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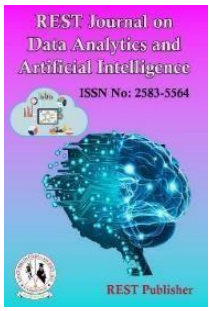

Applying Chat GPT to Robotics: Prompt Engineering and Model Capabilities

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Abstract: *This paper presents an experimental investigation into the use of ChatGPT for robotics applications. It explores prompt engineering strategies and the development of a function library to enable ChatGPT to adapt to various robotic tasks and platforms. The study evaluates ChatGPT's abilities in code synthesis, dialog management, and task execution within robotic systems.*

1. INTRODUCTION

The swift evolution within natural language understanding has propelled the emergence of expansive pretrained language frameworks. Early exemplars like BERT, GPT variants, and Codex have laid the foundation for groundbreaking achievements in text synthesis, automated translation, and programming generation. More recent architectures such as LLaMa and Mistral have further amplified these capabilities, influencing a broad spectrum of computational tasks. Among the latest innovations is ChatGPT, a generative conversational agent fine-tuned through reinforcement learning from human evaluators, distinguished by its interactive dialogic proficiency that integrates textual generation with code creation [1].

Distinct from predominantly text-centered systems, robotic platforms necessitate comprehensive comprehension of physical laws, contextual awareness of surroundings, and proficiency in executing tangible manipulations. To effectively operate within these environments, generative robotics models must encompass enriched commonsense reasoning, detailed world modeling, and the aptitude for engaging users in dialogues that translate instructions into feasible physical operations [2]. These requirements extend beyond the traditional remit of language models, which are primarily oriented toward semantic interpretation.

Contemporary endeavors integrating linguistic models with robotic systems have generally concentrated on embedding language tokens, leveraging large language model features, and incorporating multimodal data for specialized devices or scenarios. Applications encompass visually grounded navigation, human-robot linguistic interaction, and control of manipulation tasks mediated by combined visual and linguistic input [3]. Nevertheless, most existing methodologies suffer from constrained scope and rigid functionality sets, often lacking the adaptability to support iterative user feedback and dynamic behavior adjustments [4].

Large language models have also demonstrated potential in zero-shot robotics contexts, particularly for abstract agent planning or programmatic code production. These initial findings motivated an exploration of ChatGPT's utility as a multi-faceted tool for robotic applications, capitalizing on its natural language fluency, code generation aptitude, and extended dialog context retention. This combination enables flexible user engagement and on-the-fly behavior refinement. Moreover, ChatGPT's broad mathematical, geometric, and commonsense knowledge base enhances its capacity for interpreting and reasoning about the physical domain relative to earlier LLM- centric approaches focused on fixed task functions [5].

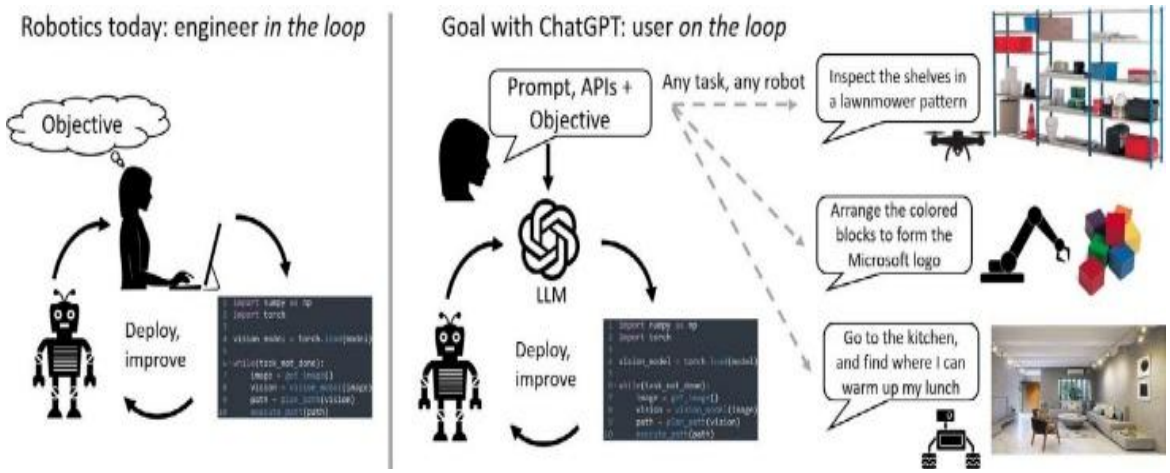

FIGURE 1. Typical robotic workflows require a domain expert to script control logic manually. The proposed approach envisions a scenario where users with minimal technical expertise interact directly with a language-driven interface, issuing high- level commands deployable across diverse robotic platforms and applications.

