

# GPT-4V(ision) for Robotics: Multimodal Task Planning from Human Demonstration

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**Abstract**—We introduce a pipeline that enhances a general-purpose Vision Language Model, GPT-4V(ision), by integrating observations of human actions to facilitate robotic manipulation. This system analyzes videos of humans performing tasks and creates executable robot programs that incorporate affordance insights. The computation starts by analyzing the videos with GPT-4V to convert environmental and action details into text, followed by a GPT-4-empowered task planner. In the following analyses, vision systems reanalyze the video with the task plan. Object names are grounded using an open-vocabulary object detector, while focus on the hand-object relation helps to detect the moment of grasping and releasing. This spatiotemporal grounding allows the vision systems to further gather affordance data (e.g., grasp type, way points, and body postures). Experiments across various scenarios demonstrate this method’s efficacy in achieving real robots’ operations from human demonstrations in a zero-shot manner. The prompts of GPT-4V/GPT-4 are available at this project page: <https://microsoft.github.io/GPT4Vision-Robot-Manipulation-Prompts/>

## I. INTRODUCTION

In light of the substantial progress in Large Language Models (LLM) and Vision Language Models (VLM) in recent years, a number of methodologies have emerged that convert language/visual input into robotic manipulative actions. While a mainstream approach is training custom models based on extensive data of robot actions [1]–[7], several studies have explored the use of general-purpose, off-the-shelf language models such as ChatGPT [8] and GPT-4 [9] through prompt engineering without additional training [10]–[17]. One key advantage of using off-the-shelf models is their flexibility; they can be adapted to various robotic hardware configurations and functionalities simply by modifying prompts. This approach removes the necessity for extensive data collection and model retraining for different hardware or scenarios, greatly improving system reusability in research and easing the transition to industrial applications. Hence, utilizing off-the-shelf models for robot manipulation represents a promising direction.

While existing research has focused on text-based task planning utilizing LLMs, there has recently been an emergence of general-purpose VLMs such as GPT-4V. Integrating these vision systems into task planning opens up the possibility of developing task planners based on *multimodal human instructions*. However, to the best of our knowledge, there has only been a limited development of pipelines for multimodal task planners that combine off-the-shelf VLMs.

This study proposes a multimodal task planner utilizing GPT-4V and GPT-4 (Fig. 1), as an example of the most recent VLM and LLM, respectively. Our system accepts either human video demonstrations, text instructions, or both, and

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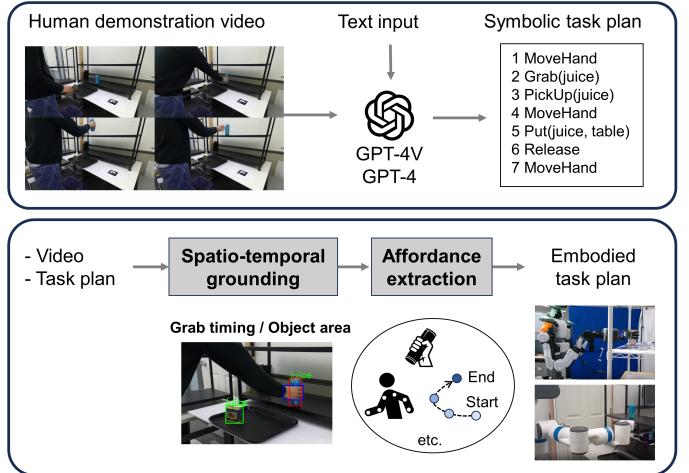


Fig. 1. This figure illustrates the proposed multimodal task planner utilizing GPT-4V and GPT-4. It highlights the system’s ability to process video demonstrations and text instructions, generating task plans and extracting key affordances for robotic execution, which are then compiled into a JSON format.

outputs symbolic task plans (i.e., a sequence of coherent task steps). When the visual data is available, the system then reanalyzes the videos in consideration of the task plan and establishes spatiotemporal correspondences between each task and the video. This process enables the extraction of various affordance information valuable for robotic execution, such as approaches to objects, grasp types, collision-avoiding waypoints, and upper limb postures. Finally, the affordance information and task plan are compiled into a hardware-independent executable file saved in JSON format. We have qualitatively checked the pipeline and confirmed the operability of the output task plan across several real robots.

