

Grounding LLMs For Robot Task Planning Using Closed-loop State Feedback

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Abstract

Planning algorithms decompose complex problems into intermediate steps that can be sequentially executed by robots to complete tasks. Recent works have employed Large Language Models (LLMs) for task planning, using natural language to generate robot policies in both simulation and real-world environments. LLMs like GPT-4 have shown promising results in generalizing to unseen tasks, but their applicability is limited due to hallucinations caused by insufficient grounding in the robot environment. The robustness of LLMs in task planning can be enhanced with environmental state information and feedback. In this paper, we introduce a novel approach to task planning that utilizes two separate LLMs for high-level planning and low-level control, improving task-related success rates and goal condition recall. Our algorithm, *BrainBody-LLM*, draws inspiration from the human neural system, emulating its brain-body architecture by dividing planning across two LLMs in a structured, hierarchical manner. BrainBody-LLM implements a closed-loop feedback mechanism, enabling learning from simulator errors to resolve execution errors in complex settings. We demonstrate the successful application of BrainBody-LLM in the VirtualHome simulation environment, achieving a 29% improvement in task-oriented success rates over competitive baselines with the GPT-4 backend. Additionally, we evaluate our algorithm on seven complex tasks using a realistic physics simulator and the Franka Research 3 robotic arm, comparing it with various state-of-the-art LLMs. Our results show advancements in the reasoning capabilities of recent LLMs, which enable them to learn from raw simulator/controller errors to correct plans, making them highly effective in robotic task planning. Demo Video: <http://tinyurl.com/2akwhvf2>.

Keywords: Robotic Task Planning, LLMs in Robotics, Closed loop feedback

1 Introduction

LLMs, trained on corpora of internet-sourced text, have demonstrated capabilities akin to artificial general intelligence (Bubeck et al., 2023). The

inherent world knowledge of LLMs, combined with their in-context learning ability is paving a new direction in robotic task planning. Prior work showed that LLMs can generate step-by-step instructions for complex tasks without any

re-training or model parameter updates (Huang et al., 2022, 2023; Sun et al., 2023; Liang et al., 2023; Yao et al., 2023; Ahn et al., 2022b; Singh et al., 2023; Song et al., 2023). Despite promising results in diverse robotic tasks, grounding LLMs in a given environment is still an open problem. Consider the task - “*Make me a coffee.*” LLMs can decompose this problem into a sequence of steps - ‘1. Walk to fridge,’ ‘2. Grab milk,’ and so on, through to ‘9. Serve cup of coffee.’ Yet, these steps are not entirely executable in a real-world environment with physical constraints. Additional steps like ‘Switch on microwave’ or ‘Open microwave doors,’ are essential for task completion. Moreover, limitations like absence of milk or water should not hinder task execution. Robots must adapt to the environment, refining plans towards successful task completion.

Thus, grounding LLMs in real-world scenes is essential. Incorporating environmental feedback into task planning allows error resolution in real-time, enhancing robot robustness and utility (Huang et al., 2023). In this paper, we introduce a novel planning algorithm that aims at mitigating two issues in existing methods: i) Our approach uses a simple prompting framework, with clear distinction of planning, feedback and execution components to avoid using expert defined heuristics and carefully constructed world models and ii) Our method eliminates human intervention through utilizing raw error messages from simulators and controllers to guide an LLM planner for robust task execution, enhancing autonomy. Our contributions are:

1. A novel planning algorithm that uses a Two-LLM system (Brain-LLM and Body-LLM) to derive executable actions from natural language instructions, leveraging a closed-loop state feedback mechanism for error resolution (Figure 1).
2. Improving task-oriented success rate by 29% average over existing state-of-the-art techniques in the VirtualHome Embodied Control environment (using a dataset of 80 tasks). BrainBody-LLM on average completes 72% of all goal conditions for a given task, improving over existing methods.
3. Deployment and testing of our LLM based planner on the Franka Research 3 robotic arm,

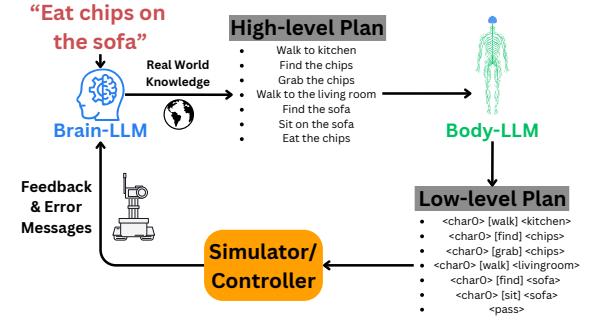


Fig. 1 Illustration of how two LLMs work together in the proposed algorithm: The Brain-LLM splits the given task, ‘*Eat chips on the sofa*’, into sequential steps using its real-world knowledge. The Body-LLM takes these steps one-by-one and determines executable actions. In instances where a corresponding action is not found in the environment, as demonstrated in the final step of this example, the Body-LLM outputs a `<pass>` token.

in 7 tasks of varied difficulties using a realistic physics simulator along with real robot experiments.

2 Background and Related Work

2.1 Foundational Models

Designing deep learning systems capable of comprehending and generating natural language has long been an attractive yet challenging task in the AI community. The emergence of transformers (Vaswani et al., 2017) and the success of pre-trained language models such as BERT (Devlin et al., 2018) have paved the way for more advanced foundational models known as Large Language Models (Touvron et al., 2023; Anil et al., 2023; Achiam et al., 2023). These LLMs are trained on extensive textual data using masked language modeling and autoregressive text prediction. The discovery of in-context learning capabilities, a feature absent in earlier models, has laid the foundation for various applications of LLMs (Brown et al., 2020). In this study, we exploit these capabilities, particularly prompt engineering, which requires no gradient updates in the foundational model.

