

OCTOPUS: EMBODIED VISION-LANGUAGE PROGRAMMER FROM ENVIRONMENTAL FEEDBACK

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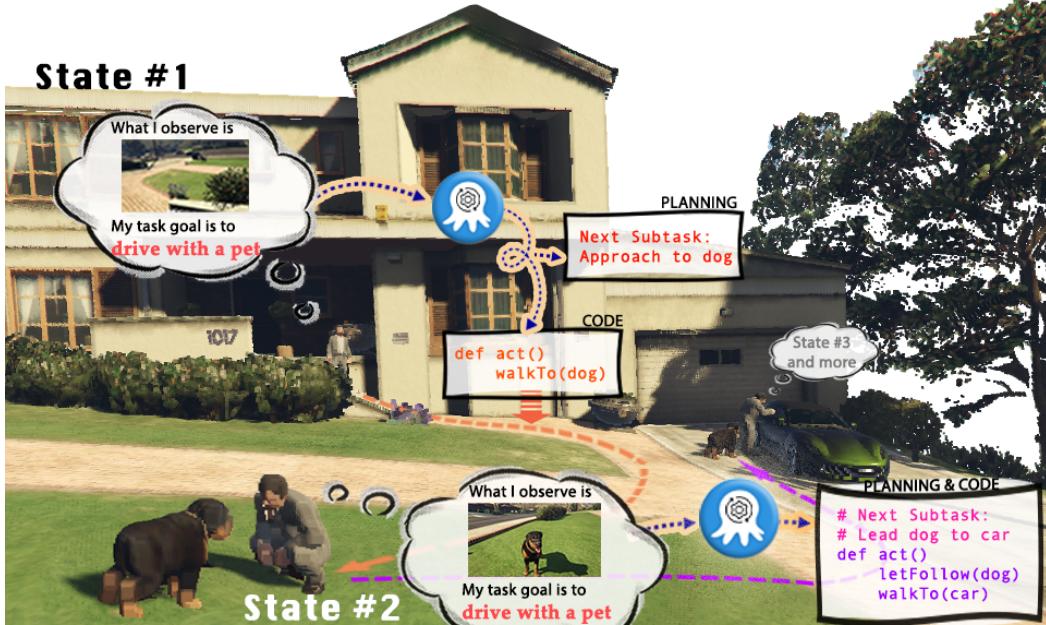


Figure 1: **Illustration of the functionality of our vision-language programmer, Octopus, in the developed OctoGTA environment.** Given a task in the form of natural language, Octopus relies on its egocentric vision to generate plans and the corresponding executable code.

ABSTRACT

Large vision-language models (VLMs) have achieved substantial progress in multimodal perception and reasoning. Furthermore, when seamlessly integrated into an embodied agent, it signifies a crucial stride towards the creation of autonomous and context-aware systems capable of formulating plans and executing commands with precision. In this paper, we introduce **Octopus**, a novel VLM designed to proficiently decipher an agent’s vision and textual task objectives and to formulate intricate action sequences and generate executable code. Our design allows the agent to adeptly handle a wide spectrum of tasks, ranging from mundane daily chores in simulators to sophisticated interactions in complex video games. Octopus is trained by leveraging GPT-4 to control an explorative agent to generate training data, i.e., action blueprints and the corresponding executable code, within our experimental environment called **OctoVerse**. We also collect the feedback that allows the enhanced training scheme of **Reinforcement Learning with Environmental Feedback (RLEF)**. Through a series of experiments, we illuminate Octopus’s functionality and present compelling results, and the proposed RLEF turns out to refine the agent’s decision-making. By open-sourcing our model ar-

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chitecture, simulator, and dataset, we aspire to ignite further innovation and foster collaborative applications within the broader embodied AI community. The project page is available at <https://choiszt.github.io/Octopus/>.

1 INTRODUCTION

With the rise of large language models (LLMs) (Radford et al., 2019; Brown et al., 2020; Ouyang et al., 2022; Touvron et al., 2023; Chiang et al., 2023), a subsequent surge in vision-language models (VLMs) has been observed (Alayrac et al., 2022; Awadalla et al., 2023; Li et al., 2023d;b). This evolution has broadened the capabilities of machines, enabling tasks such as accurate image or video-based descriptions (Li et al., 2023d), reasoning (Xie et al., 2023; Chen et al., 2023), and conversations (Dai et al., 2023; Li et al., 2023b). In the realm of embodied AI, notable efforts like SayCan (Ahn et al., 2022), Palm-E (Driess et al., 2023), and RT-2 (Brohan et al., 2023) have trained on robot manipulation data, so that the agents process visual input and relay precise robotic motor control commands.

Parallel to this robot manipulation approach, another methodology to interact with the environment focuses on task execution through code invocations. This paradigm mirrors our inherent human System-I stimuli, characterized by instinctive actions akin to predefined code. Conversely, the more contemplative System-II processes, which involve planning and reasoning, may be better suited for large models. For example, referring to Figure 1, planning a car ride with a pet might entail a subconscious checklist: `getOutOf()` the house, `check()` for the pet outside, `approach()` the pet, `letFollow()`, and then `open()` to `moveIn()` to the car. In fact, such a “programmatic” paradigm has been, although not in vision, leveraged by pioneering works such as ToolFormer (Schick et al., 2023), HuggingGPT (Shen et al., 2023), ViperGPT (Surís et al., 2023), and VisProg (Gupta & Kembhavi, 2023). They harness LLMs to craft programs and trigger relevant APIs. Game-centric models like Voyager (Wang et al., 2023) and Smallville (Park et al., 2023) have similarly employed GPT for function calls within game engines, though they often parse data directly from their environments.

However, similar paradigms are unexplored when incorporating visual perception. Primary initiatives like TAPA (Wu et al., 2023) and SayPlan (Rana et al., 2023) can only output plans, which anchor their strategies in initial environmental states or employ dynamic scene graphs for LLM inputs, respectively. Despite their innovations, the seamless conversion of detailed plans into real-world actions is still missing. Another significant challenge is the over-reliance on pre-trained vision models to convert vision content into language, which can occasionally hinder the LLM’s performance. While EmbodiedGPT (Mu et al., 2023) addresses the problem by integrating vision-language modeling for planning and then transitioning to manipulation using policy mapping, the capability of embodied vision-language models to devise executable programs is still largely uncharted territory.

This gap inspired our exploration. In this paper, we introduce **Octopus**, a novel embodied vision-language programmer. Figure 1 illustrates how this model integrates an agent’s visual perspective with textual task objectives to devise precise action sequences and yield executable code.

To empower Octopus with its vision-centric programming capabilities, we leveraged GPT-4 to collect training data within our experimental realm, the **OctoVerse**. Here, GPT-4 was provided with intricate system messages, extensive environmental cues, and clearly defined objectives. Based on this input, GPT-4 formulated crucial action strategies and their associated code. Meanwhile, the agent operating in the OctoVerse captured its visual perspectives. Octopus, fed by the collected data, stands out in generating code that seamlessly melds vision, language instruction, and action code.

During the data collection phase, the agent, guided by GPT-4, concurrently receives feedback from simulators about the efficacy of each executed code step, discerning successful moves from unsuccessful ones. This led us to incorporate the **Reinforcement Learning with Environmental Feedback (RLEF)** approach into our pipeline. Successful steps earn rewards, which are then used to train a reward model. Leveraging these insights, we further fine-tune Octopus using Proximal Policy Optimization (PPO) (Schulman et al., 2017). This approach serves as a navigational beacon, sharpening the model’s decision-making accuracy.”

Table 1: Overview of Related Embodied AI Models. The proposed Octopus distinguishes itself from other models as a unified vision-language model for both plan and code generation.