This research makes three contributions: (1) Proposing a ready-to-use multimodal task planner that utilizes off-the-shelf VLM and LLM (2) Proposing a methodology for aligning GPT-4V’s recognition with affordance information for grounded robotic manipulation (3) Making the code publicly accessible as a practical resource for the robotics research community.

## II. RELATED WORK

### A. LLM/VLM-based task planning

While a methodology to operate robots from instructions has been a research topic before the emergence of LLMs [18]–[20], recent study aim to leverage the LLM/VLMs technologies [1], [21]–[32]. Most of these studies aim to train an end-to-end custom model using specific datasets [1]–[7], [21], [22], [26], [27], [33]–[38]. For example, Brohan et al.

proposed a transformer-based model that trained based on both robotic trajectory data and internet-scale vision-language tasks [2]. However, those approach often require a large amount of data of robot data collected by experts and necessitate data recollection and model retraining when transferring or extending these to other robotic settings.

On the other hand, studies utilized off-the-shelf LLMs focus on decomposing human instructions into high-level subgoals, while pre-trained skills achieve the subgoals [12], [13], [39]. This approach is typically seen as a part of framework, called task and motion planning (TAMP) [40].

This study is positioned as a part of TAMP-based approach while extending the method to multi-modal input by leveraging off-the-shelf GPT-4V and GPT-4.

### B. Grounding visual information for robotics

The advanced language processing abilities of LLMs demonstrate the capability to interpret instructions and decompose them into robot action steps [10], [14], [15], [41]. However, executing long task steps as planned is often challenging due to unforeseen and unpredicted environmental situations. Thus, one challenge in robotics is grounding task plans in environmental information. For example, there are approaches that focus on enabling LLMs to output the pre-conditions and post-conditions (e.g., states of objects and their interrelationships) of task steps to optimize their execution [13] and detect pre-condition errors for necessary revisions to the task plan [42]. These strategies seek to achieve environment-grounded robot execution by integrating environmental information and adjusting the robot's actions at the task plan or controller level.

In this study, the open-vocabulary object detector [43] is used to ground the object names detected by GPT-4V in RGB image. Additionally, focusing on the relationship between the hand and the object enables the detection of timing and location where grasping and releasing occurred in the human demonstration.

### C. Learning affordance

The concept of Affordance, as defined by Gibson [44], refers to the potential for action that objects or situations in an environment provide to an individual. In the field of robotics, it often pertains to the meaning of executable actions in that environment, and information about areas where action is possible. For instance, Ahn et al. have proposed an approach that calculates the feasibility of robotic functions from visual information and compares it with planned tasks [5]. Huang et al. proposed using LLMs/VLMs to extract the knowledge of movable area [45].

These studies indeed define Affordance as a form of Gibson's Affordance; however, focusing on the relationship between the working environment, the objects being manipulated, and the robot, it can be considered that object manipulation involves even more constraints [46]. For example, the notion of affordance can be extended to waypoints for collision avoidance [47], grasp types [48], and upper-limb postures [49]. This information is often not taught explicitly,

thus vision systems need to extract it from human teaching demonstrations. In this study, we propose a pipeline to extract this information and provide a task plan endowed with that affordance information.

## III. MULTIMODAL TASK PLANNER

The proposed system is composed of two pipelines connected in series (Fig. 2). The first pipeline, the so-called symbolic task planner, takes teaching videos, text, or both as input, then outputs a sequence of robot actions. Here, the text input includes feedback on the GPT-4V's recognition results for correction purposes. Providing users with the opportunity to give feedback on the recognition results enables robust operation. The second pipeline, the so-called affordance analyzer, analyzes the video to determine when and where the tasks occur, and then extracts the affordance information necessary for efficient task executions.

