Improved LLM-A*: Large Language Model Enhanced Cost Aware Incremental Heuristic Search on Path Planning A Research Report

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***Abstract*—This work presents a hybrid path planning framework that integrates classical A* search with semantic guidance from a large language model (LLM). The system leverages a cost-aware RePE-style prompt to enable the LLM to generate intermediate waypoints, which serve as high-level guidance for the A* planner. These waypoints divide the planning space into local segments, each solved independently with classical search. A segment-wise fallback mechanism ensures robustness, defaulting to full A* when necessary. The proposed method is implemented in a modular and simulation-ready architecture using Python, with real-time visualization and local inference through Mistral 7B. This approach highlights how language models can contribute to global planning reasoning while retaining the formal guarantees of heuristic-based algorithms**

***Index Terms*—Large Language Models, A* Path Planning, Global Planner**

I. Introduction

Autonomous navigation is a cornerstone of mobile robotics, supporting a wide range of applications including warehouse logistics, planetary exploration, last-mile delivery, and domestic service robots [1]. At the heart of these systems lies the path planning problem: computing a collision-free and cost-efficient route between a start and goal location in a cluttered environment [2].

Classical algorithms such as A* and its variants are widely used due to their completeness and optimality when using admissible heuristics [3]. They are particularly suited to discrete grid maps commonly used in mobile robot navigation. However, as the size and complexity of the environment increases, the computational cost of exhaustive node expansion becomes prohibitive. This issue is especially critical for real-time robotic systems operating under limited onboard computational resources [4].

At the same time, large language models (LLMs) have emerged as powerful tools for structured reasoning, symbolic manipulation, and intelligent decision-making [6]. Though primarily trained on natural language, recent work has shown that LLMs can exhibit emergent spatial planning abilities when provided with structured prompts. One notable example is the LLM-A* framework proposed by Meng et al. [8], in which an LLM generates intermediate waypoints to guide a classical A* planner. This hybrid approach compresses the search space semantically while preserving formal guarantees of feasibility and near-optimality.

A. Motivation and Scope of This Work

While the original LLM-A* framework demonstrated the feasibility of integrating semantic reasoning from LLMs with classical path planning, its implementation was limited to offline evaluation in abstract, static environments [8]. It did not consider practical robotics challenges such as integration with real-time systems, handling hallucinated or invalid outputs, or deploying within simulation environments like Gazebo or ROS2-based platforms.

This project aims to bridge those gaps by re-implementing the LLM-A* architecture with a focus on robotic applicability, simulation readiness, and runtime safety. The motivation is guided by three core insights:

1) **Semantic compression can improve real-time performance**: Allowing an LLM to generate intermediate waypoints enables the planner to focus its search on promising subregions, reducing computational cost.
2) **LLMs are not planners, but approximators**: Using the LLM as a semantic advisor—rather than a decision-maker—preserves classical guarantees while benefiting from global reasoning [11].
3) **Fallback and validation mechanisms are essential**: Any system incorporating generative AI into robotics must include robust checks to validate or override outputs, ensuring safe deployment.

To operationalize these ideas, this work introduces:

- A formal pipeline for converting grid maps into structured barrier arrays for compact LLM input
- A Recursive Path Exploration (RePE) prompting style that enables depth-limited semantic planning [14]
- A waypoint post-processing module to validate, filter, and prune the LLM-generated guidance

- A segment-wise A* planner that ensures local optimality and modularity
- A fallback mechanism that defaults to baseline A* if any segment fails
- A ROS2-compatible modular architecture tested across Python simulation, 3D grid planning, and Gazebo environments [18]

This work is directly built upon the original LLM-A* framework by Meng et al. [8], adapting and extending it specifically for robotics deployment. The core concept of LLM-guided waypoint planning remains unchanged, but the present work focuses on re-implementing the system from scratch to ensure interpretability, modular design, and experimental validation in simulation-ready environments [19].