The present work introduces a framework showcasing Chat- GPT's applicability to robotics, predicated upon the development of an abstracted function interface. Considering the diversity inherent in robotic platforms, environments, and available toolkits, a plethora of libraries and APIs exist. Rather than tailoring the language model to generate platform- specific code—which demands extensive retraining—a simplified high-level function library is designed. This abstraction enables the conversational model to interpret user intentions through dialogue and translate them into ordered sequences of these generalized function invocations, which subsequently map to underlying platform APIs. Alongside, guidance on prompt engineering is provided to optimize task- solving efficacy [6].

Recent multimodal large-scale models have achieved impressive results by unifying visual and linguistic information representations, empowering tasks such as visual question answering and image captioning. While these are powerful capabilities, robotics applications typically require finer environmental comprehension, including precise object localization and spatial reasoning, which may necessitate domain- specialized models. This research assumes access to relevant environmental data through appropriate tooling, concentrating on evaluating how language models utilize such inputs to formulate sophisticated action plans and generate executable code.

Experimental results demonstrate ChatGPT's aptitude in addressing various robotic challenges in a zero-shot manner, adapting across multiple robot types and enabling iterative refinement via conversational feedback. Additionally, the study outlines current model constraints and proposes avenues for enhancement. Key contributions include:

- Presentation of a ChatGPT-based pipeline tailored for robotics, integrating techniques such as natural language dialogue, code generation prompting, XML annotations, and iterative reasoning, supported by a high-level function library for rapid intent parsing and code synthesis;
- Empirical evaluation of ChatGPT on a spectrum of robotics tasks encompassing mathematical calculations, logical reasoning, spatial transformations, and complex agent-based navigation and manipulation, with demonstrations in both simulation and real environments;
- Introduction of PromptCraft, an open collaborative plat- form facilitating community-driven refinement of prompt strategies and collective knowledge sharing in the robotics-LLM domain;
- Release of a simulation environment based on Microsoft AirSim augmented with ChatGPT integration, providing a foundational testbed for drone navigation experiments and further robotic scenario explorations.

Through this investigation, new pathways are anticipated for integrating conversational AI and robotic systems, fostering innovative interfaces that enhance intuitive human-machine collaboration. Comprehensive visual materials and demonstrations are available via the project website.

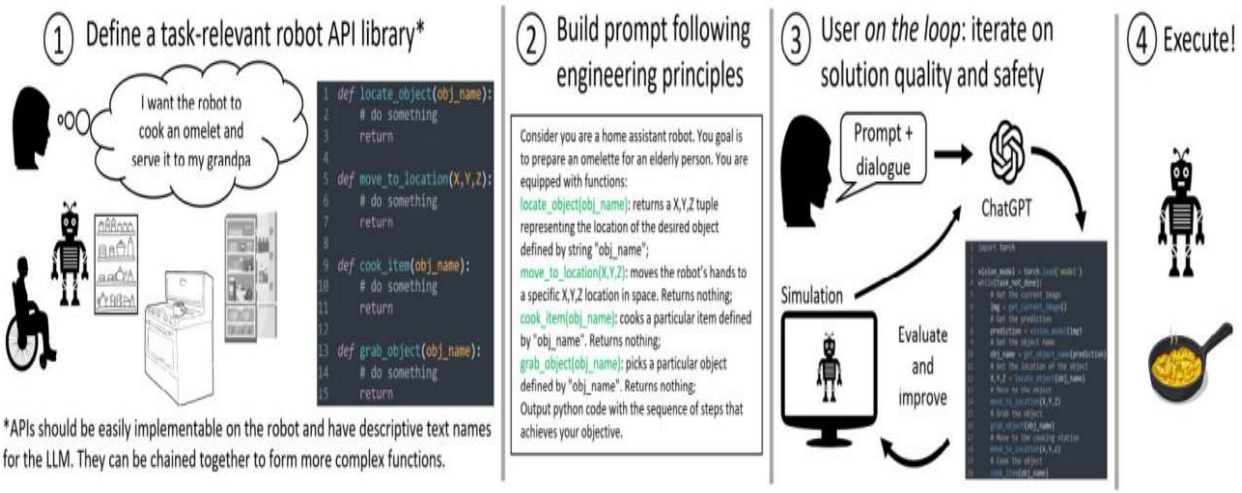

FIGURE 2. Illustration of the robotics development pipeline incorporating ChatGPT with continuous user oversight for assessing output correctness and operational safety.