In this system, the input videos are demonstrations of humans performing actions that are intended to be replicated by the robot. For the experiments in this study, we assume videos with a granularity of grasp-manipulation-release [50].

### A. Symbolic task planner

The symbolic task planner is built from three components: 1) video analysis, 2) scene analysis, and 3) task planning. Initially, when an RGB video is input, the video analysis uses GPT-4V to recognize the actions performed by humans in the video and transcribes them into text instructions in a style used in human-to-human communication (for example, 'Please throw away this empty can'). In video analysis, considering the model's token limit and latency, frames are extracted at regular intervals rather than from every frame and fed into GPT-4V. The output text is then checked and edited by the user. Alternatively, if no video input is provided, text instructions are given to the system at this stage. Figure 3 shows the example of video analyzer, suggesting that GPT-4V can successfully understand the human action from the frames.

Next, the scene analyzer compiles the expected work environment into the text information based on these instructions and the first frame of the video data or an image of the work environment. This environmental information includes a list of object names recognized by GPT-4V, the graspable properties of objects, and the spatial relationships between objects. Although these computational processes are a black box within GPT-4V, the information is output based on the knowledge of GPT-4V and the image/text input. Figure 4 shows the example of scene analyzer. As in the figure, GPT-4V successfully select the objects that are related to the manipulation. For example, a table is included in the output when the human is relocating a spam can on the table, while a table is ignored for the fridge opening task. Those results suggest that the scene analyzer can encode the scenery information in light of the human's action. We prompted GPT-4V to explain the results of the object selection process and the reasons behind those choices. This prompting practically resulted in effective outputs.

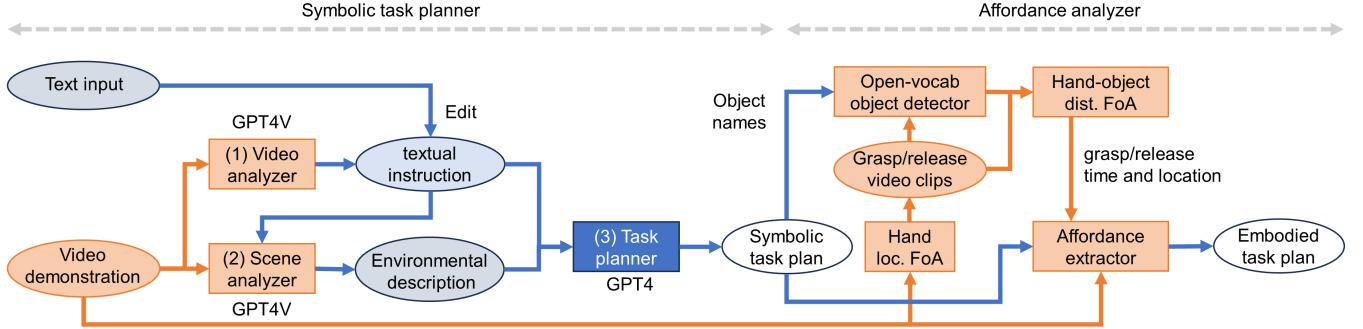


Fig. 2. Proposed pipeline of the multimodal task planner. It consists of the symbolic task planner and the affordance analyzer. Blue components/lines are text-based information, and the red components are vision-related information. FoA denotes focus-of-attention.

These are frames from a video in which a human is doing something. Understand these frames and generate a one-sentence instruction for humans to command these actions to a robot. As a reference, the necessary and sufficient human actions are defined as follows:

<...action list information...>

Response should be a sentence in a form of human-to-human communication (i.e., do not directly use the functions). Return only one sentence without including your explanation in the response.



Reach for the can on the table, grab it, and then place it on the tray nearby.