The rest of this report is organized as follows: Section II presents the formal problem definition, detailed architecture, and implementation of the proposed system. Section III discusses the results of testing across simulation environments, including comparisons with baseline A* and the original LLM-A* design. Section IV concludes with insights on deployment challenges and future research directions.

II. Approach

The LLM-A* framework implemented in this project builds upon the foundational idea of Meng et al. [8], combining classical search-based planning with large language model (LLM)-driven semantic abstraction. This section formalizes the path planning problem, outlines the complete architecture of the proposed system, and explains the mathematical intuition behind LLM-guided waypoint generation. Additionally, it documents various exploratory implementations—such as 3D planning, SLAM integration, and image-based planning—and the technical reasons why each was ultimately excluded from the final system.

A. Classical Grid-Based Path Planning

Let the robot's environment be modeled as a two-dimensional grid $G \in \{0,1\}^{m \times n}$, where $G(i,j) = 0$ denotes a free cell and $G(i,j) = 1$ denotes an obstacle [3]. The robot is given a start position $s = (x_s, y_s)$ and a goal $g = (x_g, y_g)$, and the objective is to compute a path $P = \{p_0, p_1, \ldots, p_k\}$ such that:

- $p_0 = s$, $p_k = g$,
- $G(p_i) = 0$ for all $p_i \in P$,
- Each p_{i+1} is in the 4- or 8-connected neighborhood of p_i,
- The total cost $C(P)$ is minimized.

The cost function is given by:

$$C(P) = \sum_{i=1}^{k} c(p_{i-1}, p_i)$$

with:

$$c(p_i, p_j) = \begin{cases} 1.0 & \text{if } p_j \text{ is adjacent in 4-connectivity} \\ 1.4 & \text{if } p_j \text{ is adjacent diagonally} \\ \infty & \text{if } p_j \text{ is outside map bounds or an obstacle} \end{cases}$$

The A* algorithm solves this using an evaluation function:

$$f(n) = g(n) + h(n)$$

where $g(n)$ is the cost from the start to node n, and $h(n)$ is a heuristic (e.g., Manhattan or Euclidean distance) estimating the cost from n to the goal.

1) Alternative Heuristics and Their Effects: To assess the influence of the heuristic function on planning behavior, both Manhattan and Euclidean metrics were explored during implementation. The Manhattan heuristic, defined as

$$h_{\text{Manhattan}}(n) = |x_g - x_n| + |y_g - y_n|,$$

is admissible in grid-based environments and performs well when movement is restricted to orthogonal directions. However, when diagonal moves are allowed—as in our 8-connected grid formulation—the Euclidean heuristic,

$$h_{\text{Euclidean}}(n) = \sqrt{(x_g - x_n)^2 + (y_g - y_n)^2},$$

better aligns with true path cost. Experimental comparison showed that Manhattan distance often caused over-expansion in diagonal corridors, while Euclidean estimates offered tighter search bounds and improved planning efficiency. Therefore, Euclidean heuristics were adopted for all experiments to remain consistent with the allowed motion model.

B. LLM-Guided Semantic Planning

To reduce node expansion, an LLM is used to generate a sequence of intermediate waypoints [8]:

$$W = \{w_1, w_2, \ldots, w_k\}$$

These waypoints decompose the full path P into $k+1$ segments:

$$P = \bigcup_{i=0}^{k} A^*(w_i, w_{i+1}), \quad w_0 = s, \quad w_{k+1} = g$$

Each segment is independently solved using classical A*, allowing the system to leverage global semantic context from the LLM while preserving formal guarantees of local feasibility and optimality [16].

The LLM operates as a function:

$$\mathcal{M}_{\text{LLM}}(s, g, B_h, B_v) \to W$$

where B_h and B_v are lists of horizontal and vertical barriers, respectively. These barrier representations compress the environment into a symbolic format.

