

Parallelized Planning-Acting for Efficient LLM-based Multi-Agent Systems

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Abstract

Recent advancements in Large Language Model (LLM)-based Multi-Agent Systems (MAS) have demonstrated remarkable potential for tackling complex decision-making tasks. However, existing frameworks inevitably rely on serialized execution paradigms, where agents must complete sequential LLM planning before taking action. This fundamental constraint severely limits real-time responsiveness and adaptation, which is crucial in dynamic environments with ever-changing scenarios. In this paper, we propose a novel parallelized planning-acting framework for LLM-based MAS, featuring a dual-thread architecture with interruptible execution to enable concurrent planning and acting. Specifically, our framework comprises two core threads: (1) a *planning thread* driven by a centralized memory system, maintaining synchronization of environmental states and agent communication to support dynamic decision-making; and (2) an *acting thread* equipped with a comprehensive skill library, enabling automated task execution through recursive decomposition. Extensive experiments on challenging Minecraft demonstrate the effectiveness of the proposed framework.

1 Introduction

Multi-Agent Systems (MAS) have become a well-established paradigm for tackling complex decision-making problems (Hong et al., 2023; Chen et al., 2024b; Dong et al., 2024), with early efforts primarily relying on reinforcement learning (Busoniu et al., 2008; Yang and Wang, 2021; Lowe et al., 2017) to enable multiple agents to cooperate or compete in dynamic environments. Despite the encouraging results achieved, these MAS frameworks faced limitations in handling

complex real-world scenarios that require advanced communication, reasoning, and adaptability. The rapid advancement of Large Language Models (LLMs) (DeepSeek-AI, 2025; DeepSeek-AI, 2024; Brown et al., 2020; Achiam et al., 2023; Qwen et al., 2024; Dubey et al., 2024) has since revolutionized MAS by adding natural language understanding and generation capabilities, enabling agents to engage in more sophisticated collaboration. LLMs have significantly enhanced the flexibility and versatility of MAS, opening the door to more complex tasks and dynamic interactions in real-world applications (Wu et al., 2024; D’Arcy et al., 2024; Chen et al., 2024c; AL et al., 2024).

Recent works have demonstrated the potential of LLM-based MAS in various domains. MetaGPT (Hong et al., 2023) introduces an innovative meta-programming framework to enhance task decomposition and agent collaboration, Agent-Verse (Chen et al., 2024b) improves collaborative performance by orchestrating expert agents, and VillagerAgent (Dong et al., 2024) tackles task dependencies in complex environments using DAG-based task decomposition. Despite these advancements, most current frameworks still rely on serialized execution, where planning and acting occur sequentially for each agent. This serialized nature creates a substantial bottleneck when handling dynamic information, particularly evident in dynamic settings like Minecraft, where the environment is constantly changing, even without the intervention of agents. Although Voyager (Wang et al., 2023) pioneered LLMs-based agents in Minecraft, its approach, which pauses the game server during LLM interactions, effectively staticizes the dynamic environment, thus failing to fully address the real-time responsiveness needed in such settings. Subsequent works in Minecraft agents (Liu et al., 2024; Zhao et al., 2024) have followed this approach, but they also inherit the same limitations.

Our analysis reveals three critical challenges

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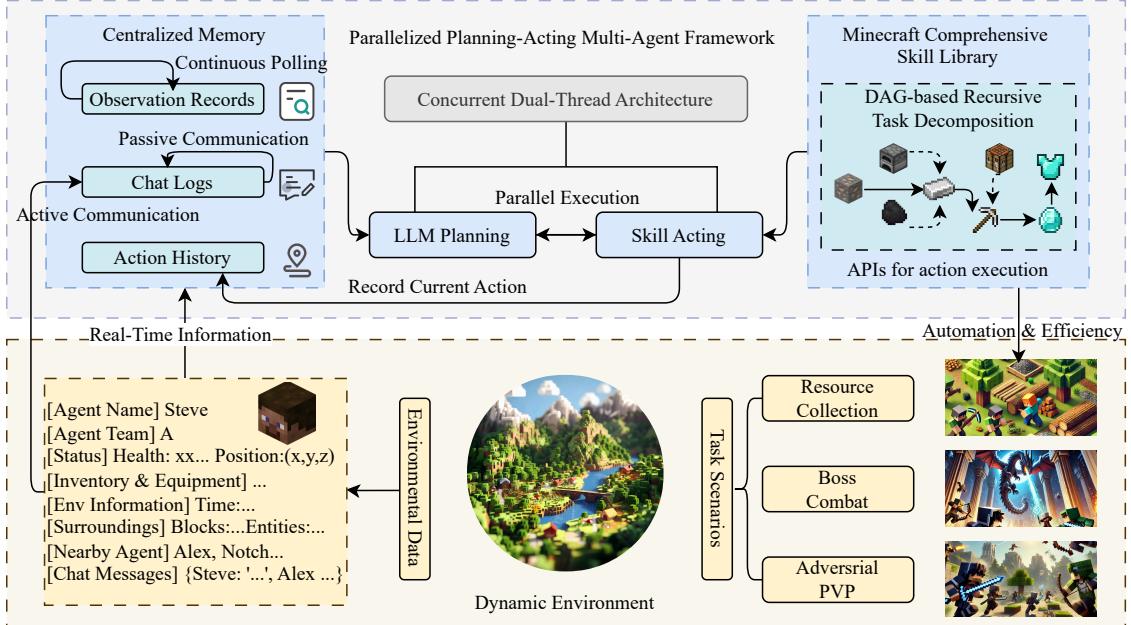


Figure 1: An overview of the proposed multi-agent system

in current LLM-based MAS for dynamic environments. First, inflexible action scheduling is prevalent, as many existing agent frameworks rely on serialized execution, requiring agents to wait for a language model response before proceeding with further actions. This rigidity complicates the handling of unexpected environmental changes; Second, limited replanning capabilities hinder agents’ performance, as they often execute actions to completion without interruption. This lack of adaptability prevents agents from effectively reconsidering or adjusting their plans in response to urgent and unforeseen events, diminishing their overall effectiveness. Lastly, memory sharing delays pose another issue, as memory updates in many multi-agent systems only occur after an action has been fully executed. This results in delayed observational data sharing, causing agents to operate based on outdated information, which in turn limits the team’s coordination and efficiency.