Please move your hand to the fridge handle, grab it, and open the fridge door.

Fig. 3. Output of the video analyzer. Top pane shows the prompt for the GPT-4V and the bottom pane shows the examples of its output for two representative videos. The five frames are extracted at regular intervals and fed into GPT-4V. Part of the prompt is shown and the whole prompt is available at <https://microsoft.github.io/GPT4Vision-Robot-Manipulation-Prompts/>

Based on the given text instructions and environmental information, the task planner outputs a sequence of tasks. Specifically, we designed a prompt to make GPT-4 decompose given instruction into a sequence of robot tasks [10]. The set of robot tasks was defined based on the change in the motion constraints on manipulated object [50], [51], following the Kuhn-Tucker theory [52]. This definition allows us to theoretically establish a necessary and sufficient set of robot actions for object manipulation. Table I shows the set of tasks and the explanations that we included in the prompt. Note that the names of arguments of tasks are given in an open-vocabulary format based on the understanding of GPT-4V. The names are grounded with the video by the affordance analyzer

This is a scene in which a robot is going to do "[ACTION]". Understand this scene and generate a scenery description to assist in task planning: Information about environments is given as python dictionary. For example:

<...example and formatting rules...>

Please take note of the following.

1. Focus only on the objects related to the given action information, if any.
2. The response should be a Python dictionary only, without any explanatory.



"objects": ["<can>", "<table>", "<tray>"],

"object\_properties": {

  "<can>": ["GRABBABLE"],  
  "<table>": [],  
  "<tray>": []

},

"spatial\_relations": {

  "<can>": ["on(<table>)"],  
  "<table>": [],  
  "<tray>": ["on(<table>)"]

},

"your\_explanation": "The human is expected to

grab the can that is on the table and place it on the tray. The table and the tray are included as they are the surfaces involved in this action. The can is marked as GRABBABLE because it is the item being manipulated. Other objects and details in the environment not related to the action, such as the human, the background elements, and the clothing, are omitted because they do not influence the task of moving the can from table to tray."



"objects": ["<fridge>", "<fridge\_handle>"],

"object\_properties": {

  "<fridge>": [],  
  "<fridge\_handle>": ["GRABBABLE"]

},

"spatial\_relations": {

  "<fridge\_handle>": ["on(<fridge>)"],  
  "<fridge>": []

},

"your\_explanation": "Human is moving their hand to the fridge handle, grabbing it, and opening the fridge door. Objects included are the fridge and fridge handle, as they are directly involved in the action. I omitted the computer monitor and other unmanipulated objects in the setting because they are not being interacted with for this task."

Fig. 4. Output of the scene analyzer. Top pane shows the prompt for the GPT-4V and the bottom pane shows the examples of its output for two representative scenes. The input to GPT-4V is the textual instruction, which is replaced with "[ACTION]" in the prompt, and the first frame of the video. Refer to Fig. 3 for the input instruction. Part of the prompt is shown and the whole prompt is available at <https://microsoft.github.io/GPT4Vision-Robot-Manipulation-Prompts/>

in a subsequent stage. Additionally, those pre/post conditions are used to enforce GPT-4 to output a coherent task sequence and not verified against the imagery in the video.

To ensure transparency in the understanding of the GPT-4 model, the task planner is designed to output explanations for the tasks, estimated environments after the operation,

**Instruction:** Reach for the can on the table, grab it, and then place it on the tray nearby.  
**Environment:**{...}

```
↓
GPT-4
{"task_sequence": [
  "MoveHand(`near the can`)",
  "Grab(<can>)",
  "PickUp(<can>)",
  "MoveHand(`above the tray`)",
  "Put(<can>, <tray>)",
  "Release(<can>)"],
 "step_instructions": [
  "Move the robot hand near the can",
  "Grab the can",
  "Pick up the can from the table",
  "Move the robot hand above the tray",
  "Put the can on the tray",
  "Release the can on the tray"],
 "environment_after": {
  "objects": ["<can>", "<table>", "<tray>"],
  "object_properties": {
    "<can>": ["GRABBABLE"],
    "<table>": [],
    "<tray>": []},
  "spatial_relations": {
    "<can>": ["on(<tray>)"],
    "<table>": [],
    "<tray>": ["on(<table>)"]},
  "instruction_summary": "Reach for the can on the table, grab it, and then place it on the tray nearby."}
```