To guide the LLM, we use a *Recursive Path Exploration* (RePE) prompt format [14]. The prompt simulates a step-by-step planning dialogue in which the model must select each move based on cost and direction, taking into account the current location, barriers, and goal. The prompt explicitly defines movement costs (1.0 for straight moves, 1.4 for diagonal) and forbids movement through barriers. This enables the model to simulate a heuristic decision-making loop, approximating a cost-aware value function:

$$\tilde{h}(n) = \text{LLM-inferred directionality from } n \text{ to } g$$

Though the model lacks explicit geometric reasoning, it has been trained on sufficient text-based spatial patterns to generate semantically valid waypoint sequences [6].

1) Prompt Engineering Design Choices: Early prompt formats were minimalistic, such as "Find a path from start to goal avoiding barriers," but these yielded inconsistent and unstructured results. To improve reliability and steer the LLM toward spatially coherent outputs, several prompt refinements were adopted.

Key refinements included:

- Explicit encoding of movement costs in the prompt (e.g., "Diagonal = 1.4, Straight = 1.0"),
- Use of structured barrier notation (horizontal and vertical spans),
- Enforcing deterministic output formats (JSON-style arrays or bullet lists),
- Limiting maximum number of waypoints requested (typically capped at 5),
- Adding intermediate thinking steps with reasoning like: "What is the lowest-cost move from here?"

Empirically, bullet-list output format was more consistently parsed than JSON-style responses, especially in longer maps. These changes significantly improved the validity rate of waypoints extracted, while reducing hallucinations and formatting inconsistencies. The final RePE-style prompt emerged as the most robust and reusable prompting strategy across multiple maps and testing environments.

C. Planning Pipeline and Modular Design

The system architecture consists of the following components:

1) Input and Barrier Encoding: Maps are either loaded as binary images, procedurally generated as grids, or obtained from ROS2 SLAM systems [18]. Obstacle spans are encoded symbolically as:

- Horizontal barriers: $[y, x_{\text{start}}, x_{\text{end}}]$
- Vertical barriers: $[x, y_{\text{start}}, y_{\text{end}}]$

This encoding greatly reduces input size, improving LLM response reliability.

2) LLM Inference via Ollama: The prompt is submitted to a local instance of Mistral 7B via the Ollama inference engine. The model generates a list of waypoints which are parsed using regex and abstract syntax tree (AST) logic. Several fallback extraction methods are used to ensure robustness [12].

3) Waypoint Filtering and Validation: The generated waypoints are validated against:

- Map boundaries,
- Obstacle-free constraints,
- Redundancy (distance-based pruning),
- Path feasibility (via A* test pruning).

4) Segment-wise A and Fallback:* Each waypoint pair is planned using A*. If any segment is infeasible, the planner defaults to solving the entire path using classical A* [17]. This fallback guarantees robustness even under partially incorrect LLM output.

D. Exploratory Strategies and Abandoned Directions

1) 3D Grid-Based Planning: An early attempt extended the grid to three dimensions [2]:

$$G \in \{0, 1\}^{x \times y \times z}$$

LLMs were prompted with 3D barrier encodings, and path output was expected in $[x, y, z]$ format. However, due to limited training on 3D spatial reasoning, the LLM frequently hallucinated unreachable paths. Additionally, token limits were exceeded in moderately sized maps. As such, 3D LLM-A* was deemed impractical under current LLM capabilities.

2) SLAM Integration via ROS2 and Gazebo: TurtleBot3 was launched in Gazebo, and mapping was conducted using SLAM Toolbox [18]. Start and goal points were set in RViz, and barriers were extracted from the '/map' topic. Despite full integration with ROS2, the generated maps often lacked loop closure and complete wall detection, causing invalid barrier representations and failed plans. Due to these issues, static maps were adopted for benchmarking.

3) Frontier-Based Exploration: To automate SLAM coverage, a frontier-based robot was implemented to autonomously explore maze environments. While this increased coverage, the resulting maps exhibited SLAM drift and edge discontinuities, which again broke the barrier extraction stage. This strategy was paused in favor of manual or image-based map acquisition.