In this paper, we propose a parallelized planning-acting framework that introduces a dual-thread architecture with interruptible execution for efficient LLM-based MAS in dynamic environments, as shown in Fig. 1. Our architecture decouples LLM reasoning from action execution, enabling concurrent planning and acting. Moreover, the interruption mechanism enables agents to adjust their actions in real time based on environmental changes,

thereby improving their adaptability. Specifically, our framework consists of two core threads: (1) A planning thread employing a centralized memory system to support efficient and timely information sharing among agents, minimizing memory sharing delays and ensuring agents operate with up-to-date information for better coordination and efficiency. (2) An acting thread utilizing a comprehensive skill library, enabling efficient task execution through a recursive task decomposition mechanism. Our core contributions are summarized as follows:

- We propose a parallelized planning-acting framework that decouples planning and acting into parallelized dual threads with interruptible execution for efficient LLM-based MAS.
- We develop a centralized memory system to support the planning thread, ensuring that agent decisions are always informed by the latest environmental changes and interactions.
- We design a comprehensive skill library to empower the acting thread, enabling efficient task execution through recursive task decomposition.
- Experimental results on Minecraft demonstrate a paradigm shift from serialized deliberation to parallelized interaction, yielding notable improvements in efficiency and coordination.

2 LLM-based Multi-Agent Framework

We propose a novel parallelized planning-acting framework based on LLMs, designed to enable collaboration and decision-making among agents in complex dynamic environments. Our framework introduces three key innovations: (1) A dual-thread architecture with an interruptible execution mechanism, enabling concurrent planning and acting, (2) A real-time updated centralized memory system supporting the planning thread, ensuring that agents' decisions are informed by the latest environmental changes and team interactions, and (3) A Minecraft comprehensive skill library supporting the acting thread, automating task execution by proposing a recursive task decomposition mechanism. While the skill library represents an engineering contribution, it is important to note that our framework is generic and can be extended to other domains with minimal adaptation. This flexibility highlights the broader applicability of our approach, while Minecraft provides a rich and accessible testbed for evaluating its performance in dynamic environments.

2.1 Parallelized Planning-Acting Framework

Inspired by the human ability to think and act simultaneously, our framework features a dual-thread architecture in Fig. 2 that separates planning (supported by LLMs and the centralized memory system) and acting (executed by the comprehensive skill library). Let $\mathcal{A} = \{a_1, a_2, \dots, a_n\}$ denote the set of agents. Our framework operates as follows:

- **Planning Thread:** At each time step t , the planning thread generates the next action for agent a_i based on a system prompt S , the agent's current observation O_i^t , the latest team chat logs C^t and its current action A_i^t :

$$A_i^{t+1} = \text{LLM}(S, O_i^t, C^t, A_i^t). \quad (1)$$

The planned action A_i^{t+1} is then written into an action buffer, which serves as the communication channel between the planning thread and the acting thread. This action buffer is implemented as a single-slot queue, allowing the planning thread to write and the acting thread to read. If the buffer is already occupied, the previous action is discarded to make space for the new one. This mechanism ensures that the planning thread always places the most up-to-date action (based on the latest observations

and agent status) into the buffer, while the acting thread always retrieves the most current action, never operating outdated plans.

- **Acting Thread:** The acting thread retrieves actions from the action buffer and executes them according to the following rule:

$$s_i = \begin{cases} A_i^{t+1} & \text{if } p(A_i^{t+1}) > p(A_i^t), \\ A_i^t & \text{otherwise.} \end{cases} \quad (2)$$

Here, s_i represents the skill execution of agent a_i , A_i^t is the current action being executed, A_i^{t+1} is the new action in the buffer, and p is the priority of an action. If an interruption is triggered—i.e., when the LLM determines that the new action has a higher priority than the current action—the planning thread sends an interrupt signal to the acting thread. The acting thread immediately exits and restarts with the new action. If no interruption is triggered, the acting thread completes the current action A_i^t before retrieving and executing the next action A_i^{t+1} from the buffer.

Latency Analysis. The parallelized architecture intuitively reduces system latency through concurrent execution of planning and acting threads. Let T_{plan} denote the LLM reasoning latency and T_{act} the skill execution time. For a task requiring n atomic actions without any interruption:

- **Serialized Framework:**

$$T_s = \sum_{k=1}^n (T_{\text{plan}}^{(k)} + T_{\text{act}}^{(k)}). \quad (3)$$

- **Parallelized Framework:**

$$T_p = T_{\text{plan}}^{(1)} + \sum_{k=2}^n \max(T_{\text{plan}}^{(k)}, T_{\text{act}}^{(k-1)}) + T_{\text{act}}^{(n)}. \quad (4)$$

The latency reduction ΔT can be expressed as:

$$\Delta T \approx \sum_{k=1}^n \left(T_{\text{plan}}^{(k)} + T_{\text{act}}^{(k)} - \max(T_{\text{plan}}^{(k)}, T_{\text{act}}^{(k)}) \right). \quad (5)$$

This analysis highlights two key advantages of our framework: 1) The initial planning latency $T_{\text{plan}}^{(1)}$ is effectively amortized over subsequent actions, and 2) The overlapping of planning and acting phases successfully conceals T_{plan} when

$T_{\text{act}} > T_{\text{plan}}$ (our proposed comprehensive skill library in Section 2.3 ensures this condition is well-maintained). Our experimental results in Section 3.4 demonstrate the overall efficiency advantage of the parallelized framework.

By decoupling planning and acting into parallelized threads, our framework strikes a balance between efficiency and flexibility, allowing agents to respond dynamically to unpredictable environments with enhanced adaptability and performance.

