LLM-PCPP: Large Language Model-Assisted Prioritized Coverage Path Planning for Complex Environments

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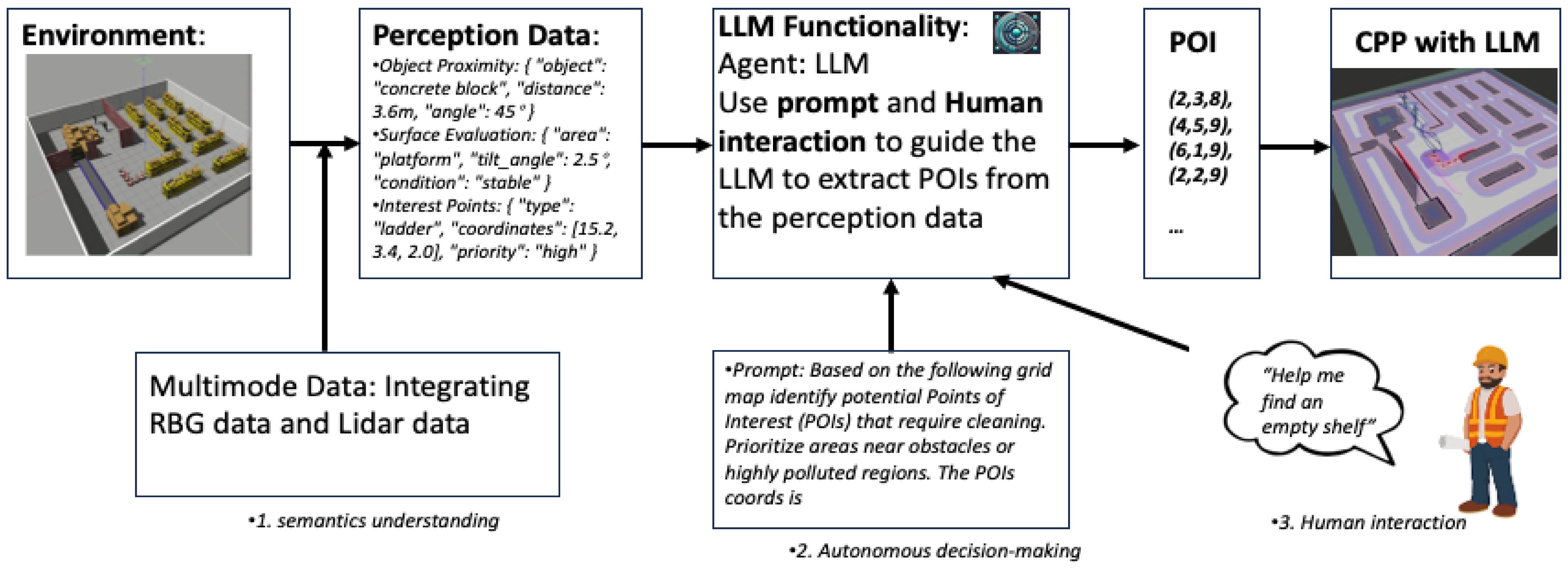
Introduction

Efficient Coverage Path Planning (CPP) is vital for robot operations[1] in complex environments, (e.g. construction sites and warehouses.) Traditional uniform CPP leads to inefficient resource use and redundant scans.

We propose **LLM-PCPP**, a novel Prioritized CPP[2], [3], [4] method that integrates **Large Language Models (LLMs)** to dynamically identify **Points of Interest (POIs)** from semantic grid maps and optimize traversal using a hybrid **LLM-A***[5] + **TSP** strategy.



Note: In this research, we assume the perception data is given.

Methodology

1. Semantic Grid Map Construction
- Real-world scenes (e.g., drone footage) → 2D grid maps with binary navigability
- Grid cells contain spatial & semantic info (natural language labels)

2. POI Identification via LLM
- LLMs (e.g., GPT-4o) analyze semantic grid map descriptions
- Output: Task-relevant POIs (hazard zones, equipment areas, cold storage)

3. Path Optimization with LLM-A*
- LLM suggests intermediate waypoints
- A* operates on reduced space → lower operations & memory

4. Optimal Traversal via TSP Solver
- OR-Tools used
- Hybrid heuristics: Cheap Arc + Constraint Refinement
- Ensures visit-once + return-to-start constraints