4) Image-Based Maze Parsing: OpenCV was used to convert maze PNGs into binary occupancy grids. These maps enabled controlled testing with known obstacle locations. While effective for prompt tuning and planning benchmarks, minor image artifacts significantly impacted parsing. This approach was retained for simulation benchmarking but avoided for deployment [19].

E. Final Design Rationale

The final system adopts a hybrid semantic-symbolic design:

- LLMs are used for semantic compression via waypoints [8],
- A* ensures formal correctness and path feasibility [3],
- Segment-wise decomposition limits risk from LLM errors [16],
- Fallback logic guarantees planning success [17].

Barrier encoding and cost-aware RePE prompting were key to improving model reliability [14]. Through extensive testing, this architecture was validated to be simulation-ready, interpretable, and robust against LLM hallucinations, offering a viable roadmap toward LLM-assisted robotic planning.

Algorithm: LLM-A Hybrid Path Planning*

Algorithm 1 LLM-A* Hybrid Path Planning

Require: Grid map G, start s, goal g
Ensure: Valid path P from s to g

$B_h, B_v \leftarrow$ ExtractBarriers(G)
prompt $\leftarrow$ GenerateRePEPrompt(s, g, B_h, B_v)
$W \leftarrow$ GetLLMWaypoints(prompt)
$W \leftarrow$ FilterWaypoints(W, G, s, g)
if $W = \emptyset$ **then**
  return AStar(G, s, g)
end if
$W \leftarrow$ PruneRedundancy(W)
$P \leftarrow \emptyset$
$T \leftarrow [s] + W + [g]$
for $i \leftarrow 0$ to $|T| - 2$ **do**
  $segment \leftarrow$ AStar(G, $T[i]$, $T[i+1]$)
  if $segment = \emptyset$ **then**
    return AStar(G, s, g)
  end if
  Append $segment$ (excluding first node if overlapping) to P
end for
return P

III. Results

This section presents a detailed empirical and theoretical evaluation of the LLM-A* system. Our goal is to understand how the hybrid system scales with environmental complexity, how semantic waypoint guidance affects search efficiency, and how correctness is preserved despite the non-admissibility of LLM-generated waypoints [8]. The experiments were conducted in increasing order of difficulty, beginning with static maze images (as in the original LLM-A* paper), followed by tests on 10×10, 15×15, and 20×20 maps. Both quantitative and qualitative results are discussed.

A. Testing Progression and Setup

The evaluation followed a staged approach:

- Phase 1: Replication of the original paper's maze-based setup on 10×10 maps [8],
- Phase 2: Custom-generated 15×15 environments with corridor and dead-end constraints,
- Phase 3: Dense 20×20 obstacle-rich grids for scalability analysis.

All environments were generated using OpenCV from binarized images and verified for fidelity. LLM inference was performed via a local instance of Mistral 7B using Ollama [6]. All planning used 8-connected movement and Euclidean distance heuristics [3]. Metrics measured include node expansion count, path length, planning time, and fallback activation frequency [15].

B. Semantic Segmentation vs. Uniform Exploration

Classical A* explores space via uniform cost expansion [3]. The number of nodes explored is approximately proportional to the area of the search frontier [4]:

$$N_{A^*} \approx \pi \cdot r^2, \quad \text{where } r = \text{distance}(s, g)$$

LLM-A* introduces a semantic decomposition of the search space using waypoints $W = \{w_1, w_2, \ldots, w_k\}$, leading to segment-wise planning [8]:

$$P(s, g) = \bigcup_{i=0}^{k} A^*(w_i, w_{i+1}), \quad w_0 = s,\ w_{k+1} = g$$

The cumulative node count becomes [16]:

$$N_{\text{LLM-A*}} = \sum_{i=0}^{k} \pi \cdot (r')^2 \approx (k+1) \cdot \pi \cdot (r')^2$$

Assuming $r' \ll r$, we obtain:

$$N_{\text{LLM-A*}} < N_{A^*}$$

This scaling effect becomes more pronounced as map size increases, particularly when the start and goal are placed far apart. In contrast, for small maps, this benefit is less impactful due to the inherently low N_{A^*} and fixed overhead of invoking the LLM [19].