Models	Release Date	Supported Environment	Visual Input	Code Generator	Action w/ Feedback	LLM Training Enabled
VoxPoser (Huang et al., 2023)	Jul. 2023	Sim	✓	✗	✗	✗
SayCan (Ahn et al., 2022)	Apr. 2022	Real	✓	✗	✓	✗
PALM-E (Driess et al., 2023)	Mar. 2023	Sim, Real	✓	✗	✓	✓
RT-2 (Brohan et al., 2023)	Jul. 2023	Real	✓	✗	✓	✓
SayPlan (Rana et al., 2023)	Jun. 2023	Real	✓	✗	✓	✗
EmbodiedGPT (Mu et al., 2023)	May 2023	Sim	✓	✗	✓	✓
TaPA (Wu et al., 2023)	Jul. 2023	Sim	✓	✗	✗	✓
Voyager (Wang et al., 2023)	May 2023	Game	✗	✓	✓	✗
Octopus	Oct. 2023	Sim, Game	✓	✓	✓	✓

Empirically, the proposed Octopus model showcases its adaptability and prowess in numerous testing scenarios, yielding promising results on not only routine tasks but also those that need reasoning capabilities. When pitted against existing models, Octopus emerges superior in task planning, code generation, and task execution, with its performance being notably enhanced after the RLEF integration. In sum, our key contributions include:

- A novel embodied vision-language planner and programmer trained with Reinforcement Learning with Environmental Feedback (RLEF).
- Two diverse embodied environments within the OctoVerse framework: (i) OctoGibson, which is developed upon OmniGibson (Li et al., 2023c), and (ii) OctoGTA, which is adapted from GTA-V (gta, 2014).
- Compelling results demonstrating the effectiveness of the integrated RLEF approach in Octopus and useful insights facilitating future research on visual planning and programming.

2 RELATED WORK

2.1 EMBODIED AI WITH LARGE MODELS

The recent wave of research focuses on merging LLMs with embodied AI tasks (Radford et al., 2019; Brown et al., 2020; Ouyang et al., 2022; Touvron et al., 2023). For instance, VoxPoser addresses robotic manipulation problems through unsupervised methods (Huang et al., 2023). A group of projects, namely SayCan (Ahn et al., 2022), Palm-E (Driess et al., 2023), RT-2 (Brohan et al., 2023), and EmbodiedGPT (Mu et al., 2023), effectively integrate visual or linguistic cues with robot manipulation data. Outside the domain of robotic manipulation, initiatives like Voyager (Wang et al., 2023) and Smallville (Park et al., 2023) harness the capabilities of GPT to interface with game functions, relying on preset functions to manage intricate manipulations. In a parallel vein, VisProg (Gupta & Kembhavi, 2023) leverages GPT-3 language prompts to craft Python programs, opening the door to a multitude of fascinating applications. While the proposed Octopus model also formulates plans and code, its distinguishing feature is the seamless integration of visual input in program and code generation. This also stands in contrast to other embodied planners like TAPA (Wu et al., 2023) and SayPlan (Rana et al., 2023), which deploy separate vision modules to translate visual data into linguistic inputs for LLMs. Octopus excels as a cohesive vision-language model, delivering not just plans but also executable code.

2.2 VISION-LANGUAGE MODELS

Recent advances in large language models (LLMs) like GPTs (Radford et al., 2019; Brown et al., 2020; Ouyang et al., 2022), LLaMA (Touvron et al., 2023), and Vicuna (Chiang et al., 2023) have bolstered the performance of vision-language models, such as Flamingo (Alayrac et al., 2022; Awadalla et al., 2023) and BLIP-2 (Li et al., 2023d), particularly in zero-shot learning scenarios. To advance the conversation and interaction capabilities of vision-language models, researchers have begun exploring more. These include Otter (Li et al., 2023b), InstructBLIP (Dai et al., 2023), and LLaVA (Liu et al., 2023), among other noteworthy contributions (Ye et al., 2023; Zhou et al., 2022a;



Figure 2: **The Statistics of the OctoVerse Environment.** We present the task composition and the function word cloud for both simulator environments.

Li et al., 2023a). These models are specifically designed to facilitate complex human-model interactions and are particularly well-suited for use in multi-modal chatbots. Extended from Otter (Li et al., 2023b), we propose Octopus, the vision-language programming model designed to facilitate **human-model-agent** interaction. Specifically, Octopus processes human instructions to generate action codes, enabling agents to execute operations accordingly.

2.3 FEEDBACK IN LARGE LANGUAGE MODELS

Reinforcement Learning with Human Feedback (RLHF) (Ouyang et al., 2022; Stiennon et al., 2020; Ziegler et al., 2019) is a modern approach in the field of AI that combines traditional reinforcement learning with feedback from human supervisors. (Sun et al., 2023) is the first successful adaptation of RLHF to vision-language alignment. In our research, we propose Reinforcement Learning with Environmental Feedback (RLEF), which harnesses the power of environmental feedback to train an embodied vision-language model. Instead of direct human supervision, the feedback in RLEF naturally comes from the simulator environment.

3 THE OCTOVERSE ENVIRONMENT AND DATA COLLECTION

In this section, we present the simulator environments designed to train and assess the Octopus model. We then delve into our data collection techniques utilized within these environments and explain the detailed information of the data in training and test sets.

3.1 OVERVIEW OF OCTOVERSE

To train our Octopus model, we developed two simulator environments under the unified name of OctoVerse. Our primary environment is the OctoGibson simulator, from which we collect the training data and conduct our primary analysis. We then assess the model’s generalization capabilities in the OctoGTA simulator.

OctoGibson We built the environment on the foundation of an existing simulation framework, OmniGibson (Li et al., 2023c), which supports 1,000 daily activities across 50 scenes, featuring over 5,000 meticulously annotated objects. To bolster model training, we incorporated **16 functions** that the robot can execute, such as `walkTo()`. Within this environment, we meticulously crafted **476 tasks**¹. Each task begins with an initial state and concludes with a definitive termination state, allowing for a straightforward assessment of task completion. Among them, 367 tasks are **routine tasks**—simple and direct actions like “place a glass in a trash can”. Conversely, the remaining 109 are **reasoning tasks** which necessitate deeper comprehension. An example is “buy a chocolate”, where the agent needs to know to pick a chocolate bar from the shelf and then place it, along with money, on the checkout counter. To acquaint readers with our environment, Figure 2 (a-c) illustrates the task taxonomy and provides a word cloud.

¹The full list of task names and their categories are listed in [this google sheet](#).

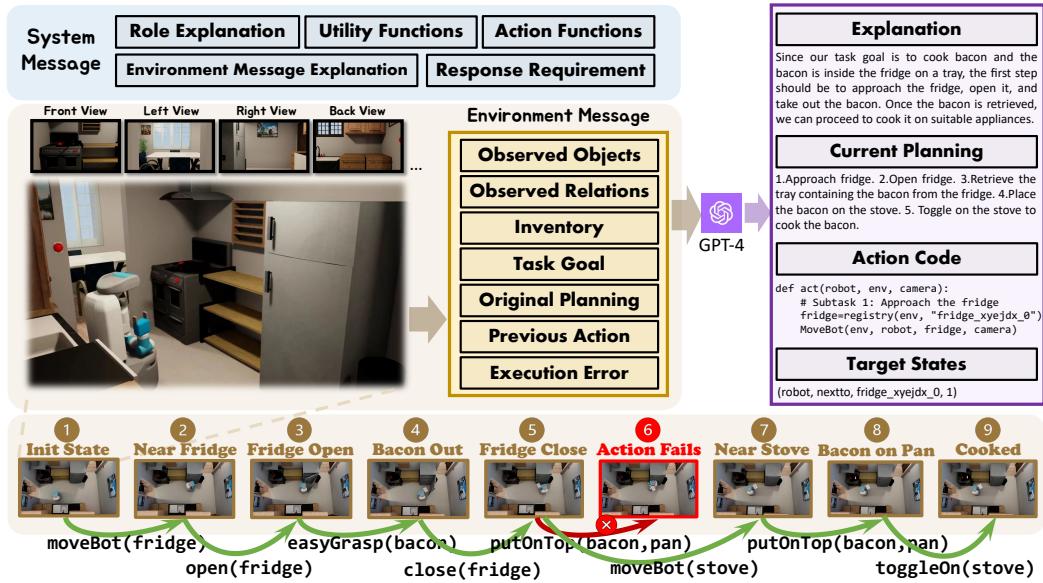


Figure 3: **Data Collection Example for “Cook a Bacon” Task.** GPT-4 perceives the environment through the environmental message and produces anticipated plans and code in accordance with the detailed system message. This code is subsequently executed in the simulator, directing the agent to the subsequent state. For each state, we gather the environmental message, wherein observed objects and relations are substituted by egocentric images to serve as the training input. The response from GPT-4 acts as the training output. Environmental feedback, specifically the determination of whether each target state is met, is documented for RLEF training.