2.2 LLMs in Robotic Task Planning

The real world knowledge contained within LLMs can be utilized in robots for common sense reasoning and generating language conditioned policies for task execution. Earlier works trained smaller LLMs like GPT-2 for agent task planning, treating it as a translation problem from natural language instructions to high level plans (Jansen, 2020; Micheli and Fleuret, 2021). More recently, training LLMs in a multi-task setup for embodied control has demonstrated robust performance in planning, video captioning, video QnA and multi-turn dialogue (Mu et al., 2024). Extremely large Vision Language Models (VLMs) trained on diverse robot demonstration data can be used to directly convert vision-language input modalities to physical actions in the real world (Brohan et al., 2022, 2023; Ahn et al., 2022a; Driess et al., 2023). Training VLMs is highly resource intensive, and accurate real world deployment requires customization through further environment specific finetuning (Wake et al., 2023).

Foundational models after GPT-3 have demonstrated excellent in-context learning abilities, which enables learning from examples in natural language without the need for expensive training and model updates. By choosing a suitable language prompt and some domain examples, LLMs can break down complex tasks into executable steps complying agent-environment constraints for high level planning (Huang et al., 2022). LLMs can be used to learn from structured data such as Planning Domain Definition Language (PDDL) or Hierarchical Linear Temporal Logic (HLTL) and combined with heuristic search based planners (Silver et al., 2022; Luo et al., 2023). LLM generated PDDL world models can be used with domain independent planning models in robotic task planning (Guan et al., 2023; Xie et al., 2023). Constructing PDDL world models is difficult in real world scenarios, where object and environment states are often revealed in runtime thus requiring human assistance for effective policy exploration.

LLM generated plans sometimes consist of hallucinatory output, when the planner uses objects or actions that do not exist in the environment. This problem is mitigated by downstream filtering mechanisms that improve the correctness of LLM generated plans. (Ren et al., 2023)

uses a conformal prediction scheme to rank LLM generated plans for a current task. High level plans can be combined with motion planning and RL control policies for physical execution (Dalal et al., 2024). Visual perception greatly aids LLM generated sequence of skills through geometric conditioned policy selection (Lin et al., 2023). Combining LLMs with visual perception through VLMs to construct 3D value maps can be used by high level planners for effective grounding in real world environments (Huang et al., 2023). Subsequent research has demonstrated application of such systems in navigation tasks through visual grounding (Shah et al., 2023; Zhou et al., 2023) or incrementally generated 3D scene graphs (Rana et al., 2023; Rajvanshi et al., 2024).

Decision making skills of goal driven LLM agents can be improved with runtime feedback (Shinn et al., 2024) or affordance function based grounding (Ahn et al., 2022b). LLMs deployed in robots can incorporate feedback through natural language, and can use it to correct erroneous plans to enhance overall task success rate (Liang et al., 2023; Valmeekam et al., 2023). Feedback from human intervention or simulator messages can improve real world alignment (Guan et al., 2023). Methods that use environmental feedback for task planning can be classified into two broad categories: static and dynamic planners. *Static planners* use feedback to check whether the robot's environment satisfies the necessary conditions outlined in the generated plan, thus preventing execution errors. In this case, the feedback does not alter the generated plans but improves task oriented success rate (Liang et al., 2023; Singh et al., 2023). On the other hand, dynamic planners use feedback from the system to assert necessary conditions and to alter the plans, improving their execution (Huang et al., 2023; Sun et al., 2023; Yao et al., 2023; Song et al., 2023). ProgPrompt, a well-known technique, was one of the pioneers of LLM-based planning for robotic tasks (Singh et al., 2023). Their algorithm used LLMs to break down complex high-level instructions into sequential steps by writing Python functions utilizing a known set of API skills. Assert statements (if-else) checked the existence of certain preconditions (e.g., whether the microwave door is open or the cup is on the table). This static planning mechanism improved both the success rate and task execution, as feedback

from assert statements was utilized by LLMs to create robust plans. Our approach distinguishes itself from ProgPrompt and other conventional dynamic planners by employing a Two-LLM system designed to assimilate error messages from a simulator and environmental states in tandem for enhanced task planning. This allows our planner to understand errors in natural language and generate corrected plans for successful execution. Thus, we move one step further from ProgPrompt by replacing simple assertion-based precondition checks with natural language and real-time feedback. To the best of our knowledge, we are the first to implement a dynamic planning algorithm for the VirtualHome Simulator and Franka Research 3 arm. More differences with other LLM based planning algorithms are described in Section 3.4.

LLM generated plans are often in natural language and need to be converted to suitable action primitives for parsing and execution (Xie et al., 2023). These action primitives must follow strict syntactic rules, as errors in these control statements can lead to downstream execution problems. A popular solution involves designing control functions in known programming languages like Python, which are then translated into rule-based action primitives (Liang et al., 2023; Singh et al., 2023). Our method uses simple action statements as execution primitives, but can be conditioned to output python code for robot execution, similar to previous studies in this area.

3 Our Proposal: BrainBody-LLM

The human brain is a sophisticated information processing system comprising a network of billions of neurons. Artificial neural networks aim to mimic brain functions, but a significant difference lies in the information processing method: the human brain functions continuously, in contrast to the discrete operation of computer algorithms (Aimone and Parekh, 2023; Korteling et al., 2021). To emulate critical cognitive functions of the human brain, particularly in terms of feedback mechanisms and adaptability, we developed the BrainBody-LLM algorithm.