*A. **Robotics API Library Design***

Robotics as a discipline benefits from a rich ecosystem of both proprietary and open-source libraries, addressing functions such as perception (object detection, segmentation), spatial mapping, motion planning, control algorithms, and grasping techniques. When clearly defined within prompts, these pre-existing capabilities become accessible for language model-driven task execution. It is imperative that function identifiers within the API are intuitively descriptive to facilitate semantic understanding and logical chaining by the model. High-level wrappers abstract away implementation specifics, for instance, a `locate_object(name)` function might interface with computer vision modules, while `navigate_to(x,y,z)` could invoke complex path planning integrated with collision avoidance. Enumerating these functions explicitly in prompts is essential to guide the model in constructing coherent action sequences adaptable to various platforms.

Effective prompt design may require decomposing APIs into modular subunits with explicit input-output specifications analogous to code documentation. Figure 3 exemplifies such an approach within a domestic culinary robotic context, illustrating how task sequencing corresponds to executable functions. Contrastive examples where API guidance is omitted or under- specified reveal tendencies toward unfocused or hallucinated model outputs, as documented in the Appendices.

Unlike inflexible symbolic AI frameworks with rigid object- function mappings, large language models possess the capacity to invent new abstractions and function definitions dynamically to suit novel problems. This property imparts robustness and adaptability to language-driven robotics solutions. Figure 4 demonstrates ChatGPT's facility to synthesize new APIs and integrate them with existing calls, facilitating problem resolution through iterative user collaboration.

```
fridge_location = locate_object("fridge")
bowl_location = locate_object("bowl")
pan_location = locate_object("pan")
stove_location = locate_object("stove")
oil_location = locate_object("oil")

# Start the omelette-making process
go_to_location(fridge_location)
pick_up("eggs")
go_to_location(bowl_location)
use_item("eggs")  # Crack eggs into the bowl
go_to_location(pan_location)
pick_up("pan")
use_item("pan")  # Place the pan on the stove
go_to_location("oil")
pick_up("oil")
go_to_location(pan_location)
use_item("oil")  # Pour oil into the pan
go_to_location("bowl")
pick_up("bowl")
go_to_location(pan_location)
use_item("bowl")  # Pour the egg mixture into the
    pan
go_to_location(stove_location)
use_item("stove")  # Turn on the stove
print("Enjoy your omelette!")
```

FIGURE 3. An exemplary prompt construction showcasing well- defined APIs for a home kitchen robot, explicitly detailing function signatures and task goals to enable precise model reasoning.

B. Explicit Task Context Specification

Providing a precise, comprehensive description of the robotic task and its operational context significantly improves response accuracy from the language model. This includes:

```
def get_ingredients():
    go_to_location(locate_object("fridge")) # Go
     to the fridge and get the eggs.
    pick_up("eggs")
    go_to_location(locate_object("bowl")) # Go to
     the counter and get the bowl.
    pick_up("bowl")
    use_item("eggs") # Crack the eggs into the
     bowl.
def heat_pan():
    go_to_location(locate_object("pan"))
    pick_up("pan")
    use_item("pan")  # Put the pan on the stove.
    go_to_location(locate_object("stove"))
    use_item("stove")  # Turn on the stove.
```

FIGURE 4. Illustration of dynamic API generation where ChatGPT extends initial function sets by creating novel abstractions, enhancing solution expressiveness beyond fixed libraries.

- **Constraints and requirements:** Detailing relevant task limits such as object weight, dimensions, or operational speed.
- **Environmental characteristics:** Describing spatial lay- outs, obstacle distributions, and other situational elements affecting task execution.
- **System state:** Reporting the current configuration and pose of the robot and associated objects.
- **Objectives:** Specifying measurable goals like assembly completion count or temporal deadlines.
- **Exemplars:** Providing illustrative task solutions or inter- action protocols to guide model responses.

If initial prompt information proves insufficient or model output is suboptimal, an iterative feedback mechanism using conversational corrections can be employed, whereby additional clarifications or constraints are supplied to refine subsequent responses. This method alleviates the need for exhaustive prompt redesigns.