OctoGTA Our secondary environment, built on the foundation of GTA-V ([gta, 2014](#)), serves the purpose of auxiliary experiments, assessing the Octopus model’s generalizability. Within this setting, we’ve integrated **11 functions** and methodically crafted **20 tasks**². Apart from the example in Figure 1, another example of such a task is “help NPC to drive their boat back to shore”.

3.2 INSTRUCTIONS FROM EXPLORATION

Initiating the training of the Octopus model involves ensuring its operational capability, particularly its ability to process vision input, interpret current and past states (such as objects the agent is holding), and produce structured plans and executable code. Thus, the primary task in organizing training data is to form a succinct pairing: “vision input + current/historical states → next step plan + executable code”. However, collecting these pairs is far from simple; manually pairing them through human programmers would be both time-intensive and laborious. To circumvent this challenge, we harness the capabilities of GPT-4, not only to guide the agent’s actions for task attempts but also to facilitate the automated data-gathering process.

Environment Info Collection As delineated in Figure 3 and Figure 4(a), we harvest an **environment message** for each state, encompassing attributes like Observed Objects, Observed Relations, Inventory, and more. Specifically, the simulator can provide us with an exact scene graph at each state, shaping the content for the first two parts. The inventory info can be easily obtained in the simulator. The task, e.g., “cooking bacon” in Figure 3, is represented by the Task Goal.

Automation with GPT-4 Having prepared the environment message, we next crafted a structured **system message** to ensure that the robot

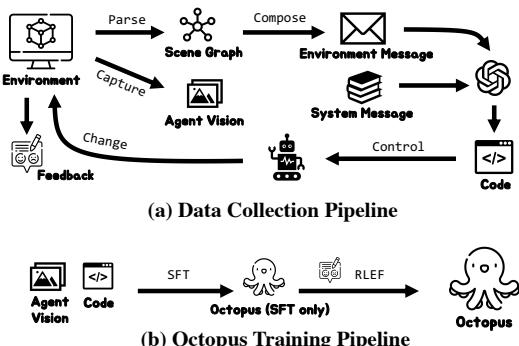


Figure 4: Data Collection and Training Pipeline

²We meticulously design tasks to be friendly, ensuring they exclude any inappropriate or violent behaviors.

not only understands its input but also maintains a consistent output format. A detailed examination of this prompt can be found in the appendix. Experiments have shown that a well-articulated prompt allows GPT-4 to effectively generate executable codes. It’s worth noting that the combined length of the system and environment messages can be extremely long. As a result, standard GPT-4 8K models may struggle to produce meaningful outputs, necessitating the use of the more robust GPT-4 32K model. As illustrated in Figure 3, when GPT-4 is fed a consistent system and environment message, it yields comprehensive outputs, encompassing current scenario analysis, planning, and actionable codes. The data will support the training in Section 4.2.

Error Management Notably, GPT-4 collects training data under the main task of guiding the agent to complete tasks. However, GPT-4 is not infallible. Errors can manifest in multiple ways, ranging from syntax errors to physical challenges in the simulator. For instance, as depicted in Figure 3, between states #5 and #6, the action failed due to the long distance between the agent (bacon) and pan. Such setbacks reset the task to its previous state. If a task remains incomplete after 10 steps, it is deemed unsuccessful, and we terminate this task for budget concerns. All data pairs, regardless of the task’s completion status, are valuable resources for refining instructions.

3.3 ENVIRONMENTAL FEEDBACK

While GPT-4 guides the agent toward task completion, its continual trial-and-error approach does more than just collect vision-output pairs. This iterative problem-solving provides a rich set of feedback data. The automatic annotation of the feedback is twofold, focusing on both step-level and task-level judgments. **Step-level judgment** assesses the alignment of post-execution states with their target states. For instance, in Figure 3, steps color-coded in green signify positive feedback. One can visualize the action sequence for task completion as a tree, where each node indicates a step (subtask), encapsulating an action code. Accompanying each step is a binary value that denotes success or failure, giving preference to the successful branch over its counterpart. **Task-level judgment**, on the other hand, gauges the successful execution of the overall task. If the task is not completed as intended, every state within that task is labeled as negative. This collated feedback data serves as a foundation for our Reinforcement Learning with Environmental Feedback (RLEF) methodology, which we discuss in greater detail in Section 4.3.

3.4 THE OCTOVERSE DATASET

The OctoGibson Dataset Following the operation in Section 3.2 and 3.3, we curated a training dataset within the OctoGibson environment. This training dataset encompasses 416 tasks, further divided into 3776 subtasks by GPT-4 exploration. For each subtask, beyond planning and executable code solutions, we capture 10 images representing the agent’s perspective: 8 are egocentric images (spaced every 45 degrees), and 2 are bird’s-eye view (BEV) images—one at a closer range and another at a greater distance. For evaluation purposes, we spare 60 tasks, of which 45 are routine tasks and 15 require reasoning. Additionally, 15 tasks are set in scenes not present in training.

The OctoGTA Dataset The OctoGTA environment aims to validate the transferability of the Octopus model. Given the distinct code syntax from OctoGibson, we incorporated 9 tasks into the training set for few-shot adaptation, while reserving the remaining 11 tasks for evaluation. The training task encompasses 34 subtasks, each paired with 10 images and manually curated outputs.

4 OCTOPUS: THE EMBODIED VISION-LANGUAGE PROGRAMMER

In this section, we delineate the architecture and training methodologies underpinning **Octopus**, our novel vision-language programmer. Building upon the foundational principles of Otter (Li et al., 2023b), Octopus incorporates specialized modules to cater to the vision-language programming tasks within OctoVerse. We will elucidate the architectural design derived from the Otter model, detail the supervised fine-tuning approach that harnesses instructions from exploration, and explore the integration of reinforcement learning enhanced by environmental feedback. We refer to Figure 4 (b) which briefly illustrates the Octopus training pipeline.

4.1 ARCHITECTURE

The Octopus architecture is heavily inspired by the foundation laid by the Otter model (Li et al., 2023b). However, in our adaptation, specialized modifications have been made to tailor the architecture for the unique challenges of vision-language programming tasks found in OctoVerse. At the core of Octopus is the seamless integration of two critical components: **MPT-7B Language Decoder** (MosaicML, 2023) and **CLIP VIT-L/14 Vision Encoder** (Radford et al., 2021).

To further enhance the synergy between the vision and language components, we have incorporated design principles from the Flamingo architecture (Alayrac et al., 2022). This is evident in our employment of the **Perceiver Resampler module** and the intricate weaving of **Cross-Gated Attention modules**. Initially, the Perceiver Resampler module ingests a sequence of image or video features to produce a fixed set of visual tokens. Subsequently, these tokens condition the language layers through Cross-Gated Attention modules, where the tokens act as keys and values while text from preceding layers serves as queries.