Our algorithm consists of two LLMs, each with a distinct contribution to the overall task execution pipeline. The Brain-LLM is designed to

Algorithm 1 BrainBody-LLM

```

1: Input:
2:  $T$                                  $\triangleright$  Task description
3:  $K$                                  $\triangleright$  Max feedback loops
4: Functions:
5:  $\phi(\text{task}, \text{feedback})$            $\triangleright$  Brain-LLM
6:  $\theta(\text{high level plan step})$        $\triangleright$  Body-LLM
7:  $\pi(\text{low level action})$              $\triangleright$  Actuator
8:  $\rho(\text{action result})$               $\triangleright$  Simulator/Perception
9: Start
10:  $k \leftarrow 0$                        $\triangleright$  feedback loop counter
11:  $f \leftarrow \text{none}$                  $\triangleright$  no feedback in the beginning
12:  $hlp \leftarrow \phi(T, f)$             $\triangleright$  high Level Plan
13:  $i \leftarrow 0$ 
14: while  $i \neq \text{length}(hlp)$  do
15:    $step \leftarrow hlp[i]$          $\triangleright$  ith step of high level plan
16:    $\delta \leftarrow \theta(step)$         $\triangleright$  low level Action
17:   if  $\delta \neq <\text{pass}>$  then
18:      $action\_result \leftarrow \pi(\delta)$ 
19:     if  $action\_result \neq \text{success}$  then
20:       if  $k \neq K$  then           $\triangleright$  Update plan
21:          $f \leftarrow \rho(action\_result)$      $\triangleright$  feedback
22:          $hlp \leftarrow \phi(T, f)$ 
23:          $k \leftarrow k + 1$ 
24:       else
25:          $i \leftarrow i + 1$            $\triangleright$  go to next step
26:       end if
27:     else                       $\triangleright$  action is successful
28:        $i \leftarrow i + 1$            $\triangleright$  go to next step
29:     end if
30:   else                       $\triangleright$  no primitive for the current action
31:      $i \leftarrow i + 1$            $\triangleright$  go to next step
32:   end if
33: end while
```

decompose a given task into high-level execution plans in natural language. High-level plans are converted by the Body-LLM into low level robot control commands, with a pre-defined syntax for environmental execution. During runtime, any error messages provided by the simulation environment, motion planning controller or human feedback can be relayed to the Brain-LLM, which then generates an updated plan from the current step to complete the original task. The updated plan is subsequently converted to control statements by the Body-LLM. Our method uses iterative planning and feedback to create a closed loop pipeline. Our complete framework of integrating two LLMs is described in Algorithm 1. All LLM prompts in our approach include in-context learning examples that inform the planner about the environmental constraints (e.g., the microwave

is closed or the TV is on) and provide accurate, manually curated task-plan example pairs. BrainBody-LLM uses these examples to uncover patterns and understand object-action relationships to generate plans for unseen tasks. Moreover, feedback through error messages further grounds the planner in the real world by informing it about erroneous steps and explaining the reasons for the failure of particular steps.

We design three prompts to ground the LLMs within the environment and produce output that is compatible with real-world or simulation experiments. Each prompt addresses a key component of our pipeline: Planning, Execution and Feedback.

3.1 Planning

The planning prompt is designed to provide Brain-LLM with all necessary information to understand the robot’s environment, the available actions within the simulator or real-world setup, and some examples to facilitate learning the planning task in a few-shot setting. These examples can be manually crafted or selected from an appropriate dataset. Each example consists of a tuple: (*Environment Information*, *Input Task*, *High Level Plans*). Given that LLMs are trained on extensive real-world datasets, they rapidly learn patterns between tasks and their high-level execution plans, as well as the grounding relations between objects and actions required for executing a given task. Using common sense reasoning, they also learn to hierarchically generate plans for a task that are consistent with previously generated plans for similar tasks while ensuring temporal continuity. Figure 2 illustrates the format of our prompt, shortened for brevity.

3.2 Execution

The Body-LLM is responsible for sequentially generating executable action primitives based on the natural language plans created by the Brain-LLM. The execution prompt includes examples of natural language steps paired with robot control statements, helping Body-LLM learn the associations necessary for task execution. The prompt also introduces a unique token, `<pass>`, which Body-LLM uses when a natural language plan lacks a realizable action in the environment. In our pipeline, the `<pass>` token allows skipping steps, which is crucial for preventing execution

errors and avoiding oscillatory behavior caused by unavailable execution statements. This helps prevent erroneous plans from repeating due to the limited context window of LLMs. Figure 3 illustrates our execution prompt.

3.3 Feedback

Error resolution in high level task planning has been explored through three primary sources of feedback: rule-based heuristics (Ding et al., 2023; Huang et al., 2022), simulator feedback (Rana et al., 2023; Silver et al., 2024; Sun et al., 2023), and human feedback (Parakh et al.; Huang et al., 2023). Our method can integrate feedback from any of these sources to prompt the Brain-LLM to update its plans. The feedback prompt informs the Brain-LLM about the occurrence of an execution error and any associated error messages from the controller, simulator, or a human. Examples of error instances and corresponding solutions through new plans are also provided. Similar to the planning prompt, these in-context examples can be chosen either manually or from a suitable dataset. Each example consists of the tuple (*Error Message*, *Explanation*, *Updated Plans*). **In our experiments, error messages are collected from the simulator or controller and indicate which action was not executed and the reason.** Often, the raw error message is unreadable, so the *Explanation* explains the problem to the Brain-LLM in natural language and why a particular step failed. LLMs have been shown to improve performance with such chain-of-thought reasoning steps (Wei et al., 2022). Finally, the updated plans are constrained to start from the error step and are conditioned on plans completed before the error step. In real-world applications, it is not feasible to restart the entire task since the robot might have already executed some plans. Thus, we constrain the Brain-LLM to always generate updated plans from the current error step. When deployed to resolve a particular error, the feedback prompt encourages the LLM to first generate a natural language reasoning for the failure, followed by step-by-step plans for error resolution. Figure 4 shows the prompt we use for Brain-LLM. In this work, we do not include any visual perception models. For simplicity, our method assumes that the locations of objects are known to the robot beforehand.