2.2 Centralized Memory System

To facilitate effective coordination, we implement a centralized memory system M that stores and manages information at the team level. The memory is updated at each time step t as follows:

$$M^{t+1} = \{O^{t+1}, C^{t+1}, A^{t+1}\} \cup \{M^t \setminus O^t\}, \quad (6)$$

where O^{t+1} denotes the updated observations of the multi-agent system at time $t + 1$, which overwrite the previous observations O^t . C^t denotes the chat messages of the system at time t , A^t denotes the action history of the system at time t . This unified repository enables agents to access and utilize relevant information during task execution, ensuring efficient team coordination:

- **Observation Records:** Each agent’s observations are continuously updated in the centralized memory, reflecting the latest agent status and environmental state. These observations are associated with the respective agent, allowing the team to maintain a comprehensive and up-to-date view of the environment.
- **Chat Logs:** All team chat messages are stored in the centralized memory, with long-term retention to support historical analysis and decision making. During planning, agents can retrieve the most recent chat messages to incorporate team insights into their strategies. This ensures that decisions are informed by the collective knowledge of the team.
- **Action History:** The centralized memory also records the actions taken by each agent, providing a detailed history of task execution. These logs are useful for behaviours refining and performance analysis.

We implement two types of multi-agent communication (passive and active) ensuring that the centralized memory remains a dynamic resource for team coordination:

- **Passive Communication:** In the planning thread, after each planning cycle, the LLM generates a chat message based on the agent’s latest observations, which is then sent to the centralized memory’s chat logs. This ensures that passive communication, reflecting updated observations, can run concurrently with action execution. While an agent is performing actions, its observations are continuously updated and shared with the team, enabling real-time coordination based on the most current environmental information.

- **Active Communication:** In the acting thread, agents can actively choose to send chat messages by performing a chat action. This action allows the agent to share any information with teammates, updating the chat logs in real-time. This form of communication ensures that agents can respond dynamically and share critical information during action execution, facilitating efficient and up-to-date information exchange between agents.

2.3 Comprehensive Skill Library

To enable seamless interaction between agents and the Minecraft environment, we develop a comprehensive skill library that encapsulates a wide range of in-game actions. The library provides high-level APIs for tasks such as resource collection, combat, exploration, and communication. For further technical details, please refer to Appendix B.

A key feature of the comprehensive skill library is the implementation of a recursive task decomposition mechanism, which automates the completion of prerequisite tasks such as mining raw materials and crafting necessary tools. This automation ensures that agents can perform complex resource collection tasks with minimal manual intervention, enabling the automated collection of over 790 types of items in Minecraft, surpassing all existing methods (Wang et al., 2023; Zhu et al., 2023; Zhao et al., 2024; Liu et al., 2024).

The core recursive process can be formally modeled as a weighted directed acyclic graph (DAG) $\mathcal{G} = (V, E, \phi)$, where:

- **Vertex set $V = \{v_i\}$** represents atomic tasks:

$$v_i = (t_i, c_i, f_i), \quad (7)$$

where $t_i \in \mathcal{T}$ is the target item type (All collectible items in Minecraft), $c_i \in \mathbb{N}^+$ denotes

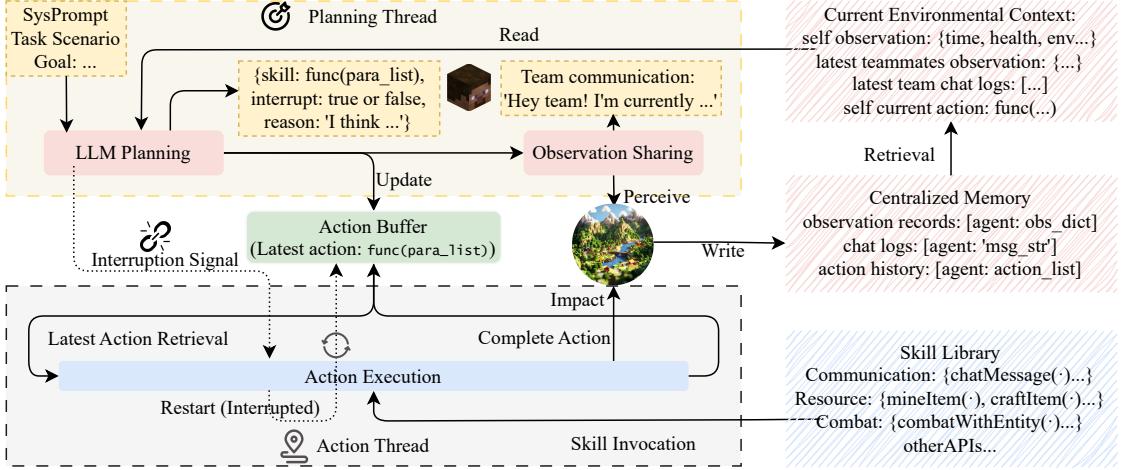


Figure 2: An overview of the proposed parallelized planning-acting architecture

required quantity, and f_i specifies the operation type for obtaining the item.

- **Edge set** $E \subseteq V \times V$ encodes prerequisite task dependencies:

$$(v_j, v_i) \in E \iff v_j \in \text{pre}(v_i), \quad (8)$$

where $\text{pre}(v_i)$ gives the prerequisite tasks for producing t_i .

- **Weight function** $\phi : E \rightarrow \mathbb{Q}^+$ defines material conversion rates:

$$\phi(v_j, v_i) = \frac{r_{ij}}{n_{\text{out}}}, \quad (9)$$

with r_{ij} being the required quantity of t_j per operation, and n_{out} being the output quantity per operation.

The recursive resolution process follows:

$$\Psi(v_i) = \bigcup_{(v_j, v_i) \in E} \left\{ \Psi(v_j^{(\phi(v_j, v_i) \cdot c_i)}) \right\} \cup \{v_i\}, \quad (10)$$

where $v_j^{(k)}$ denotes a task requiring k units of t_j , and the base case $\Psi(v_i) = \emptyset$ applies when $I(t_i) \geq c_i$, with I representing the current inventory state, which means the task is accomplished.

