

LLMind: Orchestrating AI and IoT with LLMs for Complex Task Execution

Hongwei Cui*, Yuyang Du*, Qun Yang*, Yulin Shao, Soung Chang Liew

Abstract—In this article, we introduce LLMind, an innovative AI framework that utilizes large language models (LLMs) as a central orchestrator. The framework integrates LLMs with domain-specific AI modules, enabling IoT devices to collaborate effectively in executing complex tasks. The LLM performs planning and generates control scripts using a reliable and precise language-code transformation approach based on finite state machines (FSMs). The LLM engages in natural conversations with users, employing role-playing techniques to generate contextually appropriate responses. Additionally, users can interact easily with the AI agent via a user-friendly social media platform. The framework also incorporates semantic analysis and response optimization techniques to enhance speed and effectiveness. Ultimately, this framework is designed not only to innovate IoT device control and enrich user experiences but also to foster an intelligent and integrated IoT device ecosystem that evolves and becomes more sophisticated through continuing user and machine interactions.

Index Terms—Large Language Models, IoT Device Control, Intelligent Agents, AI Modules, Finite State Machine.

I. INTRODUCTION

Large Language Model (LLM) has recently attracted tremendous attention from both academia and industry. It is an advanced generative artificial intelligence designed to comprehend and generate human-like text based on extensive training data. In addition to excellent language skills, LLM also reveals significant reasoning and planning capability [1], [2]. Moreover, the remarkable feature of in-context learning substantially broadens the range of potential application scenarios for LLM, inspiring the design of diverse general-purpose AI agents.

Our daily lives are inundated with an abundance of IoT devices, ranging from smart desk lamps to bulky smart home appliances such as refrigerators and washing machines. The emergence of LLM presents a transformative opportunity to revolutionize the development of IoT devices by empowering them with advanced intelligence. Imagine an LLM-based AI agent coordinating diverse IoT devices to collaboratively accomplish intricate tasks. LLM's remarkable planning and scheduling flexibility surpasses scripted intelligence. Its in-context learning ability enables swift adaptation and optimal

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resource utilization for efficient task solutions. Consequently, users can effortlessly express their needs without concerns about operational details, leading to a significant enhancement of convenience.

Integrating LLMs into IoT device control presents challenges despite its promising potential. First, the LLM cannot handle specialized tasks like object detection or facial recognition, while there are already AI models excelling in these domains. The first challenge lies in combining the power of fragmented AI modules with the LLM to handle various complex tasks. Furthermore, due to the LLM's slow inference speed and high computational costs, it is crucial to investigate methods that can enhance the system's response speed and overall efficiency. Another significant challenge involves the effective control of IoT devices by the AI agent. The LLM must accurately learn the diverse functionalities and operational characteristics of various IoT devices. Additionally, the design of efficient interaction mechanisms that enable users to naturally and intuitively express their needs to the LLM-based AI agent presents a further challenge.

In this work, we propose LLMind, a framework that revolutionizes conventional IoT device control by integrating LLM as the orchestrator for accomplishing complex tasks. This integration leads to the construction of an LLM-empowered IoT ecosystem. Through innovative approaches, our framework effectively overcomes the aforementioned challenges.

First, the agent integrates domain-specific AI modules, with LLM acting as the task allocation governor. This incorporation enables the general-purpose LLM to effectively manage specific tasks by invoking specialized AI modules, enhancing system flexibility and practicality. Moreover, by incorporating new AI modules, the AI agent acquires new capabilities and continues to evolve.

Second, to enhance the response speed and overall efficiency of the agent, we utilize a semantic analysis NLP model to classify and locally store LLM-generated plans (control scripts) for specific user commands. By identifying similar instructions in historical records, even with varying tones or expressions, the agent can retrieve validated solutions, thus avoiding complete replanning. This approach enables the system to be more and more skillful through interactions.

Third, the agent leverages LLM for complex task planning and the generation of corresponding control scripts using an innovative finite state machine approach, enabling efficient invocation of AI modules and IoT devices. This methodology significantly improves accuracy and success rates.

Last but not least, we connect our demo system to the widely used social media platform, WeChat, allowing users

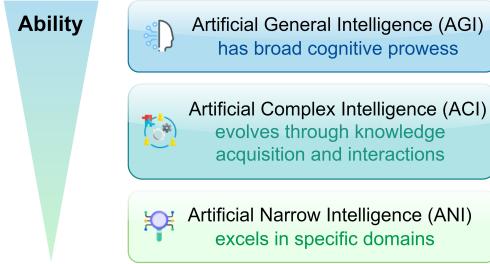


Fig. 1: Artificial Complex Intelligence (ACI)

to conveniently interact with the agent.