2. CAPABILITIES OF CHATGPT IN ADDRESSING ROBOTICS CHALLENGES

This section explores the proficiency of ChatGPT in tackling a diverse array of robotics challenges. The evaluation spans from fundamental spatiotemporal reasoning tasks to complex real-world deployments involving aerial robots and manipulation systems [7]. Several notable proficiencies exhibited by ChatGPT throughout these assessments are discussed.

Despite ChatGPT's remarkable capabilities, caution regarding safety during real-world physical robotic applications remains paramount. As depicted in Fig. 2, maintaining human oversight is critical to detect and manage any unforeseen behaviors produced by the model. Moreover, leveraging simulation environments proves advantageous for validating performance prior to actual deployment. It is important to recognize that ChatGPT functions as an assistive tool to enhance human capabilities rather than as a fully autonomous robotic control system. Appendix B includes all initial prompts employed in the experiments presented herein, with selected excerpts featured for brevity. Complete dialogues are accessible via the following repository: https://github.com/microsoft/PromptCraft-Robotics.

A. Zero-Shot Robotic Task Execution

ChatGPT demonstrates the ability to address various robotics assignments without prior exposure to sample codes, relying solely on a prompt and functional API documentation. **Example Prompt (Appendix B-A):** Compose a Python program implementing a visual servoing strategy to catch a basketball on a court. Utilize Open CV functionalities to identify the ball characterized as an orange object.

This method applies a proportional controller in which the robot's velocity vector directs it toward the ball's position. The velocity magnitude scales with the distance between robot and ball, modifiable via the gain parameter (here, 0.5).

1) Spatiotemporal Reasoning: Basketball Capture via Visual Servoing: In this task, ChatGPT successfully orchestrates a planar robot with an upward-facing camera to intercept a basketball. It proficiently utilizes the documented API, interprets visual cues to detect the ball, and commands robot velocity through proportional feedback control. Remarkably, ChatGPT generates SVG code that visually models the ball's expected appearance, implying an internal representation transcending mere text prediction.

2) Aerial Robotics: Drone Operation via Natural Language Interface: ChatGPT has been employed to program an actual drone utilizing API commands, translating vague user requests into executable flight code and soliciting clarifications when necessary. Complex flight trajectories, including circular and lawnmower inspection patterns, were coded solely based on prompt descriptions.

Example Prompt (Appendix B-B): "I want a refreshing drink from the scene."
ChatGPT parses available objects such as "coconut water" or "diet coke can," asking preference-related questions, then generates code to fly the drone to the chosen target.
For an inspection task involving an orchid partially obscured by a chair, ChatGPT computes inspection points along a semi-circular arc around the target, adjusting drone orientation accordingly:

1. *Simulated Aerial Inspection via AirSim:* In the AirSim simulation environment, ChatGPT effectively interprets com- mands to pilot a drone toward specified turbines, managing positioning constraints such as lateral offsets and altitude.

Additionally, it programs flight maneuvers such as angled lateral movements in the YZ plane and return to origin.

B. Human-in-the-Loop: Interactive Dialogue for Complex Robotics Tasks

Investigations extended to ChatGPT's capacity to engage in iterative exchanges with a human operator, refining generated code based on textual feedback. This framework facilitates curriculum learning where incremental skills are acquired and integrated for advanced tasks.

1) Robotic Manipulation: Progressive Skill Acquisition: ChatGPT was tasked with a block arrangement exercise using a robotic manipulator. The model first mastered elemental capabilities such as grasping and placing objects, then logically composed these primitives to replicate complex patterns, e.g., constructing the Microsoft logo from blocks. The resulting code executed successfully on physical hardware.

2) Drone Navigation with Obstacle Avoidance: In the Air- Sim [8]environment, ChatGPT generated an algorithm enabling a drone to reach a goal while circumventing obstacles detected via a forward-facing distance sensor. Initial code required textual feedback to improve orientation handling, after which the model incorporated these changes effectively.

C. Perception-Action Loop Construction

ChatGPT exhibits competence in constructing perception- action loops by leveraging available APIs for image capture, object detection, and control commands. This enables it to effectively translate sensory inputs into actionable outputs for navigation and manipulation tasks.

Overall, ChatGPT presents a promising assistive system for robotic applications, providing human-augmented code generation and reasoning capabilities[2]. Ensuring the safety and correctness of its generated instructions remains an essential consideration in real-world deployments.