**Instruction:** Please move your hand to the fridge handle, grab it, and open the fridge door.  
**Environment:**{...}

```
↓
GPT-4
{"task_sequence": [
  "MoveHand(`near the fridge handle`)",
  "Grab(<fridge_handle>)",
  "Open(<fridge_handle>)"],
 "step_instructions": [
  "Move the robot hand near the fridge handle",
  "Grab the fridge handle",
  "Open the fridge door"],
 "environment_after": {
  "objects": ["<fridge>", "<fridge_handle>"],
  "object_properties": {
    "<fridge>": [],
    "<fridge_handle>": ["GRABBABLE"]},
  "spatial_relations": {
    "<fridge_handle>": ["on(<fridge>)"]},
  "instruction_summary": "Move hand to the fridge handle, grab it, and open the fridge door"}
```

Fig. 5. Output of the task planner. Prompt is not shown and is available at <https://microsoft.github.io/GPT4Vision-Robot-Manipulation-Prompts/>

and the summary of the operation, as well as a set of task plans. Additionally, the task planner is a stateful system that maintains a history of past conversations within the token limits of the GPT-4 model. Therefore, users can modify and confirm the output through linguistic feedback based on the output of the task planner. Figure 5 shows the examples of computation results of the task planner. The results suggest that a set of tailored prompts results in reasonable textual instruction, environmental description, and the symbolic task plan.

### B. Affordance analyzer

The Affordance Analyzer reanalyzes the given videos using the knowledge from the symbolic task planner to acquire the affordance information necessary for the robot's effective execution. Specifically, it focuses on the relationship between hands and objects based on the task's nature and object names. It identifies the moments and locations of grasping and releasing in the video, aligning these with the task sequence. These moments serve as anchors for recognizing the affordances essential for each task. The effectiveness of focus-of-attention in detecting action grasping and releasing has been demonstrated in our prior study [53].

1) *Attention to Human Hands to Detect Grasping and Releasing:* Initially, the pipeline divides a series of videos into video clips at regular time intervals. The beginning and end frames of each video clip are then analyzed using a hand detector and an image classifier that determines whether an object is being grasped or not (Fig. 6). The clips are classified into the following patterns:

- Clips where nothing is held in the first frame, but something is grasped in the last frame indicate the occurrence of a grasp.

TABLE I  
ROBOTIC ACTIONS AND THEIR EXPLANATIONS

Action	Description
Grab(arg1)	Take hold of arg1. Preconditions: Arg1 is within reachable distance and no object is currently held. Postconditions: Arg1 is being held.
MoveHand(arg1)	Move the robot hand closer to arg1, where arg1 describes the hand's destination.
Release(arg1)	Release arg1. Preconditions: Arg1 is currently being held. Postconditions: Arg1 is no longer held.
PickUp(arg1)	Lift arg1. Preconditions: Arg1 is currently being held. Postconditions: Arg1 continues to be held.
Put(arg1, arg2)	Place arg1 onto arg2. Preconditions: Arg1 is currently being held. Postconditions: Arg1 continues to be held.
Rotate(arg1)	Open or close something by rotating arg1 along an axis. Preconditions: Arg1 is currently being held. Postconditions: Arg1 continues to be held.
Slide(arg1)	Open or close something by linearly moving arg1 along an axis. Preconditions: Arg1 is currently being held. Postconditions: Arg1 continues to be held.
MoveOnSurface(arg1)	Move arg1 across a surface. Preconditions: Arg1 is currently being held. Postconditions: Arg1 continues to be held.