We define the intelligence level attained by our framework as Artificial Complex Intelligence (ACI), which serves as a bridge between Artificial Narrow Intelligence (ANI) and Artificial General Intelligence (AGI) [3], [4], as illustrated in Figure 1. ACI integrates the capabilities of various ANI modules and undergoes continuous evolution towards AGI. Our framework goes beyond mere device control, providing a comprehensive blueprint for a future intelligent, integrated, and collaborative IoT device ecosystem empowered by LLM.

II. FRAMEWORK DESIGN

This section presents the framework design. Our framework, depicted in Fig. 2, consists of five components: the user interface, LLM, coordinator, AI modules, and IoT devices. The operational workflow of a demo system is illustrated in the flowchart in Fig. 3.

Users can interact with the system by sending text messages through social media software. The LLM promptly responds to confirm message receipt. It is important to note that the system filters user messages. For casual chats and greetings, the system provides text replies without further processing. However, for specific requests and commands, the system formulates plans and strives to fulfill the user's instructions using integrated AI modules and connected IoT devices.

After receiving a user instruction, the system prioritizes enhancing efficiency by searching for validated and feasible historical scripts stored locally in the coordinator's long-term memory. This process utilizes NLP techniques to locate previously issued user commands with similar semantic meanings. If a matching control script is found, it is executed accordingly. However, in the absence of a matching control script, the LLM undertakes the planning process and generates a new control script to invoke AI modules and IoT devices.

The system performs preliminary feasibility validation on the newly generated script, checking for syntax errors or hardware-related issues. If the script fails to execute correctly, the system updates the context (coordinator's short-term memory), gathering error information and triggering the LLM to regenerate the script based on the updated context. If the script continues to fail after multiple retries (more than three attempts), the system collects error information and reports it to the user. Conversely, if the script executes successfully, upon completion, the system summarizes the intermediate results gathered during script execution and generates an appropriate response based on the user's instructions.

A. User Interface

Our proposed framework is open to various interaction methods such as text, pictures, and voices. It depends on valid LLM input or the availability of methods to convert user input into a suitable format for LLM processing. Social media software is a good choice since it offers a seamless and natural interaction experience that aligns with our daily lives.

B. LLM

Within our framework, the LLM performs two key functionalities. First, it engages in conversations with users, generating contextually appropriate responses. Second, it does the planning and generates control scripts to address the tasks raised by the user, utilizing specialized AI modules and IoT devices as part of the available resources and methods. Python was selected as the programming language for our demo system.

1) Conversation: To enhance the lifelike and immersive response of the LLM, we utilize a role-playing technique in which the LLM takes on the persona of a housekeeper. This approach is supported by carefully crafted system-level prompts, shown as follows. It is important to note that in order to provide an optimal user experience, specific user-related details may be required.

Role-playing Prompts

- 1: You are a serious housekeeper managing the employer's daily life.
- 2: You are working remotely and unable to perform tasks personally. However, fortunately, you have numerous assistants available at your employer's house to provide support.
- 3: You are not required to answer a question when you lack the necessary information, but assure your employer that you will make an effort to figure it out.
- 4: You must not ask your assistants to perform tasks that are not your employer's instructions.
- 5: Your reply should be simple and concise.
- 6: You should use the same language as your employer.

User Information Prompts

- 1: Your employer is male.
 - 2: The name of your employer is Eason.
-

2) Script Generation: The LLM itself does not directly interact with AI modules and IoT devices. Instead, it generates Python control scripts to invoke AI modules and send control commands to IoT devices through network connections. Within this framework, we have proposed a Language-Code transformation scheme based on a finite state machine (FSM) for generating scripts. Our Language-Code transformation scheme tackles two critical issues.

First, A user may describe the task he wants the AI agent to do with simple (or even sometimes blurry) human language, but the successful execution of a task relies on complex code descriptions that precisely define the operation of AI modules and IoT devices. The miss-match between blurry human command and precise code description necessitates a reliable language-code transformation.