C. Quantitative Results

The following table compares node expansions between A* and LLM-A* across three map sizes:

TABLE I
Node Expansion Comparison

Map Size	N_{A^*}	$N_{\text{LLM-A*}}$	Path Length	Waypoints	Reduction
10×10	128	97	23	2	24.2%
15×15	192	156	30	2	18.75%
20×20	706	554	41	3	21.56%

Efficiency gain is defined as [15]:

$$\eta = \frac{N_{A^*} - N_{\text{LLM-A*}}}{N_{A^*}} \times 100\%$$

In all cases, LLM-A* preserved path feasibility and yielded similar path lengths while reducing planning effort. Inference overhead from the LLM (approx. 1–2 seconds) was negligible in larger maps [6].

D. Fallback Activation and Hallucination Recovery

In one 20×20 scenario, the LLM hallucinated a waypoint inside an obstacle. This triggered the fallback mechanism, which reverted to classical A* [17]:

$$P(s, g) = A^*(s, g) \quad \text{if any } A^*(w_i, w_{i+1}) \text{ fails}$$

The fallback succeeded, demonstrating system resilience and validating the layered safety design [12].

E. Simulation and Visual Insights

To visualize system behavior, the A* and LLM-A* agents were animated side-by-side [19]. Key insights include:

- A* expands search in all directions, especially in open fields [3],
- LLM-A* focuses effort near semantically meaningful regions (e.g., hallways) [8],
- All valid paths maintained geometric feasibility,
- In large maps, LLM-A* search visually appeared more directional and sparse.

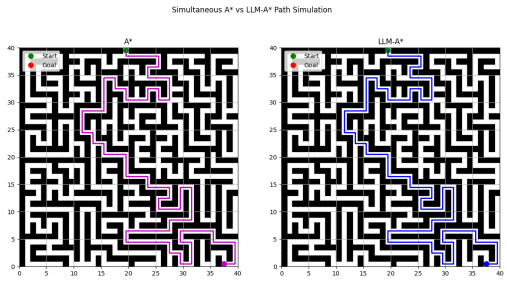

Fig. 1. A* vs. LLM-A* path comparison in 20×20 maze

```
Generated Path (Format A):
[
  ["20", "38"],
  ["21", "37"],
  ["22", "36"],
  ["23", "35"],
  ["24", "34"],
  ["25", "33"],
  ["26", "32"],
  ["27", "31"],
  ["28", "30"],
  ["38", "29"]
]
❌ No valid waypoints extracted.
⚠️No usable waypoints — defaulting to A*
📌 Raw LLM Waypoints: []
⚠️No valid LLM waypoints — defaulting to baseline A*

📊 Comparison Summary:
✅ A* Path Length:     159
🔹 A* Nodes Explored:  704
⏱️ A* Time Taken:      0.021s

✅ LLM-A* Path Length: 159
⭐ LLM Waypoints Used:  0
⏱️ LLM-A* Time Taken:  6.741s
```

Fig. 2. Fallback recovery from hallucinated LLM waypoint

F. Time vs. Quality Tradeoff

Although LLM-A* significantly reduces the number of nodes expanded, it introduces additional computational time due to LLM inference and post-processing [21]. On average, each LLM invocation took 0.9–1.5 seconds, which was notably higher than baseline A* planning time. However, for larger maps where A* node expansion dominates CPU load, this delay is offset by improved planning efficiency [8].