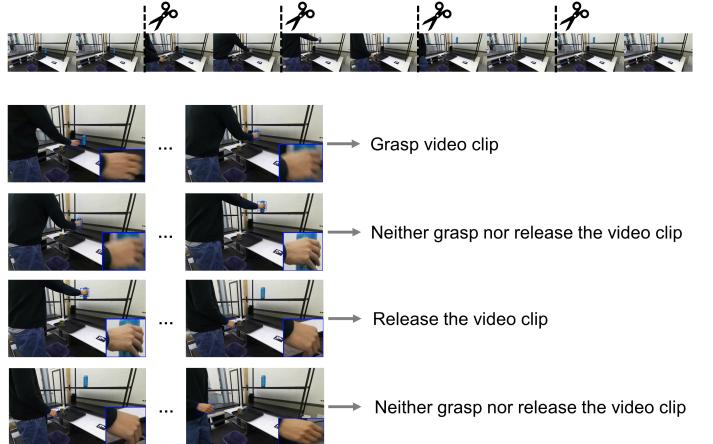


Fig. 6. Detection of grasp and release video clip. The input video is firstly split at regular time intervals. For each video clip, a hand detector detects hand regions and an image classifier determines whether an object is being grasped or not. The video clips are classified into grasp, release, other classes based on the hand statuses at the first and the last frame.

- Clips where something is held in the first frame and nothing is held in the last frame indicate the occurrence of a release.
- Other clips are classified as containing other types of actions.

This classification allows the analyzer to determine which video clips contain instances of grasping and releasing. For this purpose, a YOLO-based hand detector and recognizer were developed [54]. We have made this model available as open-source.

2) *Attention to Hand-Object Interaction to Detect the Spatiotemporal Location of Grabbing and Releasing:* The pipeline then focuses on the grasp video clip, analyzing the position and

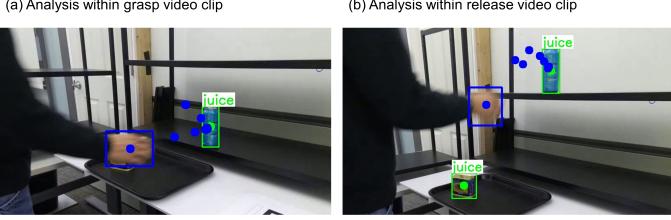


Fig. 7. Detection of the objects by focusing on the relationship between the hand and the object. The first frame and the last frame are shown for the grasp and release video clip, respectively. Green rectangles are the candidates for the object detected by the Detic model. When multiple object candidates are identified, the one closest to the hand in the video clip is deemed the grasped object. The hand positions in the video clip were illustrated as blue points. Images are spatially cropped for the visualization purpose.

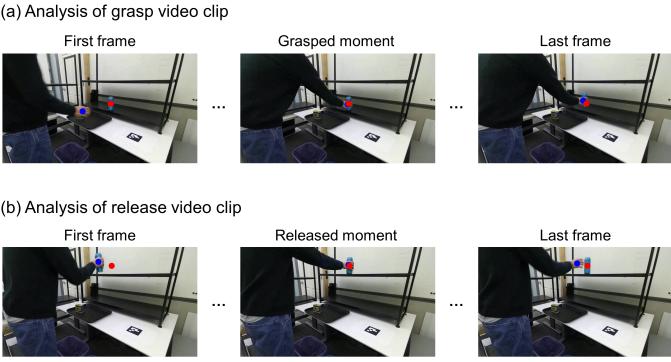


Fig. 8. Detection of the timings and the location of grasping and releasing by focusing on the relationship between the hand and the object. The human hand moved a juice can from the bottom to the top of the shelf, and thus the juice can was the manipulated object. The centers of the human hand and the object are shown as blue and red points, respectively.