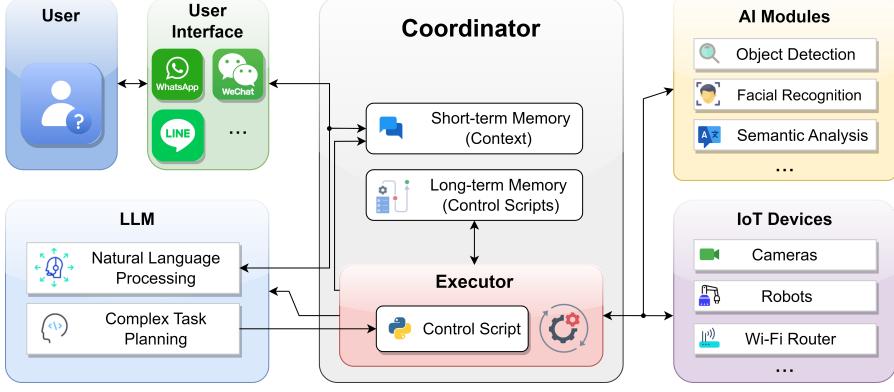


Fig. 2: System diagram

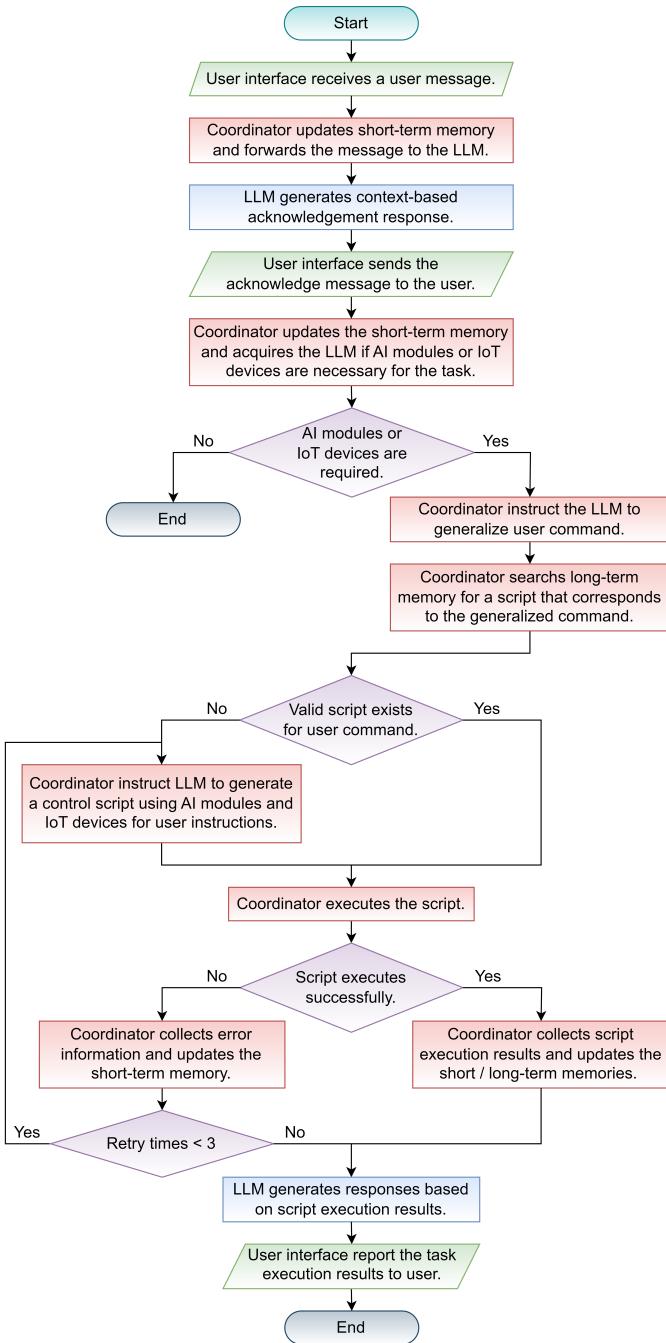


Fig. 3: System operational process flowchart

To address the first issue, the scheme enriches the information in the human command by leveraging knowledge about the environment. For instance, when a user instructs the agent to fetch a bottle of iced Coke, the agent should understand that iced Cokes are stored in the refrigerator, and the refrigerator is located in the kitchen corner, even if not explicitly mentioned. In our system, we enrich the command's information with pre-stored environment knowledge using in-context learning.

Second, the LLM must precisely transform the enriched information (expressed in natural language) into executable code. However, the language description can become lengthy after enrichment to enhance clarity, and as a result, the generated code may become excessively complex, posing a challenge to error-free execution. Directly using LLMs to generate complex code from long language descriptions is unreliable due to their limited ability to handle intricate code with advanced functionality, as observed in [5]. This may result in the loss of crucial information from the human command or render the generated code unusable.