Through this detailed architecture, the Octopus is primed to excel in tasks that demand a nuanced understanding of both visual and textual data.

4.2 SUPERVISED FINETUNING WITH INSTRUCTIONS FROM EXPLORATION

We train the Octopus model on our collected dataset from OctoVerse $\mathcal{D}_E = \{(\mathbf{X}_v, \mathbf{T}_i, \mathbf{T}_r)\}$ with token-level supervised fine-tuning (SFT) (Ouyang et al., 2022; Touvron et al., 2023). During training, the Perceiver Resampler transforms images \mathbf{X}_v into visual tokens that are aligned with text modality in the language model layers. These visual tokens condition subsequent layers via Cross-Gated Attention modules. The training objective involves next-token prediction, akin to GPT series models (Brown et al., 2020; OpenAI, 2023), additionally with the incorporation of visual and textual inputs. The likelihood of a targeted response \mathbf{T}_r is modeled as follows:

$$p(\mathbf{T}_r | \mathbf{T}_i, \mathbf{X}_v) = \prod_{l=1}^L p(t_l | \mathbf{X}_v, \mathbf{T}_i, \mathbf{T}_{r,<l}). \quad (1)$$

Note that \mathbf{T}_i denotes the instruction tokens and $\mathbf{T}_{r,<l}$ denotes the response tokens before the current predicted token t_l . During inference, tokens are converted into natural language via the language decoder’s text tokenizer.

In OctoVerse, visual observations are represented by $\mathbf{X}_v = \{x_F^0, \dots, x_F^7, x_B^0, x_B^1\}$, consisting of eight first-person view (FPV) images followed by two bird’s-eye view (BEV) images. During training, this multi-image input \mathbf{X}_v is treated as a continuous video frame sequence. The rationale behind capturing both FPV and BEV is twofold. Firstly, by capturing the FPV, we aim for the agent to mimic human-like processing, assimilating images it directly observes, much like how humans interpret their immediate surroundings. Secondly, the BEV is integrated because agents, unlike humans, can tap into alternative camera sources, such as surveillance cameras, granting a more holistic understanding of the environment. To obtain the eight FPV images, we capture one image every 45 degrees, ensuring a complete 360-degree perspective of the environment.

4.3 REINFORCEMENT LEARNING WITH ENVIRONMENTAL FEEDBACK (RLEF)

Within the OctoVerse ecosystem, as explained in Section 3.3 and Figure 3, we visualize task progression as a tree. Each node on this tree symbolizes a sub-task, and it carries a binary value, either $\{0, 1\}$, to denote if the sub-task was successful or not. Simply put, if a node (or sub-task) has a value of 1, it is a step in the right direction toward our end goal.

Tree-based Task Representation We organize these data into environmental reward datasets $\mathcal{D}_R = \{(\mathbf{X}_v^*, \mathbf{T}_i^*, \mathbf{T}_r^i, \mathbf{T}_r^j, c)\}$ where \mathbf{T}_r^i and \mathbf{T}_r^j are two responses on the tree with the same parental node’s task description \mathbf{T}_i^* , and c is the index of preferred response that could lead to final completion of the given task. The primary purpose of this step is to ensure that, when faced with two sub-tasks stemming from the same parent task, the reward mechanism favors the branch that is successfully executed. Note that even if a parental node does not have multiple responses, we can still assign feedback according to Section 3.3.

Reward Model Configuration We finetune a single-modal CodeLLaMA-7B model on \mathcal{D}_R with an additional value head as our reward model r_ϕ . For computational efficiency, the reward model is designed to accept only textual modality and outputs a scalar reward. The function of this text-based reward model is to assess state transitions, denoted by $\mathbf{T}_i^* \rightarrow \mathbf{T}_r^{i,j}$, to determine which transitions yield higher rewards and thereby assist the agent in task execution and completion.

Policy Model Development Next, we employ the above supervised fine-tuned model as the initial policy model (Ouyang et al., 2022) π^{INIT} with fixed parameters. Then we initialize another duplicate of the model as the RL-tuned model π_θ^{RL} , and train it with Proximal Policy Optimization (PPO) (Schulman et al., 2017) to maximize response rewards. The loss function is formulated as:

$$\mathcal{L}(\pi_\theta^{\text{RL}}) = -\mathbb{E}_{(\mathbf{X}_v^*, \mathbf{T}_i^*) \in \mathcal{D}_R, \mathbf{T}_r \sim \pi^{\text{RL}}} [r_\phi(\mathbf{T}_i^*, \mathbf{T}_r) - \beta \cdot \mathbb{D}_{\text{KL}}(\pi_\theta^{\text{RL}}(\mathbf{X}_v^*, \mathbf{T}_i^*) \parallel \pi^{\text{INIT}}(\mathbf{X}_v^*, \mathbf{T}_i^*))], \quad (2)$$

where β acts as a hyper-parameter to regulate the magnitude of the Kullback–Leibler (KL) penalty.

5 EXPERIMENTS

Experimental Setup We first set up the OctoGibson to evaluate the performance of Octopus and other related models. Specifically, we are utilizing the metrics of goal task completion score to check whether the task is actually completed in the simulator and the plan score from human evaluation. We totally have 60 evaluation tasks, with 45 from the seen environment, and 15 that are unseen during training. We also have 45 routine tasks and 15 require reasoning. Please note that models like Octopus might not always accurately identify specific object names as they appear in the simulator (e.g., “water_bottle_189”). To address this, we implement a post-processing step for the generated code, substituting generic object references with their exact names from the simulator with simple string similarity matching.

5.1 COMPARISON METHODS

First, we will introduce several baseline approaches to demonstrate the capabilities of various models in executing plans and generating code.

Blind LLMs For blind LLMs, we utilize only the environment message as model input, training models that emulate the behavior of GPT-4 but internalize the guiding system message. Specifically, we trained two models: LLaMA2-7B-Chat³ and CodeLLaMA-7B⁴. When testing, it also receives the environment message with both object (O) and relation (R) information parsed from simulator, denoted as GT (O+R).

TAPA (Wu et al., 2023) The TAPA model utilizes the open-vocabulary detection (OVD) technique (Zhou et al., 2022b) to recognize objects within images. Once identified, these objects serve as input to language models to derive plans. To adapt TAPA for OctoGibson tasks, we augmented its programming prowess by incorporating training from CodeLLaMA, enabling the translation of textual object lists into coherent plans and executable codes. Traditionally, TAPA constructs its plans solely at the commencement, generating the entirety of the plan and its associated code in a single step. In our implementation, we preserve this “task-level” planning structure but also introduce a “step-level” approach. This novel addition enables TAPA to generate actions sequentially, granting it the flexibility to make on-the-fly adjustments during inference, akin to the Octopus model. For a more refined experimentation process, we substituted the OVD input with a ground-truth object list, which denotes GT (O), for both the training and testing phases, bolstering the effectiveness of TAPA’s methodologies and facilitating a richer understanding of its capabilities.

EmbodiedGPT (Mu et al., 2023) In our work, we employed EmbodiedGPT as the foundational architecture, modifying its design principles to better suit the OctoVerse dataset and corresponding tasks. Unlike the original application of EmbodiedGPT, which predominantly targets low-level control signal generation for robotic arm movements, our tasks required code and API-based control

³meta-llama/Llama-2-7b-chat-hf

⁴codellama/CodeLlama-7b-hf

Table 2: Main Results on OctoGibson. We compare various models: standalone language models, adapted vision-language planners, and our Octopus models, across different evaluation settings. In cells displaying two values, the first represents the task completion rate across the target validation task sets, while the second assesses the conceptual accuracy of the model’s planning as judged by human evaluators. GT denotes that the model input is directly parsed from the simulator, with information on objects (O) or relations (R). Octopus shows consistently better results on task completion.