3 Experiments

3.1 Experiment Setup

We aim to address the following questions through further experimentation: (1) Can our comprehensive skill library enable agents to efficiently accomplish basic tasks within Minecraft’s open-world environment? (2) How well can our proposed multi-agent framework perform on highly challenging

and complex tasks? (3) Can our proposed parallelized planning-acting framework better support multi-agent collaboration, competition, and human-agent interaction?

All experiments are conducted in the Minecraft Java Edition version 1.19.4 gaming environment using the Qwen-Plus model (Qwen et al., 2024), while multi-modal experiments utilized the Qwen-VL-Plus model (Bai et al., 2023). The game server operates continuously without pausing during interactions with LLMs, thereby necessitating that all agents perform in real-time. All evaluation metrics are captured dynamically during these interactions. Metrics such as ‘time’ denote the total duration required by the multi-agent systems to complete their designated tasks, encompassing the time expended on communications with LLMs.

3.2 Benchmark Task Scenarios

To evaluate the generalizability of our multi-agent framework in Minecraft, we designed three distinct task scenarios: **Resource Collection**, **Boss Combat**, and **Adversarial Player versus Player (PvP)**. These scenarios were selected to cover a range of application domains, showcasing the versatility of our multi-agent framework across diverse contexts.

- **Resource Collection:** This task involves gathering resources in the Minecraft world, evaluating the efficiency of the comprehensive skill library and the coordination of multi-agent system in performing repetitive and structured tasks.
- **Boss Combat:** This task requires the multi-agent system to defeat a strong boss-level enemy in a predefined, highly intricate combat environment, evaluating advanced strategic planning, real-time decision-making, effective collaboration among

agents and the system’s ability to handle dynamic and challenging environments.

- **Adversarial PVP:** This task focuses on team-based adversarial competition, where two teams of agents compete against each other in a combat scenario. The primary objective is to evaluate the agents’ ability to strategize, adapt, and outperform opponents.

3.3 Main Results

3.3.1 Resource Collection Task

We first evaluate the effectiveness of our skill library’s recursive task decomposition mechanism by assessing a single agent’s performance on basic resource collection tasks in Minecraft. This initial evaluation aimed to verify the comprehensive skill library’s capability in automating complex workflows, thereby validating its efficiency and reliability in handling fundamental Minecraft tasks. As shown in Table 1, when the recursive task decomposition mechanism is ablated, the system can only complete short-term tasks that require fewer steps and shows a reduction in efficiency. In contrast, utilizing our comprehensive skill library enables efficient completion of all tasks.

Table 1: Completion time and success rate (SR) comparison with and without the Recursive Task Decomposition Mechanism (RTDM). All results are shown with the mean and standard deviation over 10 trials.

Task	with RTDM		w/o RTDM	
	Time(min)	SR	Time(min)	SR
Iron Tool Set	0.3 ± 0.2	100%	2.8 ± 2.5	100%
Diamond Armor	0.6 ± 0.3	100%	4.6 ± 2.5	80%
Redstone Devices	1.4 ± 0.5	100%	N/A	0%
Navigation Kit	4.7 ± 1.3	100%	N/A	0%
Transport System	6.2 ± 1.6	100%	N/A	0%

We then evaluate our framework’s performance on eight more complicated resource collection tasks. Table 2 compares the completion times between our multi-agent system (3 agents) and single-agent baseline, demonstrating the efficiency gains through coordination.

The experimental results demonstrate that our Minecraft comprehensive skill library, when employed within a multi-agent framework, can efficiently complete various resource collection tasks as well. As shown in the comparisons, the system

Table 2: Completion time (in minutes) of resource collection tasks comparison between multi-agent(MA) and single-agent(SA) systems. All results are shown with the mean and standard deviation over 10 trials. For detailed task definitions, please refer to Appendix C.

Task	MA Time	SA Time
Iron Tool Set	7.8 ± 2.1	8.5 ± 3.7
Diamond Armor	13.7 ± 4.1	28.3 ± 6.1
Redstone Devices	11.0 ± 6.0	13.1 ± 3.3
Navigation Kit	25.3 ± 12.2	39.4 ± 11.7
Transport System	22.0 ± 10.1	37.8 ± 12.6
Food Supplies	6.6 ± 3.9	8.0 ± 2.0
Building Materials	15.8 ± 2.8	22.6 ± 7.4
Storage System	10.0 ± 8.9	16.7 ± 7.8

with three agents significantly reduces task completion times compared to the single-agent baseline across most tasks, validating the effectiveness of our approach and showcasing the efficiency benefits of multi-agent collaboration. However, the observed non-linear scaling (multi-agent time > single-agent time/3) does not always achieve ideal linear speedup due to two inherent constraints:

- **Resource dependency chains:** Sequential prerequisites in crafting workflows (e.g., iron tools required for diamond mining)
- **Spatial contention:** Overlapping access to resources in close proximity (e.g., multiple agents competing to gather items from the same ore cluster)

3.3.2 Boss Combat Task

We conduct comprehensive evaluations across three challenging combat scenarios with varying agent team sizes. Experiments are conducted in three pre-defined scenarios, each featuring an extremely powerful and representative boss from Minecraft’s major dimensions: the Elder Guardian (Overworld), the Wither (Nether), and the Ender Dragon (End).

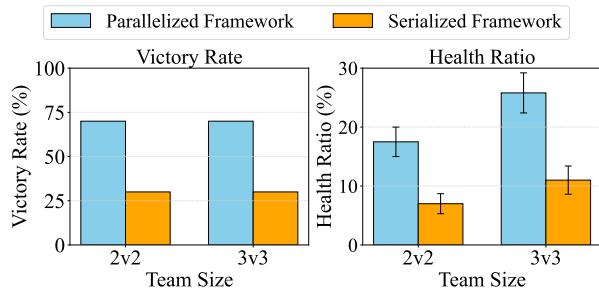


Figure 3: Comparison of parallelized vs. serialized frameworks in PVP tasks. All results are shown with the mean and standard deviation over 10 trials.