timing of the grasped object. We use Detic, an off-the-shelf, open-vocabulary object detector [43], to search for object candidates within the video, as identified in the symbolic task planner. When multiple object candidates are identified, the one closest to the hand in the video clip is deemed the grasped object. This is determined by comparing the distance between the bounding boxes of each candidate and the hand, as detected by the hand detector in every frame of the grasp video clip. Figure 7 illustrates the computation of object detection. The moment when the hand and the object are spatially closest during the Grasp clip is identified as the moment of grasping. A similar calculation is applied to the release video clips to determine the timing of release. Figure 8 shows the computation for a manipulation of moving a juice can from the bottom to the top of the shelf.

**3) Extracting Affordance from Aligned Videos:** The moments of grasping and releasing serve as anchors to align the task sequence with the video. Following this alignment, the vision analyzer extracts affordance information of the object manipulation, including:

- Affordance of the Grab task: 1) Information about the approach direction towards the object to avoid collisions with the environment. 2) The grasp type also contains knowledge about how humans efficiently perform manipulations.

- Affordance of the MoveHand task: 1) Information about waypoints during the hand's movement to avoid environmental collisions.
- Affordance of the Release task: 1) Information about the hand's withdrawal direction after releasing the object to avoid environmental collisions.
- Affordance of the PickUP task: 1) The vector of the departure direction to minimize unnecessary forces between the object and the plane.
- Affordance of the Put task: 1) Information about the approach direction towards the plane to avoid environmental collisions.
- Affordance of the Rotate task: 1) The direction of the rotation axis. 2) The position of the rotation center. 3) The angle rotation.
- Affordance of the Slide task: 1) The displacement of the sliding motion.
- Affordance of the MoveOnSurface task: 1) The axis that is vertical to the surface.

In addition to these affordances, the upper arm and forearm postures at the moments of grasping, releasing, and each waypoint are encoded as pairs of discretized directional vectors [50]. These serve as constraints for computing Inverse Kinematics in multi-degree-of-freedom arms [49], ensuring the robot does not assume unexpected postures around humans. It is noteworthy that although these affordances offer viable information for many controllers, actual robot execution may require additional information such as force feedback. The specific methods for acquiring this affordance information can be found in our previous paper [50].

#### IV. EXPERIMENTS

We have implemented the proposed pipeline as a single web interface (Fig. 9). This pipeline allows users to upload pre-recorded teaching demonstrations and let GPT-4V and GPT-4 encode task models. We then tested whether the robot could be operated with a single attempt from videos obtained in various scenarios. Here, we present several examples of its execution. Two robots were tested for the experiment: the Nextage robot (Kawada Robotics)<sup>1</sup> with six degrees of freedom in its arms, and the Fetch Mobile Manipulator (Fetch Robotics)<sup>2</sup> with seven degrees of freedom in its arm. A four-fingered robot hand, the Shadow Dexterous Hand Lite (Shadow Robotics)<sup>3</sup>, was attached to the robot. The robot skills were trained using reinforcement learning [55], [56]. All the experimental results are available at <https://microsoft.github.io/GPT4Vision-Robot-Manipulation-Prompts/>.

#### V. LIMITATION AND DISCUSSION

In this paper, we introduced a multimodal robot task planning pipeline utilizing GPT-4V. This pipeline interprets human actions in videos, integrating human textual feedback and encoding relevant environmental information. High-level symbolic task plans were formulated using GPT-4. After this