3. REASONING AND BASIC ROBOTICS TASKS

The investigation involved prompting ChatGPT to address elementary logical reasoning inquiries alongside fundamental robotics challenges, as outlined in Appendix D. It was found that ChatGPT provides a substantial basis of common-sense understanding and logical deduction skills, which can serve as a foundation for more sophisticated robotic functionalities [9]. This logical underpinning facilitates a more intuitive interaction between the user and the model, eliminating the need to define or prompt each concept from the beginning[10]. Additionally, ChatGPT inherently grasps essential robotics topics such as control systems, camera geometry, and physical design constraints, making it an advantageous platform for developing versatile and user-oriented robotics workflows.

4. REAL-TIME APPLICATION OF CHATGPT API

Previous examples predominantly showcased open-loop scenarios where ChatGPT generated code for tasks during a conversation, prior to deployment. Extending this, the real- time use of ChatGPT for robotics was explored [11], where code generation occurs live for robotic challenges. The AirSim simulator was employed to securely evaluate the generated code within a controlled setting. Interaction with the model was facilitated through the OpenAI Chat Completion Python interface, executing the produced code within a Python run- time. To enable real-time API usage, the system prompt was altered to instruct the model to consistently output well- formatted Python code, easily extracted via markdown delimiters. Regex patterns were applied to each API response to isolate Python scripts, which were then executed. To maintain simulation safety, the drone remained stationary during user requests and until execution of the generated commands.

Experiments in the AirSim environment revealed that Chat- GPT successfully produced code enabling a drone to accomplish navigation tasks like object goal finding and inspection. The experiment results are accessible. Although latency precluded usage in high-velocity real-time contexts, the drone's ability to hover allowed safe integration of the large language model (LLM). Simulation environments are ideal for such testing since erroneous outputs can be mitigated by resetting to safe states. For real-world deployment, an additional safety layer should be implemented to verify code correctness before execution, along with established robotic safety protocols (e.g., fixed speed limits or directional constraints). Future investigations are expected to focus on leveraging LLMs safely and effectively for real-time robotic control.

5. PROMPTCRAFT: A COLLABORATIVE LLM + ROBOTICS PLATFORM

Prompt engineering plays a pivotal role in eliciting de- sired behaviors from large language models, especially in

robotics where exemplary prompt resources remain scarce. To bridge this gap, *PromptCraft* was developed as an open-source community platform enabling researchers to exchange prompt engineering strategies and test algorithms within robotics simulations.

Hosted on GitHub, PromptCraft categorizes prompt exam- ples across robotics domains such as navigation, grasping, and manipulation. Contributors can submit their prompts and pro- vide peer evaluations, fostering a collaborative repository [12]. Submissions are predominantly text-based dialogues, but inclusion of videos and images demonstrating robotic performance, especially in real deployments, is encouraged.

Beyond sharing prompt examples, PromptCraft incorporates the AirSim environment augmented with a ChatGPT interface to facilitate prompt prototyping and algorithm experimentation in a simulated context. The platform welcomes new test environments to broaden its applicability. Ultimately, PromptCraft aims to nurture empirical research in prompt engineering and accelerate advancements in robotics applications using LLMs.

A. Natural Language Interaction in Robotics

Natural language processing (NLP) remains integral for enhancing human-robot communication, enabling tasks such as instruction delivery, navigation, and data retrieval. Traditional approaches often constrained users to rigid command sets [13], or involved complex probabilistic models tracking multiple action-object distributions [13]. More recent neural network- based methods model language-to-action mappings implicitly but typically require extensive labeled datasets for training [13].

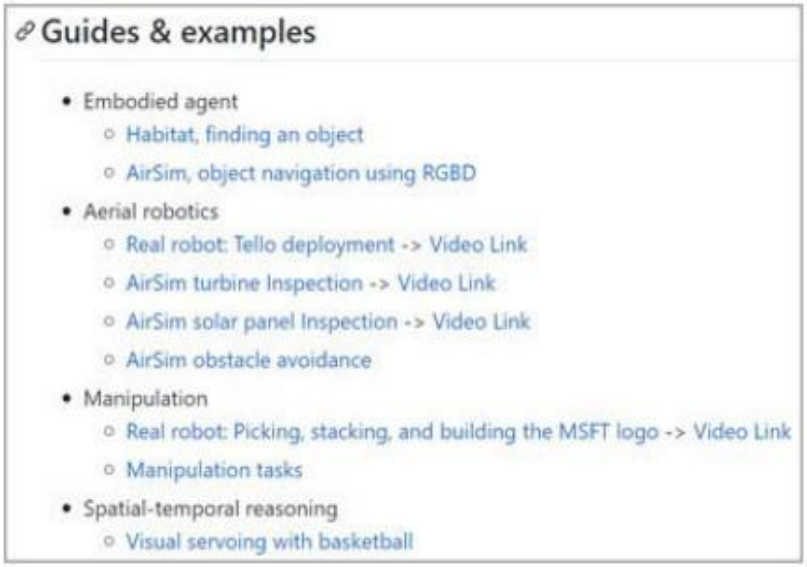

FIGURE 5. Prompt Craft open-source repository. Researchers contribute and rate prompt examples spanning various robotics categories.