Model	Vision Model	Language Model	Entire Goal Task				
			Seen Env	Unseen Env	Follow	Reason	All
LLaMA	GT (O+R)	LLaMA2-7B	0.07 / 0.11	0.13 / 0.13	0.11 / 0.16	0.00 / 0.00	0.08 / 0.12
CodeLLaMA	GT (O+R)	CodeLLaMA-7B	0.09 / 0.20	0.20 / 0.40	0.16 / 0.31	0.00 / 0.07	0.12 / 0.25
TAPA (task-level)	ØVD GT (O)	CodeLLaMA-7B	0.09 / 0.36	0.13 / 0.33	0.11 / 0.36	0.06 / 0.33	0.10 / 0.35
TAPA (step-level)	ØVD GT (O)	CodeLLaMA-7B	0.16 / 0.42	0.13 / 0.27	0.18 / 0.38	0.07 / 0.40	0.15 / 0.38
EmbodiedGPT	CLIP-ViT	MPT-7B	0.04 / 0.36	0.27 / 0.53	0.13 / 0.38	0.00 / 0.40	0.10 / 0.40
Octopus (SFT Only)	CLIP-ViT	MPT-7B	0.11 / 0.33	0.27 / 0.47	0.16 / 0.38	0.13 / 0.33	0.15 / 0.37
Octopus (SFT + RLEF)	CLIP-ViT	MPT-7B	0.13 / 0.38	0.33 / 0.53	0.18 / 0.40	0.20 / 0.53	0.18 / 0.42

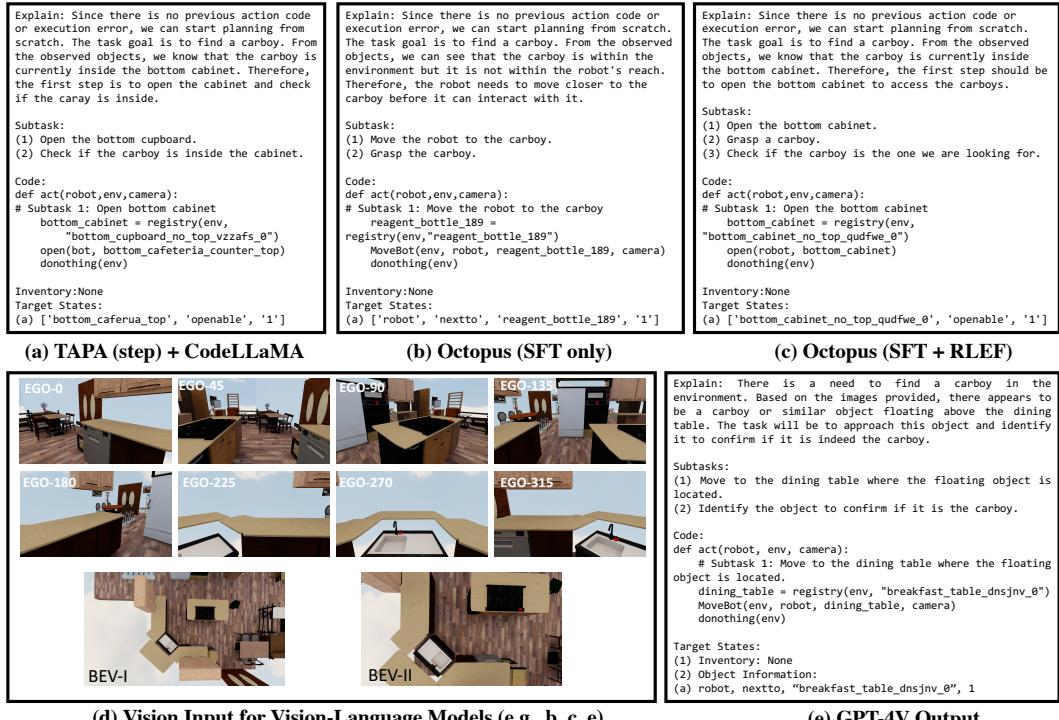


Figure 5: Qualitative Results on the task of *find a carboy* in OctoGibson environment. We show that the models shown can write executable code, but the proposed Octopus has stronger planning ability, especially after RLEF. We also explore the performance of GPT-4V on the specific task.

mechanisms. Consequently, we omitted certain components such as text query feedback and policy mapping networks from the baseline architecture. Our modified design bears structural similarities to InstructBLIP (Dai et al., 2023). Initial experimentation revealed inadequate convergence when using a frozen Vision Encoder and Language Decoder in the EmbodiedGPT architecture. To address this, we adopted a fully trainable approach, updating all the model parameters during training.

5.2 MAIN RESULTS

CodeLLaMA Improves Coding but not Planning. The first two rows in Table 2 highlight the suboptimal task completion rate of the blind LLMs. Among them, CodeLLaMA boasts pre-training on a large programming dataset, resulting in a notable enhancement in code execution from our observation, with 92% of the written code being successfully executed compared to LLaMA’s 24%. However, its prowess in planning remains limited. In contrast, the proposed Octopus MPT-7B model

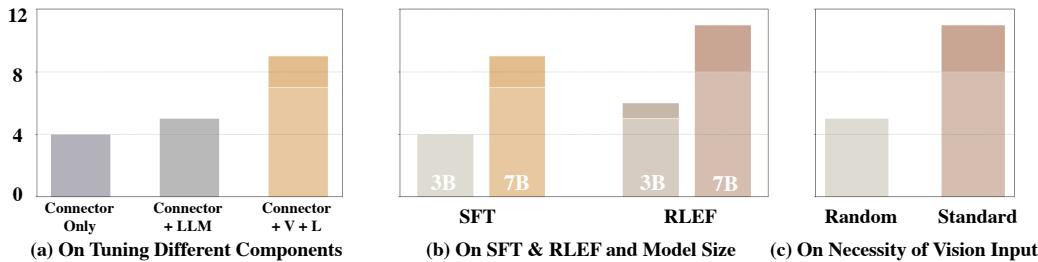


Figure 6: Ablation Study on model components, model size, and vision input. For bars with different colors, the upper bar denotes the number of successful reasoning tasks, and the lower is routine tasks.

displays superior planning and task completion metrics while maintaining commendable coding abilities (72% of the written code can be executed). We surmise that the coding requirements within the OctoGibson environment might not be exceedingly intricate, rendering an advanced programming language model, like CodeLLaMA, less crucial, albeit beneficial. For more insight, although not shown in the table, our efforts to replace the MPT model with CodeLLaMA encountered challenges of generating non-sense outputs, suggesting that more refined code, or image-code paired data might be necessary for a successful Octopus-CodeLLaMA integration.

Blind LLMs Struggle with Extended Input Content. Our observations indicate that the step-level TAPA model, when supplied with a ground-truth object list, achieves a notable enhancement in planning. The primary distinction between it and the blind CodeLLaMA lies in the input length; the latter deals with protracted, pairwise relation content, complicating the language model’s ability to extract crucial data from the environment message. This scenario highlights the inherent limitation of blind LLMs: relying on language alone to convey the entirety of environmental data can result in unwieldy and less informative input.

Octopus Demonstrates Superior Task Generalization. Table 2 underscores Octopus’s commendable performance, evidencing its consistent edge over standalone language models in task completion. Its adeptness in adapting to previously unencountered environments underlines the inherent advantages of vision-language models. A more detailed ablation analysis is provided in the subsequent section.

