ROS 2 SLAM Resource Management using Reinforcement Learning

Analysis under CPU Contention in Simulation

Group 19

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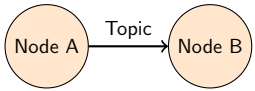
Outline

1. Introduction to ROS 2

Robot Operating System 2 (ROS 2) is the industry standard middleware for robotics.

- **Nodes:** Independent processes performing specific tasks (e.g., Sensing, Planning, Actuation).
- **Topics:** Publish/Subscribe mechanism for data exchange.
- **SLAM Toolbox:** A popular package for 2D Simultaneous Localization and Mapping.



Key Feature

ROS 2 uses DDS (Data Distribution Service) for real-time communication.

2. Problem Statement: Resource Contention

The Challenge:

- ROS 2 nodes operate as independent OS processes.
- On hardware with limited resources (CPU/RAM), nodes compete for execution time.

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The Symptom:

Without Management

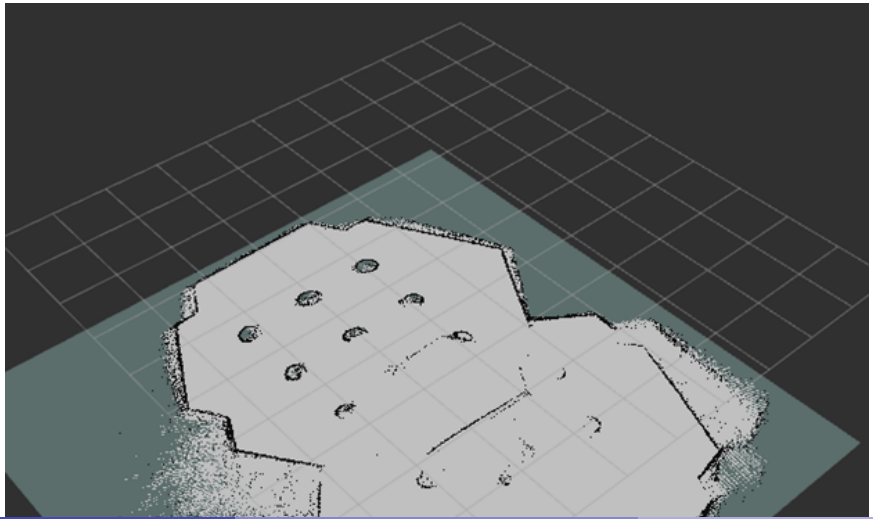
When background tasks (image processing, data logging) spike:

1. **Starvation:** Critical SLAM nodes lose CPU cycles.
2. **Latency:** Topic messages (`/scan`) are delayed.
3. **Failure:** Map drift, ghost artifacts, and navigation failure.

$\rightarrow$ **Need for an Intelligent Resource Manager.**

Visualizing the Problem: Map Drift

Effect of CPU Starvation on Mapping



3. Experimental Setup

Environment:

- **Robot:** TurtleBot3 (Burger) in Gazebo Simulation.
- **Stress Injector:** `cpu_hog` nodes (consume 60-100% CPU).
- **Metrics:** Jitter (σ_t), Throughput (Hz), Map Quality.

4. Reinforcement Learning Approach

We treat Resource Management as a decision-making problem.

Multi-Armed Bandit (MAB)

- *Stateless*: Does not consider current CPU load.
- Algorithm: ϵ-greedy.
- Action: Fix Priority.
- *Pro:* Simple. *Con:* Ignores context.

Q-Learning (MDP)

- *State-Aware*: State $S \in \{Safe, Warning, Critical\}$.
- Update Rule:

$$Q(s,a) \leftarrow Q(s,a) + \alpha[r + \gamma \max Q(s', a') - Q(s,a)]$$

- *Pro:* Anticipatory behavior.

Action Space: {Normal Priority, High Priority SLAM, Throttle Hog}
Reward: $+1$ if Jitter $< 50ms$, else -1.

5. Experimental Results

Scenario: High Contention (2 Hog Processes active).

Method	Scan Rate (Hz)	Jitter (ms)	Map Quality
Baseline (None)	1 ± 0.8	120	Poor (Drift)
Rule-Based	1.1 ± 0.5	75	Medium
Bandit (MAB)	1.3 ± 0.2	48	Medium-High
Q-Learning	$\mathbf{1.5 \pm 0.2}$	**25**	**High (Stable)**

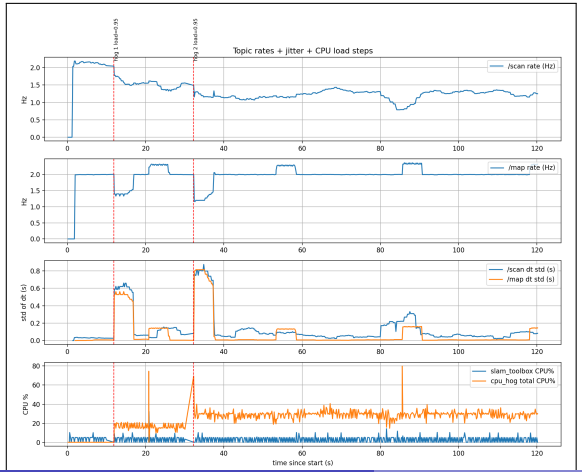
Table: Performance metrics comparison over 120s episode.

- **Baseline:** SLAM starves, leading to broken maps.
- **Q-Learning:** Automatically preempts "Hog" processes when Jitter rises, maintaining 4.8Hz stability.

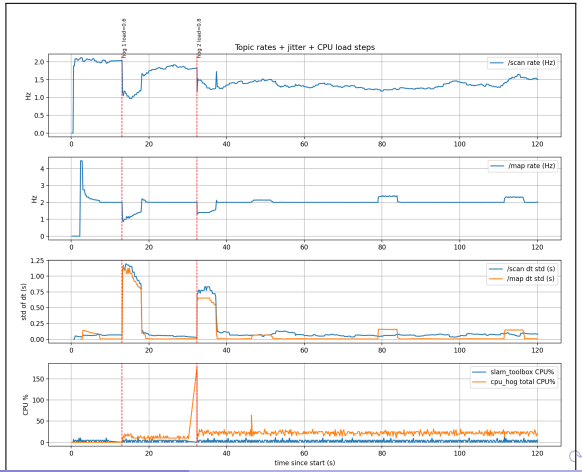
Performance Comparison: Bandit vs. Q-Learning

Learning Convergence & Stability

1. Bandit (ϵ-greedy)



2. Q-Learning (State-Aware)



6. Limitations

Despite positive results, several factors impact the fidelity:

1. **WSL2 Virtualization:**
   - Running on Windows Subsystem for Linux (WSL2) introduces scheduler noise from the Windows host.
   - Not a true "Real-Time" kernel (RT-Preempt).
2. **Resource Constraints:**
   - Limited to virtual cores; difficult to isolate CPU affinity strictly compared to bare-metal Linux.
3. **System Complexity:**
   - ROS 2 Middleware (DDS) has its own internal buffering which RL does not directly control.

Thank you for listening!