Planning Prompt for Brain-LLM

You are in the command of a mechanical robot. Your task is to split a given task into high-level steps that can be executed by the agent in the current environment. Each output step should be executable by the agent using available actions.

Some examples of Task Instruction - Step-by-step plan pairs are given below:

```
{in_context_learning_examples}
```

You have the following objects in scene: {object_list}. The list of available actions are - {actions_available}.

Use the information above to create the step-by-step plan for the given task instruction. Remember to only use the above objects and the available actions. Do not combine intermediate steps to generate compound steps. Make sure to complete all the steps needed to finish the task. Your reply should always start with "0:"

Environment Information: {environment_information}

High-level Instruction: {task_input}

Step-by-step Instructions:

Fig. 2 Format of the planning prompt used in our experiments. The planning prompt tunes LLM outputs to meet environmental constraints while generating step-by-step task execution plans. In-context learning examples of high-level tasks and their corresponding subtasks, along with a list of available objects and actions, are needed. This enables the LLM to learn patterns from the examples and create plans for unseen tasks based on the robot’s current environment.

Table 1 Comparisons highlighting robustness of BodyLLM generated action statements. Actions like “*put*” and “*putin*” require detecting primary and secondary object, which the BodyLLM excels at due to better language reasoning capabilities. The second example shows how a simple high level plan can generate ambiguity in Embedding matching output, leading to failed execution. Third example highlights how BodyLLM correctly skips plans that are not executable, whereas embedding matching creates an erroneous action plan. In all examples, output generated by BodyLLM was executable and correct.

High level Plan	BodyLLM	Embedding Matching
Put toothpaste on the toothbrush	<putin> <toothpaste> <toothbrush>	<put> <toothbrush> <toothpaste>
Close the fridge	<close> <fridge>	<switchoff> <fridge>
Wait for the toast to be ready	<pass>	<drink> <toaster>

3.4 Differences from Previous Works

Our work derives inspiration from previous methods in utilizing feedback by back-prompting LLMs for improved robotic task planning (Valmeekam et al., 2023). A hierarchical planner, which breaks down complex task instructions to intermediate planning and action primitives has been explored before (Song et al., 2023). However, we design our system to ensure minimal domain customization, and demonstrate applicability in both simulation and real world setups. Rana et al. (2023) uses two distinct LLMs for 3D scene graph search and iterative re-planning using simulator feedback. Our approach does not rely on scene graphs,

with planning and error resolution performed by the Brain-LLM and action mapping performed by Body-LLM. Huang et al. (2023) implements a closed loop feedback integrating visual perception and language conditioned robotic skills. In their approach, the LLM planner has access to vision models providing information about the environment, and it further disambiguate planning confusion by asking questions to a human operator. Our contributions lie in an effective and completely autonomous planning approach that eliminates any human-in-the-loop scenario by reinforcing feedback through error messages. There are a number of works that integrate visual

Execution Prompt for Body-LLM

You are in control of a robot. Your task is to create a single line of program in a described format based on the instructions provided to you. Agents interact in environments via programs which are instructions that describe which actions each agent should do, and with which objects. Each line of program has the following format -

Action Plan: {command_syntax}

Some examples of plan - action program pairs are given below -

{incontext_examples_execution}

You have the following objects in scene: {object_list}. The list of available actions are - {actions_available}. Return a suitable action program for the provided plan. Remember to only use the actions in the available action list and use objects in the provided object list. If you are not sure what the output should be, it is always better to <pass> instead of creating a wrong action. If you do not find an available action or an object for the given sub-task, you should simply output <pass>.

Description: {input}

Action Plan:

Fig. 3 Format of the execution prompt used in our experiments. The execution prompt tunes the Body-LLM to generate appropriate control statements in the required syntax for a given plan created by the Brain-LLM.

grounding in planning with VLMs for object manipulation (Wu et al., 2023; Liu et al., 2024,?; Huang et al., 2023) and navigation tasks (Shah et al., 2023; Zhou et al., 2023), and we leave such expansion of our planning methodology for future work. Our work can also be integrated with skill learning techniques through human-guided imitation learning as demonstrated in Parakh et al..

A two-LLM system for generating symbolic and geometric relationships for task and motion planning has shown effectiveness in robotic environments (Ding et al., 2023). Our method distinguishes itself by avoiding any human expert intervention or customization for filtering, allowing environmental feedback and error messages to automatically guide the planning LLM towards an accurate and correct real world action. Silver et al. (2024) uses two LLMs for planning and correction using execution feedback, but relies on PDDL models for effective grounding, whereas our approach eliminates this dependency and can be used in real world experiments where objects and environment states are not known during task planning.

4 Experiments with VirtualHome

To evaluate our BrainBody-LLM approach, we first utilize a simulator and a perception module that execute commands generated by our LLMs and return environment states and error messages. We use a widely-adopted robotic task simulation software, ensuring the details provided allow for replication of our results.