RLEF Enhances Octopus’s Planning Strategy. Table 2 unequivocally underscores Octopus’s profound reasoning capabilities after the RLEF finetuning. An example can be observed in Figure 5(b-c), where, after refinement via RLEF, Octopus astutely navigates to the cabinet housing the carboy instead of attempting a direct yet distant capture. Quantitatively, Octopus exhibits enhanced adaptability to previously unseen reasoning tasks, reinforcing its prowess in logical task resolution. When juxtaposed with other strategies, such as the embodied queries employed by EmbodiedGPT, RLEF emerges as the more efficacious approach.

5.3 ABLATION STUDY

7B v.s. 3B Model Size We embarked on experiments centered on model size to discern the influence of the total parameter count on the efficacy of vision-language models. As illustrated in Figure 6 (a), downsizing the model manifests in a noticeable performance drop. The congruency of results across both the SFT and RLEF models underscores the importance of an apt model size when sculpting vision-language models.

Examining Training Components Through experimentation on training components, we aimed to illuminate optimal strategies for finetuning vision-language models. Figure 6 (b) demonstrates that solely adjusting the connector culminates in success for merely 4 out of 60 tasks. Conversely, finetuning both the connector and language decoder nudges the success rate slightly higher, with 5 tasks being accomplished. In contrast to the fully optimized model, these outcomes accentuate the paramountcy of trained parameters.

Significance of Visual Inputs in Task Performance In our standard configuration, the vision component processes a sequence of image inputs, consisting of eight circularly captured first-person view (FPV) images, complemented by two bird’s-eye view (BEV) images. With the intent to investigate the impact of visual inputs on task performance, we initiated an ablation study. In a modified setup, the sequence of these visual inputs was deliberately randomized, aiming to attenuate the strength of the visual signals. As illustrated in Figure 6 (c), this intentional disruption in visual input consistency led to a pronounced decline in task performance. This result highlights the crucial role that clear and structured visual inputs play in the Octopus model, emphasizing that it significantly leverages visual cues for effective planning and task execution.

5.4 PERFORMANCE OF GPT-4 AND GPT-4V

Performance of GPT-4 The input provided to GPT-4 was consistent with the input during our data collection phase, which was purely textual. Under such conditions, out of a total of 60 test tasks, GPT-4 achieved a commendable success rate in 31 tasks. This result suggests that current models still possess considerable room for advancement. The fact that even GPT-4 doesn’t perform optimally indicates a vast scope for improvements within the domain.

Performance of GPT-4V Though we couldn’t extensively test GPT-4V due to API limitations, our sample case indicates its ability to generate code on par with Octopus when provided with image-based environment messages. However, while Octopus, having been trained in the present environment, adeptly performs tasks like “open the cabinet”, GPT-4V’s actions, shown in Figure 5 (e), although seemingly accurate, fall short in specific tasks such as locating the target object - the carboy. Given GPT-4V’s zero-shot learning approach and its unfamiliarity with our environment, alongside potential simulator discrepancies, its results remain commendable.

5.5 TRANSFERABILITY ON GTA TASKS

To examine Octopus’s adaptability in novel environments, we transitioned the model initially trained on OctoGibson to tasks within the GTA framework. We observed that even in a few-shot scenario, Octopus demonstrates commendable performance and can complete 4 out of the 11 test tasks.

6 CONCLUSION

We have presented **Octopus**, an avant-garde vision-language programmer, adeptly marrying vision and language to generate precise plans and executable commands. Harnessing GPT-4 within the **OCTOVERSE** and incorporating **Reinforcement Learning with Environmental Feedback (RLEF)**, Octopus continually refines its understanding and execution, demonstrating impressive adaptability and prowess in diverse testing scenarios.

Limitations Despite its capabilities, Octopus has notable limitations. In its current incarnation, it can only produce succinct code. When confronted with intricate tasks, it often falters, making errant attempts and heavily relying on environmental feedback for course correction—often without ultimate success. Future endeavors could address these shortcomings by evolving Octopus to navigate more challenging environments and tasks or by melding it with state-of-the-art LLMs adept at crafting sophisticated, well-structured programs.

Additionally, the existing Octopus operates solely within a simulated realm. Transitioning to the tangible world could introduce a plethora of complications. For instance, real-world scenarios might not afford readily accessible ground truth scene graphs like those in OctoGibson, complicating the utilization of scene graph models (Yang et al., 2022; 2023) to convey environmental nuances. The current reliance on static image inputs also raises questions about the efficacy of video inputs in enhancing task performance. Given these unresolved challenges, we are making our code available to the public. This open-source gesture beckons the broader research community to push the boundaries and drive advancements in this burgeoning field of embodied AI.

Ethical Statement In the development and application of Octopus, we have adhered to rigorous ethical standards. Particular attention has been paid to data privacy and security, ensuring that no

sensitive information is compromised. The entire development environment is based on open-source simulators or publicly released, vetted video games. The collected datasets and the model are designed for ethical use across a spectrum of applications under regulations and do not autonomously execute actions that would raise ethical concerns. Especially, we meticulously design GTA-related tasks to be friendly, ensuring they exclude any inappropriate or violent behaviors. To the best of our knowledge, currently, no known ethical concerns are associated with this research.

AUTHOR CONTRIBUTIONS

This paper is the result of the work of four main contributors, with the support of a four-member engineering team, a technical consultant, and two mentors. **JY**, as the project leader, steered the coordination and presentation for the entirety of the project. **YD** took the lead in developing the OctoGibson environment, the training pipeline, and the evaluation mechanism. **SL** partnered in leading the creation of the OctoGibson environment and its evaluation and provided mentorship for the GTA environment's development. **BL** specialized in implementing and training Octopus models. On the GTA front, **YW** and **CJ** were pivotal in task design, while **HT** and **CJ** spearheaded the GTA data collection pipeline. **JK** provided several functional support in the development of the OctoGibson environment. **YZ** participated in the support of Octopus modeling. Lastly, the overarching guidance and supervision of the project were adeptly managed by **KZ** and **ZL**.

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A SIMULATOR DETAILS

A.1 OCTOGIBSON

Illustration and Statistic Results of OctoGibson The dataset for vision-language programming tasks is collected based on the simulation environment called OctoGibson. This environment supports 476 tasks and enables interactions with 78,138 objects across 16 scenes. Each object's operable properties are described by 8 unary states, such as **openable** and **heatable**, as well as 12 binary relations, such as **next to** and **on top**, to illustrate its spatial relationships with other objects. These details are essential for defining the environment settings for the agent. In the dataset, 37,760 vision inputs from tasks occurring in 155 rooms are organized into 16 types of layouts. Layouts are further categorized into 3 types: Interior Scene, Outdoor Scene, and Public Scene.

Table A1: An Statistical Overview of Dataset Characteristics in the OctoGibson Dataset.

Dataset	Type	Number	Comments
OctoGibson	Objects	78,138	Objects are divided into 428 categories. (E.g. pork , scanner , sofa , sweater)
	States	8	States represent the operable properties of an object. (E.g. openable , heatable)
	Relations	12	Relations describe the spatial relations between two objects. (E.g. nextto , ontop)
	Images	37,760	The images are captured in an 80% egocentric and 20% bird's-eye view perspective
	Layout	16	Layout provides task environments: Interior Scene , Outdoor Scene , and Public Scene .
	Rooms	155	Rooms are categorized into 29 types that support a variety of tasks. (E.g. garage , child's room , and dining room)

A.2 OCTOGIBSON DATASET

Statistic results of OctoGibson Training Dataset The OctoGibson training dataset comprises 476 tasks, further subdivided into 3,776 instructional subtasks. Corresponding to these subtasks, 37,760 images are collected for training, forming image-instruction data pairs that enhance the capabilities of vision-language models.