Experiment

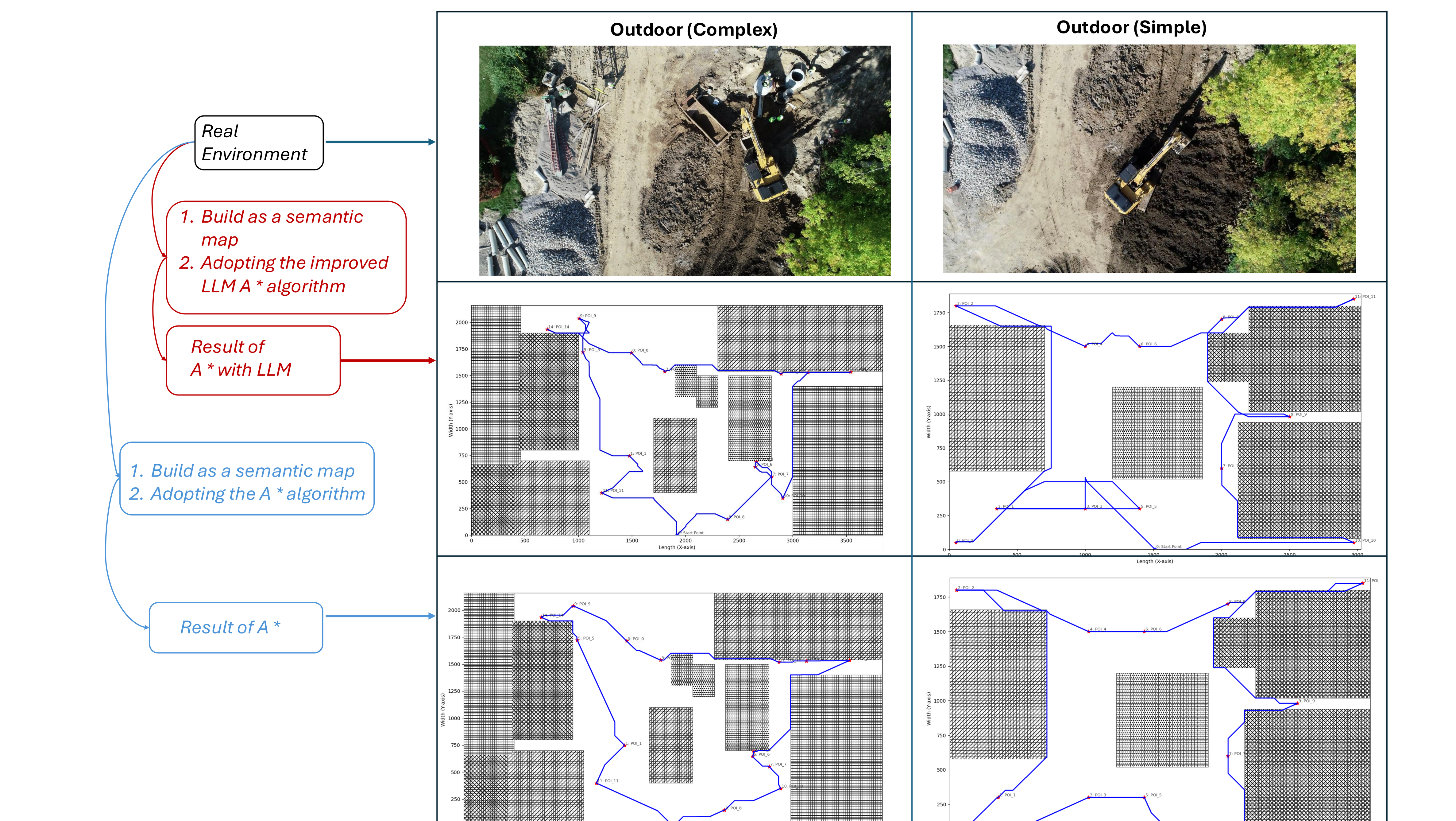
We evaluate **LLM-PCPP** in three scenarios:
- **Complex Outdoor Construction Site**
- **Simple Outdoor Construction Site**
- **Virtual Indoor Warehouse**

Each environment is converted into a semantic grid map. POIs are generated by LLMs, and paths between POIs are planned using **LLM-A*** followed by **TSP optimization**.

Key metrics evaluated:
- **Path Length**: Reflects coverage richness
- **Operations**: Measures computational steps
- **Storage**: Indicates memory usage

Table: Comparison of Experimental Results between LLM A* and A*

Scenario	Obstacle Density	Path Length ↑	Ops ↓	Memory ↓
Outdoor (Complex)	50%	13.6%	41.1%	36.9%
Outdoor (Simple)	30%	23.9%	34.2%	34.0%
Indoor (Warehouse)	30%	18.7%	41.8%	30.6%



Note: Please refer to our paper for the indoor (Warehouse) path planning results

Reference:

[1] Ci-Jyun Liang, Thai-Hoa Le, Youngjib Ham, Bharadwaj RK Mantha, Marvin H. Cheng, and Jacob J. Lin. Ethics of artificial intelligence and robotics in the architecture, engineering, and construction industry. *Automation in Construction*, 2024.

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[5] Silin Meng, Yiwei Wang, Cheng-Fu Yang, Nanyun Peng, and Kai-Wei Chang. LLM-A*: Large language model enhanced incremental heuristic search on path planning. ***EMNLP***, 2024.