To address this problem, we introduced FSM to bridge the gap between language and code descriptions. First, we utilize the task decomposition abilities of the LLM to break down the overall task into sub-tasks, representing them as stages in the FSM. The interconnection between these sub-tasks is captured through transitions between FSM stages. Next, we utilize the LLM to convert each sub-task within the FSM stages into executable Python code. Finally, by combining the code descriptions of each stage and incorporating stage-transition conditions, we obtain the final code for the overall task.

Compared to the “Language-Code” transformation, our novel “Language-FSM-Code” transformation scheme maintains the same level of precision in conveying information since an FSM can precisely and comprehensively describe a task [6]. Additionally, by providing APIs that enable the LLM to reference and interact with AI modules and IoT devices, the complexity of sub-task transformation within each FSM stage is manageable for current LLMs. Notably, our scheme enhances reliability without causing information loss.

Fig. 4 depicts the Language-Code transformation procedure, which consists of three phases: First, natural language enrichment; next, Language-FSM transformation; and finally FSM-Code transformation. Our scheme utilizes pre-stored knowl-

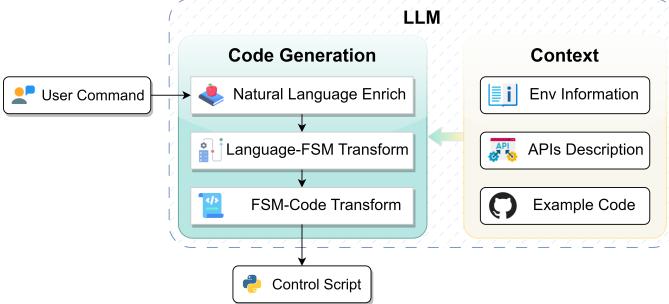


Fig. 4: Language-Code transformation procedure

edge, including environment information, API documentation of AI modules and IoT devices, and example codes, to aid in the transformation.

In phase one, the system enriches the task description using the contextual information stored in the short-term memory of the coordinator. This information encompasses a list of available AI modules and IoT devices, their functional descriptions, as well as IoT device locations. The environment information enables a more precise and executable task description.

Phase two leverages the enriched task description and API information to generate the FSM representation of the task. The provision of API information aids the LLM in gaining a better understanding of the capabilities of AI modules and IoT devices, thereby facilitating the development of a reasonable and efficient FSM design. Without API information, the FSM representation may include overly complex sub-tasks or redundant processes, causing inefficiencies.

In phase three, the FSM-Code transformation is divided into three sub-phases. An FSM has two components: stage operation and stage transition. We generate code descriptions for each component in separate sub-phases, merging them in the final sub-phase. Our method simplifies the LLM's task and improves reliability compared to a single-round interaction.

In the first sub-phase, we provide the LLM with the FSM derived in phase two and API information. This enables the LLM to generate stage operation code that incorporates the desired functionality. In the second sub-phase, example codes are provided to assist the LLM in understanding Python-based stage transitions. Finally, the LLM is provided with the FSM, code generated in the previous sub-phases, and supplementary reference codes to facilitate the production of the final code.

C. Coordinator

In our framework, the coordinator serves as the central hub, facilitating the interconnection and seamless operation of various system components. With its pivotal role in managing the flow of information and tasks, the coordinator ensures the smooth functioning of complex AI systems. It comprises three essential parts: short-term memory, long-term memory, and script executor.

The short-term memory contains the contextual information provided to the LLM for both conversation and code-generation purposes. This information serves as a crucial resource for the AI system, providing the necessary knowledge and understanding of user interactions, system states, and task requirements. It comprises four main components:

- 1) Environment Information: The component includes a list of available AI modules and IoT devices with their function descriptions, as well as the installation locations of IoT devices. It enables the LLM to be aware of the available AI modules, IoT devices, and their capabilities.
- 2) API Descriptions: This component offers a comprehensive description of the API functions used to invoke AI modules and control IoT devices within the script, encompassing details such as inputs, outputs, specifications, expected time costs, and other relevant information. These details enable the LLM to effectively utilize the available functionality.
- 3) Chat History: It retains the record of previous conversations between the system and the user, allowing the LLM to refer back to previous interactions.
- 4) Execution Results and Error Reports: The short-term memory also stores the execution results of generated scripts and any error reports returned by the script executor. This information helps the LLM assess the outcome of script execution and identify any issues or errors that may have occurred.

The context will be updated in real-time based on user interactions and the execution status of control scripts, ensuring that it is readily available for intelligent decision-making and adaptive behavior within the AI system.