4.1 VirtualHome: Simulator For Embodied Control

VirtualHome (VH) serves as our robotic control software, simulating a Human-In-A-Household scenario with support for multiple agents (Puig et al., 2018). The simulator features a variety of interactive household objects with predefined states like “open,” “closed,” “on,” and “off.” VH represents the agent as a humanoid avatar capable of interacting with these objects via low level control statements. Additionally, the simulator includes an in-built perception module that provides real-time information about objects in the scene, their states, and positions. Success and failure messages (with reasoning) for robotic

Feedback Prompt for Brain-LLM

You are in the command of a robot. Given a high level task and associated subtasks, a controller executed the commands by converting them to robotic syntax for object manipulation. However, not all subtasks were successful, and your job is to examine an error in execution, and suggest a revised action plan in continuation with previously executed commands.

Some examples of high level tasks, generated subtasks, error step and error message are given below. Go through them to understand the type of errors that are encountered, and learn how the revised plan can solve the encountered error -

```
{incontext_examples_error_resolution}
```

For the given task: {input}, a generated Initial Plan was: {init_plan}. The robot received the following feedback message: {feedback_message}

You have the following objects in scene: {object_list}. The list of available actions are - {actions_available}.

Use the information above to create an updated step-by-step plan for the given task such that this error does not occur again. Remember to only use the above objects and the available actions. Do not combine intermediate steps to generate compound steps. Your response should always start with numbering from the error step:

Environment Information: {env_information}

High-level Instruction: {input}

Explanation:

New plan:

Fig. 4 Format of the feedback prompt used in our experiments. The feedback prompt informs the LLM of an execution error and provides examples of how similar errors can be resolved. The LLM learns from these examples, and uses the given environmental conditions, available actions and creates a new updated plan to resolve the error, conditioned on already executed plans before the error step.

commands are also provided. We use the environmental states and error messages from the in-built simulator as input to the feedback prompt described in Figure 4. For our experiments, we use the latest VirtualHome v2.3.0.

4.2 Dataset

We observed that many tasks from the original VH dataset, which were manually annotated, are no longer executable in the latest simulator version. Therefore, we utilize the train-validation-test subset of samples as used in Singh et al. (2023). Each sample comprises a tuple: a task description, a step-by-step plan (both in natural language), and corresponding VH commands. The dataset is divided into training, validation, and test splits, containing 35, 25, and 10 tuples, respectively. Our planning prompt uses examples of task descriptions and high-level plans from the

dataset, whereas the execution prompt uses high-level plans and their corresponding VH commands as in-context learning examples.

4.3 Models Used

Since our approach relies on pre-trained foundational models that embody real-world knowledge and support incontext learning through prompting, we use three popular LLMs trained on vast amounts of data: PaLM 2 text-bison-001 (Anil et al., 2023), GPT-3.5 (Brown et al., 2020), and GPT-4 (Achiam et al., 2023). These models are accessed via their API calls.

4.4 Baselines

For fair comparisons, we selected baselines tested in similar scenarios—without visual perception-based grounding or human feedback. Our study benchmarks against two recent works that use

LLMs for agent control in the VH environment (Singh et al., 2023; Huang et al., 2022). Additionally, we developed a baseline model (Baseline-LLM) to translate task descriptions, expressed in natural language, directly into VH commands for execution without any intermediate high-level plans. Unlike the BrainBody-LLM, the Baseline-LLM uses a single LLM without any environmental feedback but with the same training dataset. These comparisons will highlight the efficacy of our BrainBody-LLM in the context of LLM-based embodied control. Some in-context learning examples used in our prompt structure are described in Appendix A.

4.5 Evaluation Metrics

We use three metrics for evaluating the plans produced by BrainBody-LLM and the baselines. **Executability (EXEC)** measures the proportion of steps in the plan that are executable within the VH environment. This metric does not assess the correctness of individual action plans in achieving the final goal. Thus, while EXEC primarily evaluates the performance of the Body-LLM in our approach, Brain-LLM generated plans influence this score too, as impractical plans result in misaligned commands.

Goal Conditions Recall (GCR) measures the percentage of satisfied goal conditions for a given task. It is calculated as the ratio of satisfied goal conditions to the total required goal conditions. For example, consider the task of bringing a coffee pot and a cupcake to the coffee table in Virtual-Home. Both the coffee pot and the cupcake must be on the coffee table at the end of the task execution. If neither item is carried to the table, the GCR is 0. If one item is moved to the table, the GCR is 0.5. If both items are successfully moved to the table, the task is considered successful, and the GCR is 1.

Success Rate (SR) quantifies the rate of successful tasks completed by an algorithm. For a task to be counted as successful, all task-relevant goal conditions should be satisfied. In other words, the SR of a task is 1 if and only if its GCR is 1. To calculate the overall SR, an average is taken over the SR of the tasks in a dataset.

4.6 Observations and Results

Our test set consists of 10 tasks in Virtual Home as described in Table 2. For each experiment, we run our algorithm five times with a temperature of 0.5 and report average scores across the runs. We study three variants of our algorithm: BrainBody-LLM (with feedback), BrainBody-LLM (without feedback) and Base-LLM (without Body-LLM and intermediate high level planning).

Obtained results demonstrate that feedback based planning and correction methods such as ProgPrompt and BrainBody-LLM (with feedback) outperform baselines that do not use feedback. Without feedback based error resolution, non-realizable plans are skipped which leads to unsatisfied goal conditions. ProgPrompt uses assert statements (if-else conditionals) to validate necessary environmental conditions before executing a given step. BrainBody-LLM (with feedback) uses error messages (in natural language) to guide the Brain-LLM towards a better plan and subsequent improved goal conditions satisfaction. Our approach exhibited overall enhancement in both SR and GCR metrics, outperforming ProgPrompt with the same LLM backend of GPT-4. This highlights the limitation of using simple assert based feedback signals. **Our approach allows the LLM to comprehend raw error messages from the simulator, and with its advanced reasoning capabilities, self-diagnose and correct generated plans for improved success.** Modifying the backend LLM from GPT-3.5 to GPT-4 improves our scores, motivating further improvements as LLMs become more powerful and their context window increases. In our approach, GPT-4 was the top performer, followed by PaLM 2 text-bison-001 and GPT-3.5.