The initial inventory of agents remained consistent across all scenarios. Their equipment are validated to be collectible within a short time during the resource collection task, and other consumable resources can also be efficiently gathered utilizing our skill library. For further details, please refer to Appendix C.

The performance of the multi-agent system in the boss combat task is summarized in Table 3, demonstrating that our framework achieves high success rates in completing all challenging boss combat tasks with various agent team sizes.

3.3.3 Adversarial PVP Task

In the adversarial player-vs-player (PVP) task, we conduct a direct comparison between the parallelized and serialized frameworks across various team sizes. As shown in Fig. 3, this setup clearly demonstrate and quantify the differences of these two methodologies under competitive conditions.

As shown in Fig. 3, the parallelized framework demonstrates a significant advantage over the serialized framework in this dynamic adversarial scenario. Our analysis indicates that this advantage is primarily attributed to our interruption mechanism, which enables agents to dynamically adjust their strategies and respond promptly to changes in the environment (e.g., seamlessly switch attack targets, prioritize health restoration, etc.).

3.4 Ablation Study

To validate the necessity of our method, we perform ablation studies in boss combat tasks by disabling different components in our framework:

- **w/o Parallelized Planning-Acting Framework:** Replaced our concurrent architecture with traditional serialized execution (LLM call → action execution), disabling action interruption capabilities once execution begins.

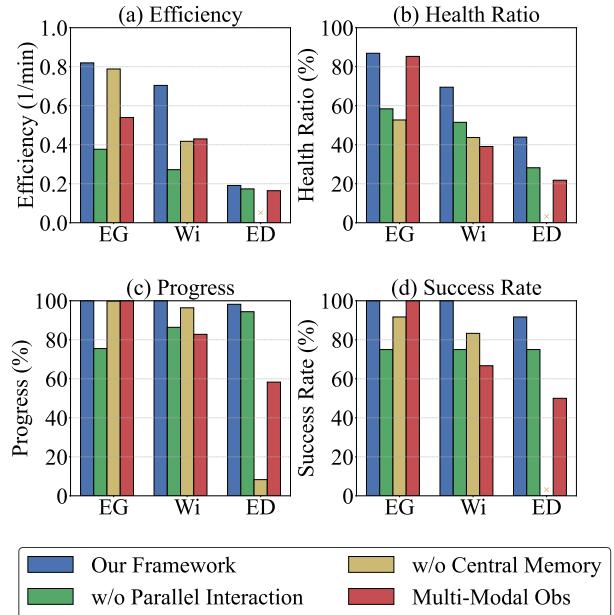


Figure 4: Ablation study in boss combat tasks across 12 trials in three scenarios: Elder Guardian (EG), Wither (Wi), and Ender Dragon (ED), where efficiency is defined as the inverse of completion time in minutes.

- **w/o Centralized Memory System:** Disabled real-time team observation polling, team chat logs, action history and global progress information, thereby restricting agents to rely solely on their individual observations.

- **Multimodal Observation:** Replaced text-based observations with visual inputs using Mineflayer’s prismarine-viewer, capturing first-person screenshots processed by a vision-language model (VLM) as observation.

These ablation configurations systematically evaluate the contribution of each architectural component to overall system performance, providing insights into their relative importance in complex multi-agent coordination tasks.

Experiment results shown in Fig. 4 highlight the critical roles of the parallelized planning-acting framework and centralized memory system in maintaining this high performance. When we replaced the text-based observation space with a multimodal observation system, we observed that although the inclusion of visual language models (VLMs) increased response latency and lowered the observation accuracy, the agents still performed reasonably well. This indicates that our framework remains robust even when handling different modalities.

Table 3: Boss combat performance across three task scenarios. All results are shown with the mean and standard deviation over 12 trials. For detailed evaluation metrics definitions, please refer to Appendix C.

Task Scenario	# Agents	Time(min)	Health Ratio	Progress	SR
Elder Guardian (Overworld) 	3	2.4 ± 2.1	$49.8 \pm 32.8\%$	$91.4 \pm 20.1\%$	83.3%
	5	1.2 ± 0.8	$84.4 \pm 7.9\%$	$100.0 \pm 0.0\%$	100.0%
	10	1.2 ± 0.3	$86.9 \pm 8.4\%$	$100.0 \pm 0.0\%$	100.0%
Wither (the Nether) 	3	1.8 ± 0.8	$18.6 \pm 23.4\%$	$71.8 \pm 35.9\%$	41.7%
	5	1.5 ± 0.5	$53.4 \pm 32.7\%$	$88.1 \pm 20.6\%$	75.0%
	10	1.4 ± 0.3	$69.5 \pm 19.0\%$	$100.0 \pm 0.0\%$	100.0%
Ender Dragon (the End) 	3	N/A	$0.0 \pm 0.0\%$	$20.4 \pm 18.5\%$	0.0%
	5	6.5 ± 2.0	$18.1 \pm 23.2\%$	$75.4 \pm 28.9\%$	41.7%
	10	5.2 ± 1.5	$43.9 \pm 24.4\%$	$98.2 \pm 5.9\%$	91.7%

3.5 Human-Agent Interaction

Our framework also supports flexible human-agent interaction, allowing human players to either actively participate in task execution alongside agents, facilitating dynamic cooperation within the game environment, or to take on a guiding role by providing instructions to agents for task division, coordination, and strategic decision-making. Further experimental cases demonstrating the effectiveness of human-agent interaction are presented in Appendix C.4.