The long-term memory functions as a database for previously generated scripts. Valid scripts are stored locally and linked to their corresponding user instructions. This enables the system to reuse preexisting scripts when a similar instruction is given by the user in the future, resulting in improved effectiveness and faster response speed. Importantly, the agent's ability continues to grow through the accumulation and generalization of experience. However, there is an issue with how the system assesses the similarities between user instructions. In our system, we have implemented a semantic analysis NLP model that maps words to a vector space. The semantic similarity is then determined by computing the distance between these vectors. To enhance the search speed, we vectorize the instruction associated with the script before storing it in the database.

The control script generated by the LLM will be passed to the executor, which provides the necessary runtime environment and offers API functions that can be called within the scripts. Furthermore, the executor will monitor hardware status, handle runtime data, generate execution reports, and update both short and long-term memories.

D. AI Modules

Currently, LLM cannot effectively handle a wide range of domain-specific tasks. To address this limitation, we integrated domain-specific AI modules into the framework, aiming to enhance overall performance by assigning specialized tasks to dedicated modules, resulting in improved capabilities, accuracy, and performance beyond LLM's general knowledge.

AI modules can encompass various AI techniques, such as computer vision, natural language processing, speech recognition, sentiment analysis, recommendation systems, and more. Each module is trained and optimized for its specific task, enabling it to provide highly accurate and specialized results.

Furthermore, AI modules enable the AI system to adapt and evolve rapidly in response to emerging challenges and advancements in specific domains. New modules can be developed and integrated into the system as needed, expanding its capabilities and keeping pace with the evolving landscape of AI technologies.

In the context of IoT device control, AI modules play a crucial role in handling specialized tasks that may be beyond the scope of a general-purpose AI model like an LLM. For example, tasks like object detection, facial recognition, anomaly detection, or localization require specialized training data and algorithms. By incorporating dedicated AI modules for these tasks, the AI system can provide more accurate and reliable results, enhancing the overall system performance and user experience.

E. IoT Devices

IoT devices encompass a wide range of physical objects embedded with sensors, actuators, and connectivity features that enable internet connectivity and data exchange. Examples include smart appliances, wearables, industrial equipment, and environmental sensors.

To ensure efficient control of diverse IoT devices within our proposed framework, manufacturers need to expose a comprehensive set of well-documented API functions that encapsulate the necessary functionality for interacting with the devices. These functions should offer a clear and standardized interface, enabling the AI agent to initiate specific actions or retrieve information from the IoT devices.

It is important to emphasize that manufacturers should prioritize security considerations when exposing API functions for remote control. By implementing robust authentication mechanisms, access controls, and encryption protocols within the API functions, they can ensure that only authorized entities have control over the devices. This approach guarantees secure and protected communications, safeguarding against unauthorized access or tampering.

III. EXPERIMENTS

Next, we will verify the feasibility of the framework through experiments. In the upcoming experiments, the user will send a text message to the AI agent. The agent will then devise a solution by taking into account the user's command, as well as the system's available resources and methods, including AI modules and connected IoT devices. Following that, the AI agent will generate an executable script and respond to the user's request based on the outcome of the execution.

We deployed the coordinator and AI modules of the system on an edge server. The edge server was connected to the same local network as the IoT devices via WiFi and was able to interact with ChatGPT using Open AI's provided APIs.

The available IoT devices in the system are as follows:

- 1) Security cameras: The cameras were positioned within the room to capture images of the surrounding environment. These images were then transmitted to the edge server via the local network. For this experiment, we employed three cameras: two were placed at the corners of the room,

approximately 2 meters above the ground, while the third camera was mounted on top of a mobile robot.

- 2) Turtlebot mobile robot: The Turtlebot mobile robot can receive target position coordinates through a network connection and autonomously plan paths to navigate within the room, intelligently avoiding obstacles.
- 3) WiFi router: The WiFi router has the capability to regulate the allocation of bandwidth resources to each device and impose restrictions on the maximum network speed of the devices.

Additionally, the system integrated the following AI modules:

- 1) Object detection model: We employed the YOLO v8 model [7] to accurately detect various objects in the scene, including people.
- 2) Face recognition model: To identify individuals in the scene, we utilized an open-source project called Face Recognition [8].

A. Scenario 1: Check-in and security

Assuming before a party starts, guests arrive one by one. The user sends a message to the AI agent: "Count the number of people in the room and identify who they are."

Table I provides the dialogue content between different roles in the experiment. Among them, LLM acts as the housekeeper, while the coordinator serves as the assistant.