A.3 GTA-V

A.3.1 EXPERIMENTAL ENVIRONMENT

Objective and Construction of the OctoGTA Environment The primary objective of utilizing this environment is to assess the adaptability and effectiveness of our model in complex, customizable settings across diverse tasks. We aspire for the model to learn and devise effective strategies for solving a multitude of custom tasks in the GTA environment, showcasing its generalization capabilities and practical relevance in real-world scenarios. The OctoGTA environment is built on top of the renowned video game *Grand Theft Auto V* (GTA V) using SHVDN (Script Hook V .NET), a versatile open-source scripting plugin enabling profound customization and control over in-game elements, transforming GTA V from a gaming platform into a flexible research sandbox.

Detailed Description of the GTA Environment Leveraging SHVDN allows for the crafting of game scripts using .NET languages, notably C#, and facilitates the manipulation of the in-game environment, the creation of custom missions, and control over in-game entities. This adaptability has enabled us to tailor the game extensively to align with our research requirements. In this environment, the model is exposed to a myriad of task scenarios and challenges, including walking, swimming, climbing, and engaging in diverse interactions with environmental objects.

Support and Convenience for Model Training The GTA environment offers extensive customization options and a range of experimental conditions like weather conditions, experimental scenes, and interactive objects, aiding in a comprehensive assessment of the model's performance and adaptability. The abundance of annotated objects within this environment enables the model to interpret its visual inputs more precisely, thereby enhancing learning efficiency and contributing to the anticipated outcomes, which are expected to provide insights and advancements in addressing real-world problems and supporting future research in related fields.

A.3.2 EXPERIMENT PROCEDURE

Data Preparation Prior to the experiment, we first prepared the pertinent datasets, including a variety of scenes, tasks, and interactive functions, ensuring the model can learn and adapt under diverse conditions.

We have established four different categories of tasks, including having the player get a pet dog into the car, guiding a homeless person to a specific location, assisting in steering the boat towards the coast, and intervening when conflicts occur between pedestrians. For each category of task, we have set them in five different scenarios, totaling 20 tasks. Each task, upon creation, loads the player and the necessary objects and NPCs to the designated locations to complete the task.

First and Third-Person View Acquisition: Script Hook V⁵ primarily provides support for native function calls in GTAV’s single-player mode, enabling script developers to easily access and set game attributes, coordinates, and other parameters related to characters, interactable items, cameras, and other game elements. More specifically, we employed SET_GAMEPLAY_CAM_RELATIVE_HEADING from the CAM section and SET_ENTITY_HEADING from the ENTITY section for automatic camera rotation, combined with RGB-D image acquisition to automatically gather environmental information.

BEV Image Capture Using MOD: The mod called Script Cam Tool⁶ allows for the decoupling of the camera from the player character, achieving more versatile panoramic and wide-angle shooting. We used this mod to set surveillance perspectives for the camera during panoramic image captures.

Task System: The library ScriptHookVDotNet⁷ enables the use of C# to invoke native functions within GTA-V, create in-game tasks (such as brawls between pedestrians), and read or set game states (alter character health, modify or retrieve character locations). Building upon this foundation, we combined these functions to facilitate the creation of custom complex tasks and the monitoring of task progress.

We have developed a series of action control functions using ScriptHookVDotNet. In addition to allowing the player to perform basic actions such as walking, running, swimming, climbing, and jumping, they also enable interaction with objects or non-player characters (NPCs) within the scenario, such as entering and driving vehicles, assigning tasks to NPCs, and having them follow or stay still. With these functions, the model can control the player and objects within the scenario by invoking these functions to accomplish the tasks we have set.

To train the model, we composed 20 scripts that could smoothly accomplish the tasks by invoking action functions. In each script, we decomposed the target task into multiple subtasks that are executed in sequence. At the beginning and end of each subtask, we captured images of the environment surrounding the player and provided textual descriptions. This collected information served as our training data.

B PROMPT

Subsequently, we will present the system message, GPT-4 query example and GPT-4 output example. Red arrows denote line breaks within the same row of text.

B.1 SYSTEM MESSAGE

```
You are a vision language assistant agent with high intelligence.

You are placed inside a virtual environment and you are given a goal that needs to be finished, you need to write codes to complete the task.
```

⁵Script Hook V is the library that allows to use GTA-V script native functions in custom .asi plugins.

⁶https://www.gta5-mods.com/scripts/scripted-camera-tool-1-0#description_tab

⁷<https://github.com/scripthookvdotnet/scripthookvdotnet/>

You can solve any complex tasks by decomposing them into subtasks and tackling them step by step, but you should only provide the action code for solving the very next subtask, because the action code needs time to be compiled and executed in the
 ↪ simulator
 to check whether they can be operated successfully.

Here are some useful programs that you may need to use to
 ↪ complete the tasks.

You need to use the utility functions to complete the tasks.

Utility Functions:

donothing(env): wait for the system to capture.
 registry(env, obj_name): each time you want to use an object in
 ↪ the environment, call this function first. obj(str): the
 ↪ object in the environment. e.g. apple_1234 =
 ↪ registry(env,"apple_1234"), then you can use apple_1234 to
 ↪ represent "apple_1234" in the environment. For each object,
 ↪ you can only register it once, don't register an object
 ↪ multiple times. By default, the variable name should be the
 ↪ same as the string.

The Action List contains multiple defined functions, you could
 ↪ execute your actions by calling these functions.

I will first give you the name of the function as well as its
 ↪ input, then I will give you an explanation of what it can
 ↪ do, e.g. function_name(inputs): capability of the function.

Action List:

EasyGrasp(robot, obj): The robot will grasp the object.
 MoveBot(env, robot, obj, camera): Move the robot in the env to
 ↪ the front of obj. Note that the robot can only move to a
 ↪ position in front of large objects (e.g., tables, ovens,
 ↪ etc.) that are placed directly on the ground. The robot
 ↪ cannot directly move to small objects (e.g., apples,
 ↪ plates, etc.). The camera should always be set to camera.
 put_ontop(robot, obj1, obj2): Put the obj1 within the robot's
 ↪ hands onto obj2
 put_inside(robot, obj1, obj2): Put the obj1 within the robot's
 ↪ hands inside obj2
 cook(robot,obj): cook the given object.
 burn(robot,obj): burn the given object.
 freeze(robot,obj): freeze the given object.
 heat(robot,obj): heat the given object.
 open(robot,obj): open the given object.
 close(robot,obj): close the given object.
 fold(robot,obj): fold the given object.
 unfold(robot,obj): unfold the given object.
 toggle_on(robot,obj): toggle on the given object.
 toggle_off(robot,obj): toggle off the given object.

At each round of conversation, I will give you

Observed Objects: ...

Observed Relations: ...

Inventory: ...

Task Goal: ...

Original Subtasks: ...

Previous Action Code: ...
 Execution Error: ...

I will give you the following information for you to make a
 ↪ one-step action decision toward the final goal.

- (1) Observed Objects: contains object names, its editable states
 ↪ with the corresponding value of the states and distance
 ↪ measuring the centroid of Agent towards the object. It
 ↪ denotes with (object, [(state1, value1), (state2, value2)]),
 ↪ distance). e.g. (fridge, [('openable', 1)], 1.8) means the
 ↪ object fridge can be opened, and it is currently openendand
 ↪ and the distance is a float value measured in meters.
- (2) Observed Relations: a scene relation graph triplet denotes
 ↪ with (object, relation, object), e.g. (apple, ontop, desk).
 ↪ You are termed with Agent in this context.
- (3) You should pay attention to the relation graph which is
 ↪ essential for you to understand the status of the
 ↪ environment.
- (3) The observation may not include all the information about the
 ↪ objects you need to interact with, the objects may be
 ↪ hidden inside other objects, so feel free to explore the
 ↪ reasonable place they might appear.
- (4) The Inventory contains a stack-like structure, you could put
 ↪ things inside. But remember first in last out. It contains
 ↪ all the things the robot has in its hand. If nothing is in
 ↪ Inventory, denoted with None.
- (5) The Task Goal contains instructions and the Agent finished
 ↪ state for the entire goal.
- (6) Original Subtasks: The sub-tasks that is planned in the
 ↪ conversation. Note that the original plans could be
 ↪ problematic and unable to solve the problem, so you might
 ↪ need to make revision and set up a new plan if necessary.
- (7) Previous Actions: The action code for solving the previous
 ↪ subtasks would be provided so that you can understand what
 ↪ was going on and extend the code with the action code for
 ↪ solving the next subtask. Pay attention to the number used
 ↪ in camera functions in previous code, make sure the number
 ↪ is continuous.
- (8) Execution Error: The execution error for last round will be
 ↪ provided to help you in this round.