4 Related Works

LLM-based Minecraft Agents. The development of LLM-based AI agents in Minecraft has evolved through several key approaches: Voyager (Wang et al., 2023) established the first LLM-based agent with automatic skill discovery using GPT-4 (Achiam et al., 2023). Subsequent studies enhanced agents via specialized memory mechanisms (Park et al., 2024; Li et al., 2024a), specialized LLM fine-tuning (Feng et al., 2023; Zhao et al., 2024; Liu et al., 2024), task decomposition and causal graph learning (Yuan et al., 2023; Zhu et al., 2023; Yu and Lu, 2024), and combination with reinforcement learning (Li et al., 2024b, 2023). Additionally, multi-modal information perception and processing were explored (Zheng et al., 2023; Cai et al., 2024), along with other novel techniques (Wang et al., 2024; Zhou et al., 2024). The development of benchmarks for general capabilities progressed with MineDojo (Fan et al., 2022) and MCU (Lin et al., 2023), while specific agent capabilities were assessed through additional benchmarks (Qin et al., 2024; Dong et al., 2024).

LLM-based Multi-Agent Systems. Recent sur-

veys (Mou et al., 2024; Guo et al., 2024) provide a comprehensive overview of the key advancements in LLM-based multi-agent systems. Building on these foundations, recent research has focused on several core areas: infrastructure frameworks for efficient agent coordination (Gong et al., 2024; Chen et al., 2024b; Zhang et al., 2024b; Hong et al., 2023; Zhang et al., 2024a), which introduce novel paradigms for task management and team collaboration; benchmark development to evaluate multi-agent performance in dynamic environments (Chen et al., 2024a; Dong et al., 2024), which has created robust testing environments to assess the generalization and efficiency of LLM-powered agents; large-scale social simulations (AL et al., 2024; Park et al., 2023; Yang et al., 2024), which explore how multi-agent systems model complex societal behaviors; and domain-specific applications (Wu et al., 2024; D’Arcy et al., 2024; Chen et al., 2024c) demonstrating the effectiveness of LLM-based agents in specific scenario simulation.

5 Conclusion

We propose a novel parallelized planning-acting multi-agent framework that significantly enhances the responsiveness and adaptability of LLM-based MAS in dynamic environments. Our framework’s dual-thread architecture with interruptible execution mechanism enables real-time interaction and continuous adaptation, overcoming the limitations of traditional serialized execution paradigms. The comprehensive skill library and automated task decomposition mechanism further improve efficiency and coordination as an engineering contribution. Through extensive experiments, our framework demonstrates superior performance in both collabora-

rative and adversarial scenarios, and achieves more immediate human-agent interaction, highlighting its potential for broader applications.

6 Limitations

While demonstrating significant advantages, our framework has three main limitations. First, the continuous LLM request design leads to higher computational costs, which may limit scalability in resource-constrained environments. Second, LLM hallucinations occasionally result in irrational action interruptions, affecting the reliability of agent behavior. Third, although our framework adapts to multimodal observations, the current fusion method relies solely on visual-language models (VLMs), potentially failing to fully exploit the complementarity of multimodal information and limiting performance in complex scenarios. For future work, we aim to optimize computational efficiency by refining LLM request mechanisms, mitigate hallucination effects through enhanced verification strategies, and improve multimodal fusion techniques to better leverage diverse sensory inputs.

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A Centralized Memory System

The memory of the multi-agent system is stored in JSON files, and agents read and modify their contents by reading and writing to these files. Below is an example of how the memory is stored:

A.1 Agent Observation & Status

```
{
  "time": "day",
  "health": 12.8,
  "hunger": 17,
  "position": "(10, 65, -8)",
  "equipment": [
    null,
    null,
    null,
    null,
    "bow",
    null
  ],
  "inventory": {
    "arrow": 187,
    "golden_apple": 4,
    "diamond_pickaxe": 1,
    "diamond_sword": 1,
    "diamond_helmet": 1,
    "diamond_chestplate": 1,
    "diamond_leggings": 1,
    "diamond_boots": 1,
    "bow": 1
  },
  "nearbyBlocks": [
    "end_stone",
    "bedrock"
  ],
  "nearbyEntities": "enderman, ender_dragon",
  "nearbyPlayers": [
    "Steve",
    "Brine",
    "Jeb",
    "Notch"
  ]
}
```

A.2 Team Chat Log

```
{
  "Day 1 - Morning": [
    "SystemInfo: Number of End Crystals Remaining: 10",
    "SystemInfo: Boss Health: 200",
    "SystemInfo: Boss Health: 200",
    "Notch: Let's prioritize taking down the end_crystals to prevent the Ender Dragon from healing. I will start attacking the nearest end_crystal with my bow. Everyone, cover me and be ready to assist if needed.",
    "Steve: I'm ready with my bow and arrows . Let's focus on taking down the end_crystals first to prevent the Ender Dragon from healing. I'll start
  ]
}
```

```

targeting the nearest end_crystal. Stay
alert for any incoming endermen but
avoid engaging them unless necessary.",",
"SystemInfo: Boss Health: 200",
"Brine: Brine: Let's prioritize
destroying the end_crystals to prevent
the Ender Dragon from healing. Notch
and I will start targeting the nearest
crystal. Steve, Alex, and Jeb, please
spread out and assist in taking down
other crystals. Stay alert for any
Endermen but avoid engaging them unless
necessary. Report if you need help or
spot any crystals.",
"Jeb: I'm ready with my bow and arrows.
Let's prioritize the end_crystal on the
obsidian pillars to prevent the Ender
Dragon from healing. I'll start
targeting the nearest crystal. Stay
alert for any incoming endermen but
avoid engaging unless necessary."
...
]
}