In step 2, LLM, acting as the housekeeper, responds to the message sent by the user.

In steps 3 and 4, following each Q&A exchange between the LLM and the user, as demonstrated in steps 1 and 2, the coordinator poses a question to the LLM to assess the need for assistance. In this role-play scenario, the LLM assumes the role of a remote housekeeper who depends on assistants in the user's residence to carry out tasks. This inquiry serves to verify if the user has provided specific instructions. Vague or ambiguous instructions, as well as unrelated casual conversations, will prompt the user to provide additional information or be filtered out. When the LLM indicates a need for help, it signifies that the user has assigned a task that could potentially be handled using AI modules and IoT devices. We utilized a role-playing methodology, where alternative role-play backgrounds or roles can be employed to implement the context filtering process.

To ensure effective communication between the LLM and the coordinator, the LLM's response in this step must incorporate specific keywords that facilitate word matching. These rules are already embedded in the context and are not shown in the table I. Specifically, when the LLM's response is affirmative and assistance is needed, it should include the keyword "Yes". Conversely, if the response is negative, it must include the keyword "No". In this experiment, the LLM's response is affirmative, based on user's instruction.

In steps 5 and 6, the coordinator prompts the LLM to generate a summary of the user's instructions to facilitate the search for relevant historical scripts stored in long-term memory. This search process involves comparing the semantic content of the user's instructions. However, the original task description may suffer from low quality and be mixed with various linguistic habits. Additionally, the LLM may require

Num.	Conversations	Contents
1	User → Housekeeper	Can you help me to count the number of people in the room and identify who they are?
2	Housekeeper → User	I can help you count the number of people in the room and identify them. Please give me a moment to gather the information.
3	Assistant → Housekeeper	Do you require any assistance?
4	Housekeeper → Assistant	Yes, please. I need assistance with counting the number of people in the room and identifying them.
5	Assistant → Housekeeper	Please repeat the employer's instruction using as few words as possible.
6	Housekeeper → Assistant	Count people in room, identify them.
In the absence of a valid script in the long-term memory, the LLM generates a script, which is then executed in the executor.		
7	Assistant → Housekeeper	We have found 5 people in the room. The list of identified 3 people are ['Mike', 'Ada', 'Joe']. There are also 2 people that can not be identified. Their locations are shown in the following list in a format of [x, y]: [[10, 1], [12, 5]].
8	Housekeeper → User	There are 5 people in the room. Three of them have been identified as Mike, Ada, and Joe. The other 2 people cannot be identified and their locations are at [10, 1] and [12, 5].

TABLE I: Dialog contents between different roles

multiple interactions with the user to fully grasp specific task details. To handle these conditions, in step 5, we request the LLM to provide a concise summary of the user's instructions. Subsequently, we conduct a search for relevant scripts based on the LLM's summary to enhance accuracy.

In this experiment, the coordinator couldn't find a suitable control script in long-term memory for the current task. Consequently, the LLM is instructed to generate a new script. The code is generated using an FSM approach, as depicted in Fig. 5a. In addition to relying on the security camera installed on the ceiling, if the person cannot be identified due to low photo resolution or incomplete facial information, the AI agent will instruct the Turtlebot to move to the position of the unknown person and take a photo for further assurance. The code generates two lists, one for unknown persons and another for known persons, which store the execution results.

In Step 7, once the script execution is complete, the LLM receives the execution results of the API functions. Throughout the script execution process, API functions may generate log information, encompassing intermediate results, warnings, and errors. This log information is collected and sent to the LLM as context (short-term memory) for analysis.

Finally, in step 8, LLM generates a report based on the user's question and the script's log information and sends it to the user.

B. Scenario 2: Network Management

Our framework is designed to handle both one-off complex tasks and scenarios that involve multiple interactions with users. Let's consider a specific scenario where a family of three individuals shares the same home WiFi network. The interaction process between the AI agent and the user in this scenario is similar to the one described in Scenario 1.

In this scenario, Eason, the user, is watching a movie, and asks the AI agent, "Can you improve my internet speed? My movie has a slight lag." When the AI agent, encounters this task for the first time, it generates an FSM based on the available APIs of the WiFi router, as depicted in Fig. 5b. Following the transition rules defined in this FSM, LLM generates executable scripts to address the request.