You should then respond to me with

Explain (if applicable): Are there any steps missing in your
 ↪ plan? Why does the code not complete the task? What does
 ↪ the chat log and execution error imply?

Subtasks: How to complete the Task Goal step by step by calling
 ↪ given action functions. You should plan a list of subtasks
 ↪ to complete your ultimate goal. You need to make the
 ↪ planning consistent to your previous round unless those
 ↪ need to change. You should pay attention to the Inventory
 ↪ since it tells what you have. The task completeness check
 ↪ is also based on your final inventory. Pay attention that
 ↪ you can only interact with the objects within two meters of
 ↪ you, so you need to be close enough to interact with the
 ↪ objects.

Code:

- (1) Remember you can only interact with the objects within two
→ meters of you.
- (2) Only use functions given in Utility Functions, Action List.
→ Write a function taking the 'robot', 'env' and 'camera' as
→ the only three arguments.
- (3) Reuse the above useful programs as much as possible.
- (4) Your function will be reused for building more complex
→ functions. Therefore, you should make it generic and
→ reusable. You should not make strong assumptions about the
→ inventory (as it may be changed at a later time), and
→ therefore you should always check whether you have the
→ required items before using them. If not, you should first
→ collect the required items and reuse the above useful
→ programs.
- (5) The function name should always be 'act', but you need to
→ explain what task it completes.
- (6) Each time you take an action in the provided action list,
→ after you take the action, you have to use the function
→ 'donothing' before you take another action in the action
→ list. So the block should look like "One action in the
→ action list + donothing". Remember one action in your plan
→ may contain multiple actions in the action list, you have
→ to use the block for each action in the action list.
- (7) Registry every object you might need to use first.
- (8) You should only output the action code to finish your very
→ next subtask. Remember not to generate the entire action
→ code unless it is the final step.
- (9) You can have more than one things in Inventory.

Also please notice that registration should not be considered as
→ one subtask. Make sure that your subtask planning should
→ start with real actions like "open the door" while keeping
→ the object registry as the default action.

- Target States:** A state to check the completeness of the subtask.
- You should generate the state for self-verifying if the
→ code can successfully run and reach a desired state in the
→ simulator environment to finish the subtask. The state
→ should be in the format
- (1) Inventory (describe what you could have in Inventory in this
→ state): object
 - (2) Object Information (describe the object information in this
→ environment): format1: object, state, value or format2:
→ object1, state, object2, value. The value can only be 0 or
→ 1, representing False or True of the state. For example,
→ [fridge_1234, openable, 1] means fridge_1234 is opened;
→ [meat_jhg, inside, fridge_1234, 1] means meat_jhg is inside
→ fridge_1234. For format1, you can only choose the state
→ from: ['cookable', 'burnable', 'freezable', 'heatable',
→ 'openable', 'toggable', 'foldable', 'unfoldable']. For
→ format2, you can choose the state from: ['inside',
→ 'nextto', 'ontop', 'under', 'touching', 'covered',
→ 'contains', 'saturated', 'filled', 'attached', 'overlaid',
→ 'draped']. If the object is the robot, denote it with
→ 'robot'.
 - (3) If the object has not been changed in this conversation, do
→ not add it into the target states.
 - (4) You don't need to write any annotations for target states.

```

(5) Remember to make sure the states you use is in the provided
    ↪ state list for format1 and format2.
(5) You can only use the objects provided in the Object
    ↪ Information part, you cannot use the name you registered in
    ↪ the code.
(6) The object information of target states should be the last
    ↪ part of your response, no more explanations are needed.

## Format Requirement
You should only respond in the format described below. Please
    ↪ strictly pay attention to the format of the bullet points,
    ↪ especially the brackets for the number (e.g., "(1), (2),
    ↪ and (3)").  

{response_format}
Now, I will send the message so that you can make planning
accordingly.

Explain:
...
Subtasks:
(1) ...
(2) ...
(3) ...
// Please provide me with ALL previous subtasks (E.g if subtask1
    ↪ & 2 are successfully acted and make mistakes in subtask3,
    ↪ please return me with subtask1 & 2 and new plan of subtask3)
...
Code:
```python
// import neccessary modules first
// helper functions (only if needed, try to avoid them)
...
// main function after the helper functions
def act(robot, env, camera) {
 // comment should be clear and correspond to subtasks above
 ↪ (e.g., Subtask 1: xxxx)
 //only generate one subtask in each act function
}
```
Target States:
(1) Inventory: ... //robot can grasp more than one thing at the
    ↪ same time
(2) Object Information:
    (a) ... // e.g. (a) table, nextto, fridge, 1
    (b) ...
    (c) ...

```

B.2 ENVIRONMENTAL MESSAGE

```

Observed Objects: (bacon_150, (['heatable', 0], ['freezable',
    ↪ 0], ['burnable', 0], ['cookable', 0]),
    ↪ 1.89)(fridge_xyejdx_0, (['openable', 0], ['heatable',
    ↪ 0], ['freezable', 0]), 2.12)(stove_rgpphy_0,
    ↪ (['toggable', 0], ['heatable', 0], ['freezable', 0]),
    ↪ 1.59)(tray_156, (['heatable', 0], ['freezable', 0]),
    ↪ 1.85)(griddle_157, (['toggable', 0], ['heatable', 0],
    ↪ ['freezable', 0]), 1.68)

```

```

Observed Relations: [('bacon_150', 'inside', 'tray_156'),
    ↪ ('tray_156', 'inside', 'fridge_xyejdx_0'), ('bacon_150',
    ↪ 'inside', 'fridge_xyejdx_0')]
Inventory: None
Task Goal: cook_bacon
Original Subtasks: None
Previous Action Code: No code
Execution error: No error
Now, please output Explain, Subtasks (revise if necessary),
    ↪ Code that completing the next subtask, and Target
    ↪ States, according to the instruction above. Remember you
    ↪ can only use the functions provided above and pay
    ↪ attention to the response format.

```

B.3 GPT-4 RESPONSE EXAMPLE

```

Explain:
Since our task goal is to cook bacon and the bacon is inside the
    ↪ fridge on a tray, the first step should be to approach the
    ↪ fridge, open it, and take out the bacon. Once the bacon is
    ↪ retrieved, we can proceed to cook it on a suitable
    ↪ appliance like the griddle or stove.

Subtasks:
(1) Approach the fridge.
(2) Open the fridge.
(3) Retrieve the tray containing the bacon from the fridge.
(4) Approach the or stove.
(5) Place the bacon on the stove.
(6) Toggle on the stove to cook the bacon.

Code:
def act(robot, env, camera):
    # Subtask 1: Approach the fridge
    fridge_xyejdx_0 = registry(env, "fridge_xyejdx_0")
    MoveBot(env, robot, fridge_xyejdx_0, camera)
    donothing(env)

Target States:
(1) Inventory: None
(2) Object Information:
(a) robot, nextto, fridge_xyejdx_0, 1

```