B. Large Language and Vision Models in Robotics

The Transformer architecture [13] has significantly advanced NLP and demonstrated utility in robotic control, planning, object recognition, and navigation [13]. Often, transformers serve as feature extractors across multiple modalities, integrated with pretrained vision and language models [13]. Systems like SayCan leverage LLMs to rank robotic actions based on free-text commands [13], while RT-1 adopts an end-to-end mapping from language to motor commands [13]. Zero-shot task planning via LLM prompting has also been investigated [13]. Socratic Models combine multiple models communicating through text to overcome individual limitations [13]. Unlike these, the present approach emphasizes the conversational nature of ChatGPT to iteratively refine robot behavior interactively, offering a generalized pipeline applicable across robotic domains.

c. Prompting LLMs and Links to Symbolic AI

High-level API-based prompting for robotics aligns with symbolic AI paradigms, which utilize logical rules to represent

knowledge [13]. While classical symbolic AI struggled with acquiring new knowledge and handling out-of-distribution data, LLMs exhibit potential to surmount these challenges by synthesizing new primitives from existing concepts.

6. CONCLUSION AND FUTURE DIRECTIONS

This work introduced a framework harnessing ChatGPT for robotics, centered on crafting and implementing an API library tailored for robotic control, compatible with prompt engineering methodologies. The framework supports code generation for robotic tasks, with mechanisms for user-in-the- loop validation via simulations and manual reviews. Applica- tions ranged from fundamental common-sense robotics queries to aerial vehicle navigation, manipulation, and visual guidance. The demonstrated results represent an initial exploration of LLM integration in robotics. The current focus lies on using ChatGPT during development phases; future work will investigate deploying LLMs directly in robotic operational settings. The PromptCraft platform aims to facilitate such progress.

Most examples involved open-loop code generation without subsequent feedback. Given the importance of closed-loop control in robotics, forthcoming research should explore how LLMs can incorporate feedback via textual or specialized signals. This could involve cloud-hosted models or optimized local LLM deployments leveraging quantization techniques.

Caution is advised against relinquishing full robotic control to LLMs, particularly in safety-critical domains, due to the potential for erroneous outputs. Rigorous testing, validation, and human oversight are essential to ensure reliability and safety. Future efforts will likely establish methodologies for designing robust pipelines integrating LLMs safely into robotic systems.

A. Deployment Considerations

Two primary paradigms for using LLMs in robotics were discussed: pre-deployment code generation and real-time code generation. The former is preferred for safety-sensitive tasks, whereas the latter may serve as an exploratory tool for non- critical functions. Ensuring code safety and correctness before robot execution is vital, especially in live settings. Latency issues can be mitigated if robotic platforms (e.g., drones) can safely maintain a static state during code generation. Here, the LLM functions as a high-level planner, while low-level control remains embedded within the robot hardware—a practical strategy. Additionally, a verification layer must be integrated to assess generated code feasibility and safety prior to enactment.

$$J(\pi) = \mathbb{E}_{\tau\sim\pi}\left[\sum_{t=0}^{T} r(s_t, a_t)\right] - \lambda \left\|\pi - \pi_{\text{old}}\right\|^2 \qquad (1)$$

Equation (1) represents a modified policy optimization objective where the expected cumulative reward under policy π is maximized while penalizing large deviations from the previous policy π_{old} via an L_2 norm regularization weighted by λ. This adjustment ensures smooth policy updates enhancing stability during iterative improvements

$$\hat{y} = \sigma\left(W_2\,\text{ReLU}\left(W_1 x + b_1\right) + b_2\right) \qquad (2)$$

Equation (2) illustrates a two-layer neural network trans- formation with learnable parameters W_1, W_2, b_1, b_2, and non-linear activation ReLU followed by a sigmoid σ at output, representing a generic module used in robotics control or perception tasks.

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