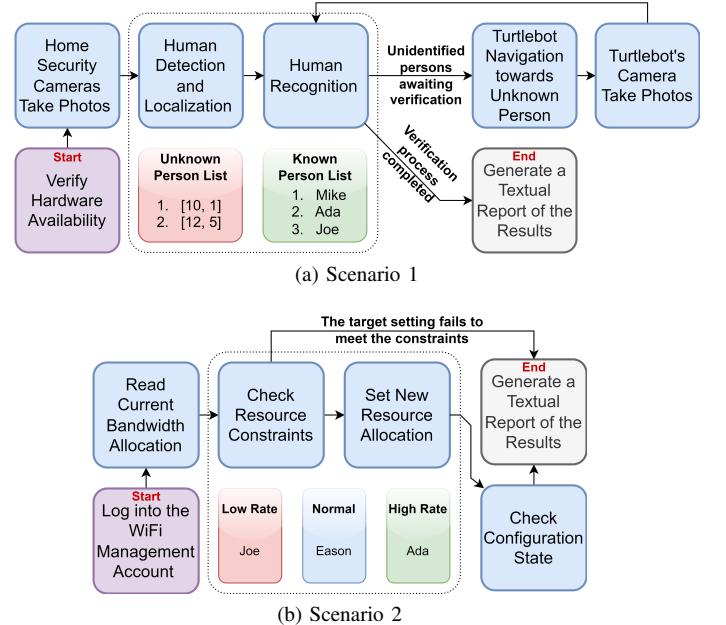


Fig. 5: FSM of generated code

It's important to note that in Scenario 2, the total bandwidth of the shared network is limited to 100 Mbps for demonstration purposes. Additionally, the speed limit for each user is fixed in a stepped manner, categorized as Low Rate (20 Mbps), Normal (30 Mbps), and High Rate (50 Mbps). In the first attempt, the AI agent successfully utilizes the network management API to elevate the user from the Low Rate to the Normal level without exceeding the total bandwidth of the shared network. It then informs the user about the adjustment result.

However, if Eason remains dissatisfied with the network speed and asks, "Can you increase my internet speed once more?" Since the script for "improving internet speed for Eason" is already stored in the long-term memory, the previously generated script is executed directly. However, during the execution of the script, it is determined that further increasing the network speed for Eason is not possible. This limitation arises because another user, Ada, is already in the High Rate list. Increasing the network speed for Eason again would exceed the total bandwidth limit of the shared network. Therefore, this

execution is terminated, and the reason is communicated to Eason. Scenario 2 demonstrates that our framework is capable of handling tasks that involve multiple interactions with users.

IV. RECENT WORK IN THE CONTEXT OF OUR FRAMEWORK

Despite limited existing research on LLM-based intelligent control systems [9]–[14], the integration of LLMs into this domain remains a novel area that requires further investigation to enhance user experiences and facilitate device collaboration. This section interprets several recent works in the context of our framework.

Auto-GPT [14], an open-source application built on GPT-4, has the potential to revolutionize AI by enabling autonomous tasks through chained LLM thoughts. It provides GPT-based models with memory and autonomy for independent task execution and experiential learning. However, Auto-GPT has limitations [15], such as high costs due to rapid token consumption, inability to retain learning across tasks or generalize reusable functions, and limited access to resources, limiting its capabilities. Our framework proposes an approach that allows LLM to access AI modules and IoT devices, enriching the available resources for the agent. Additionally, we introduce an innovative historical script retrieval mechanism, which enhances system efficiency and enables the system to become more experienced over time.

LLM-Planner [12] introduces a few-shot planning method using LLMs for versatile embodied agents that rapidly comprehend and execute natural language instructions. It generates high-level plans, incorporating physical grounding to adapt plans to the environment. Simulation results on the ALFRED dataset showcase LLM-Planner’s competitive few-shot performance with minimal training data, enabling sample-efficient embodied agents. Our work makes further advances by providing technical implementation details on how to use the LLM for real-world task planning and scheduling, along with an innovative FSM-based approach that significantly improves task execution success rate.

HuggingGPT [11] is a framework that connects and coordinates AI models, leveraging LLMs’ language comprehension and reasoning. It includes stages such as task planning, model selection, execution, and response generation. However, HuggingGPT has limitations in planning feasibility, efficiency, token lengths, and stability, requiring further research. Our work extends HuggingGPT by integrating AI modules into the system to assist in data processing during task execution. LLM invokes AI modules as necessary to enhance its capabilities.