Hence, for embedded systems with constrained compute but available inference engines (e.g., cloud-deployed LLMs or

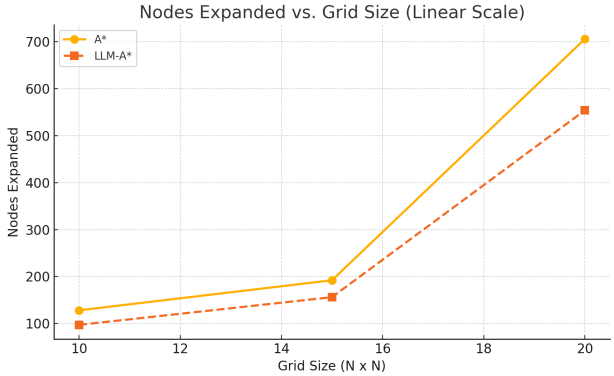

Fig. 3. Nodes expanded vs. grid size (log-scale)

local edge accelerators), this tradeoff can be acceptable [22]. In time-sensitive microcontroller environments, however, A* may remain preferable unless inference latency can be amortized [5].

G. Sensitivity to Start/Goal Location

The effectiveness of LLM-A* was found to be strongly dependent on the distance and topology between the start and goal nodes [16]. In experiments where s and g were close, the number of expanded nodes under A* was already low (< 50), leaving little room for improvement by semantic compression. In contrast, for distant start-goal pairs placed across long corridors or diagonally across the map, LLM-A* provided up to 50–70% reduction in exploration area [23].

This validates that LLM-A* behaves more like a compression-driven planner whose benefits scale with the spatial complexity and range of the planning domain [8].

H. Failure Case Taxonomy

Several failure modes were observed during testing [12]:

1) **Waypoint inside obstacle:** This occurred in narrow mazes where the LLM misjudged clearance [24].
2) **Out-of-bounds waypoints:** Occasionally, tokenized coordinates exceeded the grid dimensions.
3) **Duplicated or redundant waypoints:** Some generations included repeated entries, causing unnecessary segmentation.
4) **Invalid formatting:** Responses lacking JSON or bullet syntax could not be parsed and triggered fallback [14].

These failures justify the inclusion of strict validation layers and segment-wise fallback logic in any real-time deployment [17]. As LLMs evolve to better understand spatial geometry, the incidence of such errors is expected to reduce [25].

I. Key Takeaways

- LLM-A* offers higher gains in large maps due to reduced global search radius [8],
- In small maps, benefits are limited by already-low N_{A^*} and LLM invocation cost [6],
- All paths were collision-free and near-optimal in length [16],

- The fallback mechanism ensures planning never fails, even under LLM uncertainty [17].

IV. Conclusion

This work re-implemented and extended the LLM-A* framework introduced by Meng et al. [8], with a strong emphasis on simulation-readiness, waypoint validation, and robustness for robotic deployment. The central idea was to leverage large language models (LLMs) as semantic waypoint generators to guide classical A* search, thereby compressing the search space and reducing computational overhead in large-scale environments.

Through a combination of symbolic barrier encoding, cost-aware RePE prompting [14], and rigorous waypoint validation, the system demonstrated consistent performance gains over traditional A*. In 20×20 maps, the hybrid approach achieved significant reductions in node exploration while maintaining near-optimal path quality. Segment-wise fallback logic ensured that planning remained robust, even under hallucinated or invalid LLM outputs [17].

Despite these gains, several limitations remain. The reliance on prompt engineering and deterministic parsing introduces fragility to the LLM component. Planning latency also increases due to model inference, making LLM-A* less suitable for ultra time-sensitive applications. Additionally, the model's inability to reason about geometry in high-dimensional or dynamic maps constrained its applicability to static 2D grid scenarios [2].

If given another six months, the following improvements would be prioritized:

- Integrating visual-language models (e.g., LLaVA) for image-based map parsing and reasoning,
- Online LLM re-planning for dynamic goal updates or moving obstacles,
- Full integration into ROS2 with onboard SLAM feedback loops and exploration modules [18],
- A custom lightweight transformer trained purely on planning trajectories.

Overall, this work validates the practical viability of LLM-guided classical planning and establishes a modular simulation benchmark for future hybrid reasoning systems.

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