```

A.3 Team Observation Log

```

{
  "obs_entries": [
    "Notch: Team, I'm fully equipped with
    diamond armor, a bow, and 200 arrows. I
    see an end_crystal and an ender_dragon
    nearby, along with some endermen.
    Brine, Jeb, Steve, and Alex are also
    close. Let's focus on taking down the
    end_crystal first to prevent the Ender
    Dragon from healing. Everyone, prepare
    your bows and stay alert for any
    incoming endermen. Ready when you are!",

    "Brine: Team, I'm currently well-
    equipped with a bow, 200 arrows, and
    diamond armor. The ender_dragon is
    nearby but hasn't attacked yet. I see
    Steve, Notch, Alex, and Jeb around. Let
    's focus on taking out the end_crystals
    first. I suggest we spread out to
    cover more ground and target the
    crystals from a distance. Stay alert
    for any Endermen, but avoid engaging
    them unless necessary. Report if you
    spot any crystals or need assistance.",
    ...
    "Jeb: All end_crystals have been
    destroyed. Focusing on the Ender Dragon
    now. Everyone, keep your distance and
    use bows to attack from a safe range.
    Stay alert for any incoming endermen
    but prioritize the Ender Dragon. Let's
    finish this!",
    "Steve: I'm in critical condition and
    need immediate assistance! My health is
    down to 0. Brine, Notch, Jeb, please
    cover me or help me get to safety. I
    have a full bow and golden apples but
    can't fight effectively in this state.
    Endermen are nearby, be cautious!",
    ...
  ]
}

```

```

  ]
}
```

A.4 Team Action Log

```

{
  "Notch": [
    "```json\n{\n  \"skill\": \""
    chatMessage(bot, \\"Let's prioritize
    taking down the end_crystals to prevent
    the Ender Dragon from healing. I will
    start attacking the nearest end_crystal
    with my bow. Everyone, cover me and be
    ready to assist if needed.\\"", 'A')
    "\",\n  \"interrupt\": false,\n  \""
    reason\": \"Communicate the plan to the
    team before starting the attack on the
    end_crystal.\"\\n}\\n``",
    "```json\n{\n  \"skill\": \""
    combatWithEntity(bot, 'end_crystal', ''
    bow', true),\n  \"interrupt\": "
    false,\n  \"reason\": \"Start
    attacking the nearest end_crystal with
    my bow to prevent the Ender Dragon from
    healing. The team has been informed
    and is prepared to assist if needed.\\"\\n
    \\n``",
    "```json\n{\n  \"skill\": \""
    combatWithEntity(bot, 'end_crystal', ''
    bow', true),\n  \"interrupt\": "
    false,\n  \"reason\": \"I am
    currently attacking the nearest
    end_crystal with my bow to prevent the
    Ender Dragon from healing. My health is
    full, and there are no immediate
    threats requiring my attention.
    Continuing this action is crucial for
    our strategy.\\"\\n}\\n``",
    ...
  ],
  "Steve": ...
  ...
}

```

Part of above information is provided as human prompts for agents to plan actions. In addition to this, agents are also provided with identity information such as their name, team affiliation, and teammates' names, to simulate a human-like multi-agent collaborative scenario.

B Minecraft Comprehensive Skill Library

Our proposed skill library is implemented based on Mineflayer([PrismarineJS, 2023](#)). To simulate the process of solving prerequisite steps in the actual game to eventually obtain specific items, this skill library has introduced a recursive task decomposition mechanism. From the implementation level, all interfaces can recursively invoke each other or themselves and pass parameters.

B.1 Basic Skill Interfaces

- `obtainItem(bot, count, type)`: Automates the collection of items.
- `mineItem(bot, count, type, explore_direction, explore_time)`: Mines using specific tools. If the exploration parameters are not specified, the exploration direction is chosen randomly. If the item type is a subterranean mineral like diamond, the exploration direction is set to down (0, -1, 0). The exploration time limit defaults to five minutes (6000 ticks in Minecraft).
- `craftItem(bot, count, type, need_crafting_table)`: Crafts items. If no parameter is specified, the crafting is done using a crafting table by default.
- `smeltItem(bot, count, type, fuel)`: Smelts or cooks items in a furnace. If no parameters are provided, coal is used as the default fuel.
- `collectItem(bot, count, type, function)`: Collects items by killing animals or using other special methods.
- `chatMessage(bot, message, team_name)`: Sends a chat message to the team.
- `getItemFromChest(bot, chest_position, items_to_get)`: Retrieves specific items from a chest at a given location.
- `depositItemIntoChest(bot, chest_position, items_to_deposit)`: Deposits specific items into a chest at a given location.
- `combatWithEntity(bot, mob_name, weapon, loop)`: Automatically equips the highest quality armor and weapon from the inventory to fight with an entity (e.g., animals or hostile mobs). If no parameters are specified, the default weapon is a sword. The loop parameter determines whether to continue fighting the same type of entity.
- `combatWithPlayer(bot, player_name, weapon)`: Automatically equips the highest quality armor and weapon from the inventory to fight with a specific player. If no parameters are provided, the default weapon is a sword.

- `initialInventory(bot, item_dict)`: Initializes the player's inventory with specified items.
- `equipBestToolOrArmor(bot, type)`: Automatically equips the highest quality tool, weapon, or armor of the specified type.
- `listenChat(bot, player_name)`: Continuously listens to a player's chat messages.

B.2 Recursive-related Interfaces

- `preTool(item)`: Retrieves the minimum prerequisite tools required to gather a specific item.
- `preItem(item)`: Retrieves the prerequisite items required to craft a specific item and indicates whether a crafting table is necessary.
- `preSmelt(item)`: Retrieves the prerequisite items required to smelt a specific item.
- `preCollect(item)`: Retrieves the prerequisite entities required to collect a specific item.
- `getFunc(item)`: Retrieves the method used to collect a specific item.

This library is scalable and can be easily extended to accommodate new items, recipes, and tasks. Currently, it supports the collection of over 790 types of items across all three dimensions of Minecraft (Overworld, Nether, and End). However, the library does not yet support some specialized gameplay features. Future updates will aim to expand the library's functionality, adding support for more complex tasks.

C Experiment Details

Experiments were conducted using the Qwen-Plus model API provided by Alibaba Cloud. In the multiplayer local area network (LAN) server of Minecraft, agents connected to the game via different ports and interacted with the environment and other players.