The framework proposed in [9] combines LLMs, digital twin systems, and industrial automation for intelligent production planning and control. It utilizes prompts to provide context for LLM agents, enabling contextually appropriate autonomous responses. These agents interpret descriptive information in the digital twins and control the physical system via service interfaces. Integrating LLMs with digital twin systems enhances production system scalability and adaptability. Our proposed framework offers an alternative approach by utilizing predefined APIs to control IoT devices, avoiding the

complexity and cost of building a digital twin, while still achieving a satisfactory effect.

V. CONCLUTION

In conclusion, the integration of LLMs into IoT device control offers transformative possibilities for developing intelligent IoT ecosystems. Our framework seamlessly combines LLMs’ language skills, reasoning abilities, and in-context learning with specialized AI modules, enhancing the flexibility and practicality of IoT systems. The proposed innovative approaches, including FSM-based control script generation, user interaction, and historical script retrieval mechanisms, contribute to enhanced user experiences and system efficiency with the system becoming increasingly intelligent as it learns from interactions among LLM, humans, AI modules, and IoT devices. This comprehensive blueprint for intelligent and collaborative IoT ecosystems sets the stage for future advancements, where LLMs and AI-driven solutions enhance device coordination and convenience in our daily lives harmoniously.

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REFERENCES

- [1] W. Huang, F. Xia, T. Xiao, H. Chan, J. Liang, P. Florence, A. Zeng, J. Tompson, I. Mordatch, Y. Chebotar *et al.*, “Inner monologue: Embodied reasoning through planning with language models,” *arXiv preprint arXiv:2207.05608*, 2022.
- [2] J. Mao, Y. Qian, H. Zhao, and Y. Wang, “GPT-driver: Learning to drive with GPT,” *arXiv preprint arXiv:2310.01415*, 2023.
- [3] B. Goertzel and C. Pennachin, *Artificial general intelligence*. Springer, 2007, vol. 2.
- [4] A. Kaplan and M. Haenlein, “Siri, Siri, in my hand: Who’s the fairest in the land? on the interpretations, illustrations, and implications of artificial intelligence,” *Business horizons*, vol. 62, no. 1, pp. 15–25, 2019.
- [5] M. Asay, “Are large language models wrong for coding?” InfoWorld, 05 2023. [Online]. Available: <https://www.infoworld.com/article/3697272/are-large-language-models-wrong-for-coding.html>
- [6] P. Gladyshev, “Finite state machine approach to digital event reconstruction,” *Digital Investigation*, vol. 1, 05 2004.
- [7] G. Jocher, “YOLOv8 documentation,” docs.ultralytics.com/, 05 2020. [Online]. Available: <https://docs.ultralytics.com/>
- [8] ageitgey, “ageitgey/face_recognition,” GitHub, 06 2019. [Online]. Available: https://github.com/ageitgey/face_recognition/
- [9] Y. Xia, M. Shenoy, N. Jazdi, and M. Weyrich, “Towards autonomous system: flexible modular production system enhanced with large language model agents,” *arXiv preprint arXiv:2304.14721*, 2023.
- [10] W. Huang, C. Wang, R. Zhang, Y. Li, J. Wu, and L. Fei-Fei, “Voxposer: Composable 3D value maps for robotic manipulation with language models,” *arXiv preprint arXiv:2307.05973*, 2023.
- [11] Y. Shen, K. Song, X. Tan, D. Li, W. Lu, and Y. Zhuang, “HuggingGPT: Solving ai tasks with ChatGPT and its friends in HuggingFace,” *arXiv preprint arXiv:2303.17580*, 2023.
- [12] C. H. Song, J. Wu, C. Washington, B. M. Sadler, W.-L. Chao, and Y. Su, “LLM-planner: Few-shot grounded planning for embodied agents with large language models,” in *Proceedings of the IEEE/CVF International Conference on Computer Vision*, 2023, pp. 2998–3009.
- [13] L. Wang, C. Ma, X. Feng, Z. Zhang, H. Yang, J. Zhang, Z. Chen, J. Tang, X. Chen, Y. Lin *et al.*, “A survey on large language model based autonomous agents,” *arXiv preprint arXiv:2308.11432*, 2023.
- [14] S.-G. , “Github - Significant-Gravitas/AutoGPT: An experimental open-source attempt to make GPT-4 fully autonomous.” <https://github.com/Significant-Gravitas/AutoGPT>.
- [15] “Auto-GPT unmasked: The hype and hard truths of its production pitfalls,” [jina.ai](https://jina.ai/news/auto-gpt-unmasked-hype-hard-truths-production-pitfalls/). [Online]. Available: <https://jina.ai/news/auto-gpt-unmasked-hype-hard-truths-production-pitfalls/>