BrainBody-LLM works best with the GPT-4 backend, utilizing simulator feedback for error resolution demonstrating a perfect score in 7-out-of-10 tasks (Table 3). Improved task-object mapping (plate → plate and not dish bowl, bread → breadslice) and spotting non-executable commands (using <pass> token) boosts EXEC. GPT-4 and feedback-enhanced planning reveals creative problem-solving. Figure 5 (LHS) shows how feedback reinforces task planning in VH environment. By utilizing error messages from the simulator, GPT-4 can generate revised plans that avoid repeating previous mistakes. The extensive world

Table 2 Comparing LLM-based planning algorithms for the Virtual Home Simulator Environment

Technique	Feedback	LLM	SR	GCR
Huang et al. (2022)	✗	GPT-3	0.00±0.00	0.21±0.03
ProgPrompt(Singh et al., 2023)	✓	GPT-3	0.34±0.08	0.65±0.05
		CODEX	0.40±0.11	0.67±0.08
		GPT-4	0.42±0.08	0.65±0.04
Base-LLM	✗	PALM	0.30±0.00	0.38±0.08
		GPT-3.5	0.16±0.05	0.68±0.03
BB-LLM	✗	PALM	0.30±0.08	0.61±0.13
		GPT-3.5	0.26±0.15	0.57±0.06
		GPT-4	0.38±0.13	0.70±0.01
BB-LLM	✓	PALM	0.40±0.00	0.59±0.01
		GPT-3.5	0.36±0.18	0.72±0.04
		GPT-4	0.54±0.09	0.69±0.04

Table 3 Best Score Comparison across models, showcasing GPT-4’s superior execution with feedback, achieving perfect scores in 70% of tasks, and highlighting its innovative problem-solving.

Task	PaLM 2 text-bison-001			GPT-3.5			GPT-4		
	SR	GCR	EXEC	SR	GCR	EXEC	SR	GCR	EXEC
Bring coffeepot and cupcake to coffee table	0	0.08	0.36	0	0.31	1	1	1	0.50
Brush teeth	1	1	1	0	0.28	0.43	1	1	0.50
Eat chips on the sofa	0	0.08	0.75	0	0.96	0.88	1	0.92	0.75
Make toast	0	0.98	0.38	1	1	0.57	1	1	0.42
Microwave Salmon	1	1	0.90	0	0.84	0.69	0	0.90	0.89
Put salmon in the fridge	1	1	1	1	1	0.88	1	1	0.88
Throw away apple	0	0.16	0.75	1	1	0.82	0	0.16	0.57
Turn off light	1	1	1	1	1	1	1	1	0.75
Wash the plate	0	0.16	1	0	0.13	0.54	0	0.10	0.91
Watch TV	0	0	0.67	1	1	0.80	1	1	0.80

knowledge embedded in these models empowers them to not only comprehend the problem but also to formulate innovative and unexpected solutions, surpassing human intuition in certain cases.

LLMs are prone to hallucinations, and using two LLMs can cause compounded errors. The `<pass>` token allows the BodyLLM to skip a hallucinated or infeasible high-level plan created by the BrainLLM. However, we observed that in many cases, the BodyLLM attempts to devise a suitable action plan, which is often non-executable. Compared to ProgPrompt, which uses assertion-based pre-condition checks before executing a command, our method scores lower in EXEC (84.40% compared to ProgPrompt’s 91.60%, both with GPT-4 as the backend LLM). Incorporating assertion-based checks into our

framework will help further improve EXEC. Notably, human-level EXEC, calculated by manually assigning action statements to high-level instructions, stands at 94%. This highlights the challenges in utilizing simulation environments like VirtualHome for our experiments, as many logical and syntactically correct statements were not executed due to simulator limitations in object properties.

Our closed-loop feedback mechanism for LLM-based planning is potentially susceptible to oscillatory behaviors that occur when a Body-LLM-generated action primitive is syntactically correct but not executable due to physical constraints in the environment. An unresolved plan repeats itself and compounds the error through multiple feedback loops. Increasing the number of feedback

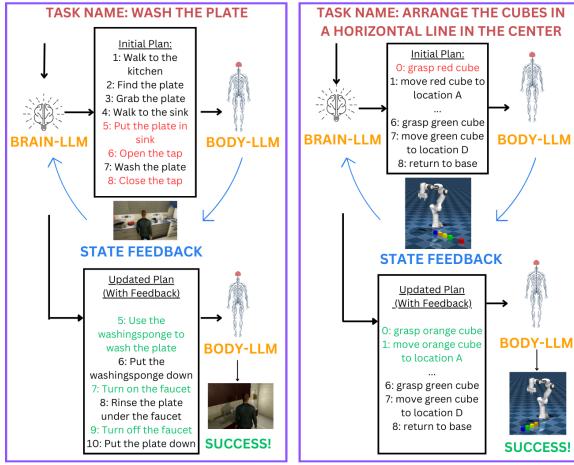


Fig. 5 GPT-4 planning with and without feedback: Example 1 and Example 2 shows refinement of plans with context cues in VH and Franka Arm Simulation, respectively.

loops does not always enhance the model’s performance. Incorporating additional sensor modalities into the LLM-planning framework can help prevent such issues. For instance, an image-level scene graph description of the environment can inform the LLM of existing conditions, allowing it to revise erroneous plans accordingly.