<sup>1</sup><https://nextage.kawadarobot.co.jp/>

<sup>2</sup><https://fetchrobotics.com/>

<sup>3</sup><https://www.shadowrobot.com/dexterous-hand-series/>

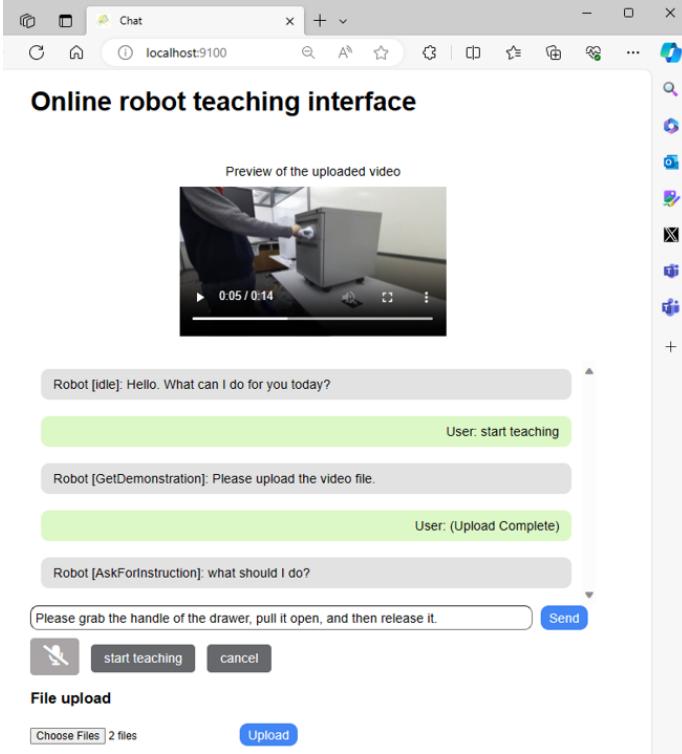


Fig. 9. A web interface to operate the proposed pipeline.

planning phase, videos were re-examined to extract affordance information useful for manipulation. By employing an open-vocabulary object detector, we correlated the objects recognized by GPT-4V with those in the images. Further, focusing on the interaction between hands and objects during video re-analysis, we identified the specific moments and locations for object grasping and releasing. These methods allowed us to align the task plans created by GPT-4V and GPT-4 with human demonstrations.

While preliminary experiments in various scenarios have demonstrated the effectiveness of this pipeline, there are notable limitations:

- **Extension to Long Steps:** The grounding technique was confined to grasping and releasing tasks, limiting the range of extracted affordance information. Extracting affordances for extensive task sequences is challenging. Addressing this would require precise identification of the start and end points for a broader range of tasks. The required granularity for robotic tasks, which is often more refined than human movement patterns, presents an ongoing challenge for accurate action recognition.
- **Higher-order Pre- and Post-conditions:** The pipeline primarily considered object relationships to determine pre- and post-task conditions. Yet, the criteria for completing a task frequently surpass simple object interactions. For example, a MoveOnSurface task for cleaning should not only ensure the continuous contact of the held object (like a sponge) with the surface but also the removal of dirt from that surface. While GPT-4V or GPT-4 may comprehend such complex objectives, the



Fig. 10. Examples of the robot execution based on human demonstration data. Top pane: moving the can of spam from the desk to the tray. Bottom pane: Opening a refrigerator. Bottom pane: relocating the juice between the shelves. All the experimental results are available at <https://microsoft.github.io/GPT4Vision-Robot-Manipulation-Prompts/>

development of methodologies to ground these conditions in video analysis is still in its infancy and requires further exploration.

- **Optimization of Prompts:** As indicated in other research, the success of task planning with VLMs/LLMs is heavily influenced by the design of prompts. Accumulating practical expertise in prompt engineering is crucial for the research community to enhance the effectiveness of these models.

## VI. CONCLUSION

We have introduced a novel multimodal robot task planning pipeline utilizing GPT-4V, effectively converting human actions from videos into robot-executable programs. As the proposed task planner is based on off-the-shelf models, it offers flexibility in application across a wide range of robotic hardware and scenarios. We hope that this study will serve as a practical resource for the robotics research community and inspire further developments in this field.

## ACKNOWLEDGMENT

This study was conceptualized, conducted, and written by the authors, and an AI (OpenAI's GPT-4 model) was used for proofreading.

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