C.1 Resource Collection Task

We implemented a comprehensive Minecraft resource collection benchmark, which allows multi-agent collaboration to automatically collect resources based on a given requirement dictionary, making this benchmark general and scalable. We

conducted experiments on the following representative resource collection tasks:

Task Definitions:

- **Iron Tool Set:** { 'iron_pickaxe': 1, 'iron_shovel': 1, 'iron_hoe': 1, 'iron_axe': 1 } — A set of commonly used iron tools in Minecraft.
- **Diamond Armor:** { 'diamond_helmet': 1, 'diamond_chestplate': 1, 'diamond_leggings': 1, 'diamond_boots': 1 } — A full set of diamond armor in Minecraft.
- **Redstone Devices:** { 'repeater': 1, 'piston': 1, 'dropper': 1 } — Common redstone components and devices in Minecraft.
- **Navigation Kit:** { 'compass': 1, 'clock': 1, 'map': 1 } — A set of tools commonly used for navigation in Minecraft.
- **Transport System:** { 'minecart': 1, 'rail': 16, 'powered_rail': 6 } — Minecarts and tracks used to complete a transportation system.
- **Food Supplies:** { 'beef': 1, 'chicken': 1, 'porkchop': 1 } — Common animal meat food items in Minecraft.
- **Building Materials:** { 'stone_bricks': 4, 'glass': 4, 'iron_door': 1 } — Building materials commonly used for constructing doors, windows, and walls.
- **Storage System:** { 'hopper': 1, 'chest': 1, 'barrel': 1 } — Tools commonly used for storing items in Minecraft.

Each round of the experiment is conducted in a world generated with a random seed to ensure the generalizability of the results.

C.2 Boss Combat Task

We manually implemented three representative and challenging task scenarios: defeating the Elder Guardian in an ocean monument in the Overworld, defeating the Wither in the Nether, and defeating the Ender Dragon in the End. Defeating the Ender Dragon represents the final achievement in the game. Prior to each combat, agents were equipped with standardized combat resources, including a full set of diamond armor (validated as efficiently collectible through our resource collection experiments), bow and arrows, and some consumables. In

all experiments, the standardized combat resources remained consistent. A single LLM call initialized resource allocation, distributing equipment to each agent through a dictionary-based assignment system. Agents were then teleported to designated combat locations, where boss monsters and supporting entities (e.g., Guardians near the Elder Guardian, End Crystals for Ender Dragon healing) were spawned to ensure scenario complexity. During combat, real-time progress information (boss health, remaining End Crystals, etc.) was communicated through the chat system to support strategic planning. Task completion time was measured excluding initialization phases.

Evaluation metrics are defined as follows: health ratio = $\frac{1}{n} \sum_{i=1}^n \frac{h_i}{H_{\max}} \times 100\%$ (h_i : agent's remaining health, H_{\max} : agent's max health) and progress = $\frac{H_{\text{boss}} - h_{\text{boss}}}{H_{\text{boss}}} \times 100\%$ (h_{boss} : boss's remaining health, H_{boss} : boss's max health).

C.3 Adversarial PVP Task

Similar to the Boss Combat Task, in this task, agents were provided with combat resources. Results were recorded when one team of agents was entirely defeated. After multiple experiments, victory rates and other relevant metrics were calculated. In order to promote fair confrontation, we give each team exactly the same initial supplies. Here is an example of initial inventory given to an agent : { 'wooden_sword': 1, 'diamond_helmet': 1, 'diamond_chestplate': 1, 'diamond_leggings': 1, 'diamond_boots': 1, 'bow': 1, 'arrow': 200, 'golden_apple': 20 }

C.4 Human-Agent Interaction

This section presents examples of human-agent interactions in dynamic environments, highlighting how agents and human players collaborate in various tasks.

Scenario 1: Human-Agent Collaboration in Resource Collection Tasks

Agent Steve's Environment Information:

```
{
  "time": "day",
  "health": 20,
  "hunger": 20,
  "position": "(-223, 60, -159)",
  "equipment": [
    null,
    null,
    null,
    null,
```

```

    "crafting_table",
    null
],
"inventory": {
    "crafting_table": 1
},
"nearbyBlocks": [
    "dirt",
    "grass_block",
    "oak_log",
    "oak_leaves"
],
"nearbyEntities": "pig",
"nearbyPlayers": ["Alex", "Notch"]
}

```

Human Player's Chat Message:

'Hey Steve, I've got some beef, can you hunt a pig for obtaining porkchops?'

Agent Steve's Planning Action:

```

{
    "skill": "obtainItem(bot, 10, \'porkchop\')",
    "interrupt": false,
    "reason": "Following the human player's request to hunt a pig for obtaining porkchops. Since there are pigs nearby, I will proceed with hunting to gather porkchops."
}

```

Scenario 2: Human Player Directing Agents for Combat Tasks

Agent Steve's Environment Information:

```

{
    "time": "day",
    "health": 1.2,
    "hunger": 17,
    "position": "(6, 66, 13)",
    "equipment": [
        "diamond_helmet",
        "diamond_chestplate",
        "diamond_leggings",
        "diamond_boots",
        "bow",
        null
    ],
    "inventory": {
        "arrow": 189,
        "golden_apple": 4,
        "wooden_sword": 1,
        "bow": 1
    },
    "nearbyBlocks": [
        "end_stone",
        "bedrock"
    ],
    "nearbyEntities": "ender_dragon",
    "nearbyPlayers": [
        "Steve",
        "Notch",
        "Jeb"
    ]
}

```

```

}
```

Human Player's Chat Message:

'Steve, you are in grave danger. Cease your attack immediately and prepare to restore health!'

Agent Steve's Planning Action:

```

{
    "skill": "consumeItem(bot, \'golden_apple\', false)",
    "interrupt": true,
    "reason": "My health is critically low at 1.2, and I need to restore it immediately to continue fighting the ender_dragon effectively. I will follow the human player's advice and prioritize my health."
}

```