Ablation Study on Feedback Loops: The two LLMs in our approach interact with each other through feedback messages from the simulator. Without feedback, error messages from incorrect plans are not utilized for correction. We ablate the number of feedback loops K (Algorithm 1) used in our experiments. Our results indicate a consistent improvement across all evaluation metrics as the number of feedback loops increases, without significant fluctuations, as depicted in Figure 6.

Need for Body-LLM: In our approach, the Body-LLM performs an association task between natural language high-level plans and low-level control statements for task execution. Such association tasks can also be performed with a simple text-matching algorithm that aligns natural language steps with a fixed set of executable actions and objects using a joint text embedding space. However, this approach may not be robust for real-world deployment, as the Brain-LLM might not explicitly state the action to perform. To test this, we use a simple BERT embedding matching technique that computes the cosine similarity

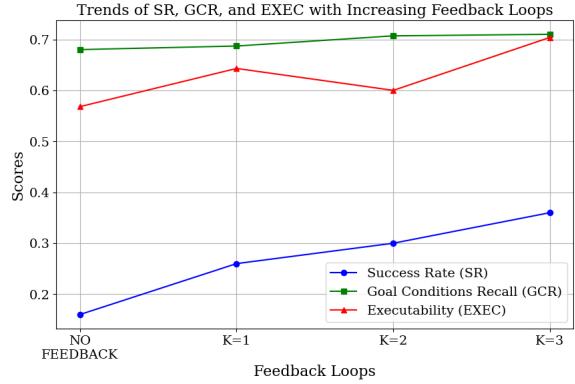


Fig. 6 Impact of Feedback Loops on Evaluation Metrics. The graph demonstrates a clear upward trend in all evaluation metrics as the number of feedback loops increases, without significant fluctuations. Notably, upon incrementing the value of K beyond 3, the metrics stabilize around a consistent value. This value aligns with the results reported at $K=3$; therefore, data for values higher than $K=3$ are not included in the analysis.

between high-level plans created by Brain-LLM and the subsequent available list of objects and actions separately. The object and action with the maximum cosine similarity are used to construct the action primitive for a given plan. We demonstrate three examples in Table 1 where this approach performed incorrectly compared to Body-LLM. Robust planning and successful execution in the real world require accurate low-level controls, which are handled by Body-LLM in our approach. Leveraging powerful LLMs allows for an improved association between natural language plans and low-level control commands.

5 Experiments with the Franka Robotic Arm

In this section, we demonstrate how BrainBody-LLM extends to real-world robot task planning using the Franka Research 3 (FR3) robotic arm. Our experiments, integrating a 7 DOF robotic arm with advanced LLMs like PaLM 2, GPT-3.5, and GPT-4, show promising results in autonomous robotic task planning and execution. All our experiments assume that the initial locations of objects and available target locations are known to the LLMs through environmental information communicated via prompts. This assumption can

Table 4 BrainBody-LLM Franka Arm Simulation Results. GPT-4 succeeds in all tasks including the difficult ones that require processing more than one possible feedback steps.

Task	Unreachable Obj./Loc.	Diff.	GPT-4	GPT-3.5	PaLM 2
Move the cubes to the right side of the environment only.	No	Easy	Success	Success	Success
Use the cubes to form the shape of the capital letter ‘L’. The shape consists of a horizontal and a vertical line intersecting at a right angle.	No	Medium	Success	Success	Fail
Arrange cubes in a horizontal line in the center of the work space, ordering them from left to right based on their color in sequence of the visible spectrum.	Yes	Medium	Success	Fail	Success
Arrange objects in the scene such that left and right side of the environment has exactly one cube and one cylinder. Each object needs to be assigned a unique location.	Yes	Medium	Success	Fail	Success
Create a triangle in the right part of the working space using reddish cubes.	Yes	Hard	Success	Fail	Fail
Create a plus sign in the working place using the cubes.	Yes	Hard	Success	Fail	Fail
Segregate objects based on geometric shapes into left and right part of work space. Objects of different shapes should not be on the same part of work space.	Yes	Hard	Success	Fail	Fail

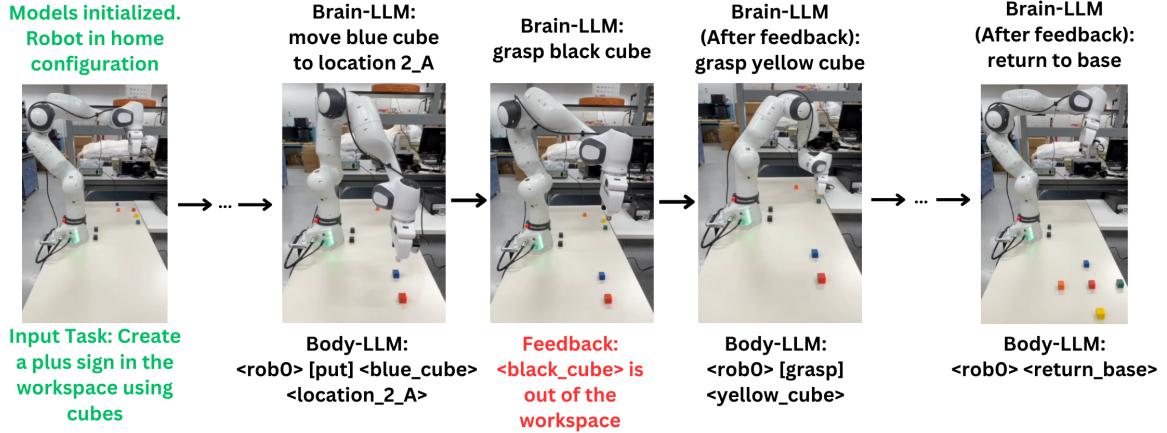


Fig. 7 Demonstration of our BrainBody-LLM algorithm (GPT-4 - Backend), operating on a Franka Research 3 Robotic Arm. It successfully completes the sixth task in table 4 by creating a "Plus" sign right side of the environment and subsequently returning to its initial position.

be removed with visual perception modules that identify and locate objects (Minderer et al., 2022).

