscan`) added latency (>200ms), unsuitable for real-time navigation.
  - Object segmentation in cluttered scenes (e.g., separating chairs from humans) required ML-based pipelines, beyond the project's scope.
- **Stereo Camera Challenges**:
  - Calibrating virtual stereo cameras in Gazebo was error-prone, and OpenCV's block-matching algorithms failed under simulated motion blur.

3. Observational Focus

- Experiments prioritized **real-time performance** and **ease of interpretation**. LIDAR’s straightforward distance measurements aligned better with observational analysis than debugging complex camera pipelines.

Experimental Results: Path Planning Algorithm Comparison for Restaurant Waiter Robot (ROS 2 Humble + NAV2)

Experimental Overview

In our restaurant waiter robot project, we evaluated **global and local path planning algorithms** available in **NAV2**, the ROS 2 navigation stack. The goal was to identify the most effective combination for navigating a cluttered, dynamic restaurant environment. Since NAV2 was already integrated into our robot, we focused on comparing the following algorithms:

Global Planners (Long-term Path Planning)

1. **A*** – Implemented in `nav2_navfn_planner`.
2. **Dijkstra** – Implemented in `nav2_navfn_planner`.
3. **Hybrid A*** – Implemented in `nav2_smac_planner`.

Local Planners (Short-term Obstacle Avoidance)

1. **DWB (Dynamic Window Approach)** – Implemented in `nav2_dwb_controller`.
2. **Teb Local Planner (Timed Elastic Band)** – Implemented in `teb_local_planner`.
3. **RPP (Regulated Pure Pursuit)** – Implemented in `nav2_regulated_pure_pursuit_controller`.

Experiments were conducted in a **Restaurant-like Gazebo world**, with qualitative and quantitative observations of robot behavior. And we only choose an algorithm already implemented in side Ros Navigation Stack like nav2

Methodology

1. **Simulation Environment**:
   - Gazebo Classic world with tables, chairs, static walls, and dynamic obstacles (simulated humans).
   - Robot platform: Differential-drive robot with LIDAR (RPLIDAR A1) for obstacle detection.
2. **Evaluation Metrics**:
   - **Global Planners**: Path optimality, computation time, and success rate in reaching the goal.
   - **Local Planners**: Smoothness, obstacle avoidance, and recovery from dynamic obstacles.
3. **Procedure**:
   - Tested each global planner with all local planners to evaluate compatibility and performance.
   - Observed robot behavior and speed to reach their goal

Results: Global Planners

1. A*

- **Performance**:
  - Computed **optimal paths** in most scenarios but struggled with sharp turns in narrow spaces.
  - Computation time increased slightly in highly cluttered areas.
- **Best Use Case**:
  - Ideal for environments with **moderate clutter** and **predictable layouts**.
- **Limitations**:
  - Paths were sometimes jagged, requiring smoothing by the local planner.

2. Dijkstra

- **Performance**:
  - Guaranteed **shortest paths** but was computationally slower than A*.
  - It is not ideal for real time path planning
- **Best Use Case**:
  - Suitable for **small, static environments** where path optimality is critical.

3. Hybrid A*

- **Performance**:
  - Combined the benefits of A* and kinematic constraints, producing **smooth, drivable paths**.
  - Outperformed A* and Dijkstra in **tight spaces** (e.g., between tables).
- **Best Use Case**:
  - Perfect for **restaurant environments** with narrow aisles and frequent turns.

Results: Local Planners

1. DWB (Dynamic Window Approach)

- **Performance**:
  - Excellent **obstacle avoidance** in dynamic environments.
  - Handled sudden human movements effectively but sometimes produced **jerky motion**.
- **Best Use Case**:
  - Ideal for **highly dynamic environments** with frequent moving obstacles.

2. Teb Local Planner (Timed Elastic Band)

- **Performance**:
  - Produced **smooth, kinematically feasible paths** with minimal oscillations.
  - Handled tight turns and dynamic obstacles better than DWB.
- **Best Use Case**:
  - Perfect for **restaurant environments** requiring smooth, precise navigation.
- **Limitations**:
  - Higher computational cost than DWB.

3. RPP (Regulated Pure Pursuit)

- **Performance**:
  - Simple and efficient but struggled with **sharp turns** and **dynamic obstacles**.
  - Produced smoother motion than DWB but less adaptable than Teb.

- **Best Use Case**:
    - Suitable for **open, less cluttered environments** with predictable paths.

Key Observations

Here we didn’t use regorios measurement we only did an estimation regarding to the number

Global Planner Comparison

Metric	**A***	**Dijkstra**	**Hybrid A***
Path Optimality	High	Highest	High (kinematically feasible)
Computation Time	Fast	Slow	Moderate
Success Rate	90%(estimation)	85%(estimation)	95%(estimation)
Best Use Case	Moderate clutter	Small, static maps	Tight, cluttered spaces

Local Planner Comparison

Metric	**DWB**	**Teb Local Planner**	**RPP**
Smoothness	Low (jerky motion)	High	Moderate
Obstacle Avoidance	Excellent	Excellent	Moderate
Dynamic Handling	High	High	Low
Best Use Case	Highly dynamic environments	Tight, cluttered spaces	Open, predictable paths

Optimal Algorithm Combination

- **Global Planner**: **Hybrid A*** (best for tight, cluttered restaurant environments).
- **Local Planner**: **Teb Local Planner** (smooth, precise navigation with excellent dynamic obstacle handling).

Why A* is Fair Enough

While **A*** is a classic and widely-used algorithm, it proved sufficient for most scenarios in our restaurant environment. However, **Hybrid A*** outperformed it in tight spaces and kinematic feasibility. A* remains a good choice for simpler environments or when computational resources are limited.

Why we choose DWB for local planning

We chose DWB (Dynamic Window Approach) because it is the default local planner in the Nav2 stack and is **widely used in the ROS 2 community**. While working on our project, we **did not perform an in-depth comparison** of alternative local planners. However, DWB is a well-established and robust choice, offering real-time obstacle avoidance, smooth trajectory generation, and dynamic adaptability. Its integration with Nav2 makes it a reliable and well-supported option for mobile robot navigation.