5.1 Task Design

We designed seven pick-and-place tasks for the Franka arm, utilizing basic shapes such as cubes and cylinders to construct specific configurations in a tabletop setup. During execution, the task description and environmental information about the objects and available target locations in the scene are provided to the Brain-LLM. Some of the objects and target locations in the environment may be unreachable by the arm. The LLM planner must utilize controller errors to correct plans that involve unreachable objects or locations. Therefore, these tasks not only test the precision and spatial reasoning of the task planners but also their adaptability to errors, evaluating the feasibility of an autonomous end-to-end robotic system.

The tasks listed in Table 4 vary in terms of whether unreachable objects or locations are presented to them. The first two tasks, in which the Brain-LLM is not provided with any unreachable objects or locations, do not necessitate a feedback step. In contrast, it is likely that at least one feedback step is required to complete the remaining tasks. We classify these tasks into three levels of difficulty: Easy, Medium, and Hard, based on the minimum number of feedback iterations needed for successful task completion. Examples used in our prompts are described in Appendix B.

5.2 Results on Franka Research 3 Simulation Environment

We used a popular simulation environment for the FR3, which employs differential optimization and control barrier functions for pick-and-place tasks (Dai et al., 2023). Scene objects were created with MuJoCo (Todorov et al., 2012), and we developed scripts for API integration with three LLMs—PaLM 2, GPT-3.5, and GPT-4—using the prompt structure described in Section 3. Our tabletop environment consisted of objects distributed in both accessible and inaccessible parts of the workspace. This setup tested the LLM-based planner’s ability to adapt to out-of-workspace errors in real-time and revise plans accordingly. Extensive trajectory testing was conducted to avoid singularity points. We used a Python-based control repository¹ for the FR3 arm.

Our results show that GPT-4 excelled in all tasks, while GPT-3.5 completed 2 out of 7 tasks, and PaLM 2 achieved 3 out of 7 tasks. All models managed the first, simpler task without feedback loops. Figure 5 (RHS) demonstrates one of the tasks successfully completed by our algorithm.

5.3 Results on the Franka Robotic Arm

One of the chosen tasks involved arranging cubes to form a plus sign (*Create a plus sign in the working space using the cubes*), testing the planners’ logical and spatial reasoning along with their error resolution effectiveness. We selected this task for our real-world experiment since it involved multiple feedback steps and had a higher difficulty level than the other tasks. Figure 7 shows the setup and GPT-4’s successful task execution, illustrating its capability to control a 7 DOF robotic arm in object manipulation tasks.

GPT-3.5 struggled with plan adjustments after feedback, often failing to resolve incorrect steps. After utilizing all feedback loops, the incorrect plans were either executed or ignored by the Body-LLM, resulting in a low success rate. PaLM 2 occasionally generated incorrect plans but adeptly revised plans post-feedback, as seen in the third and fourth tasks in Table 4. However, not all plans led to an error, and in some tasks, although the execution was completed, the final configuration created did not match the specified task.

While PaLM 2 demonstrated planning and error correction capabilities, and GPT-3.5 showed good spatial reasoning, GPT-4 improved on both these models by effectively utilizing run-time feedback errors for accurate task planning.

5.4 Guidelines for Adapting BrainBody-LLM to Diverse Robotic Environments

The BrainBody-LLM framework is designed to enable direct autonomous planning across a broad spectrum of robotic tasks, both in simulation and real-world environments. Apart from our experiments in VirtualHome, datasets such as ALFRED (Shridhar et al., 2020), VRKitchen (Gao et al., 2019), and TEACH (Padmakumar et al., 2021) also employ high-level plans for task execution, making them ideal candidates for integration

¹<https://github.com/Rooholla-KhorramBakht/FR3Py>

with our framework. Given that prompt-based experiments can be time-consuming, we propose a streamlined yet effective approach for adapting BrainBody-LLM to custom robotic tasks and environments:

1. Data and prompt preparation:

- (a) *Prepare in-context learning examples.* Develop examples for the prompt frameworks defined in Section 3. The planning phase (BrainLLM) includes environment setup, task name, and high-level plans. The execution phase (BodyLLM) involves translating high-level plans into low-level controls. The feedback phase (BrainLLM) encompasses error messages, explanations, and updated plans. Examples of data tuples for each phase are provided in Appendix A and Appendix B for VirtualHome and Franka experiments respectively.
- (b) *Incorporate prepared examples in prompting frameworks.* Add collected examples to the prompts of structures defined in Figures 2, 3, and 4 to create final prompts for the LLM API call.

2. Task specific modifications:

- (a) *Define the environment.* Specify the list of objects and actions available to the robot. In our prompts, the variables *object_list* and *actions_available* are used to ground the LLM in the environment, minimizing hallucinations.
- (b) *Incorporate special instructions.* Depending on the task requirements, it may be necessary to include specific instructions to ensure that the LLM adheres to the environment’s constraints. PaLM 2 and GPT-3.5 are particularly sensitive to prompt variations. For example, emphasizing critical instructions using exclamation points and bold formatting enhances the LLM’s performance.

3. General guidelines for prompt engineering in robotic task planning:

- (a) *Optimize prompt length.* Longer prompts can cause the LLM to lose important context and increase the cost of API calls. These issues are largely mitigated in GPT-4, which offers advanced context retention and greater parameter complexity.

- (b) *Customize for real-world tasks.* Adapting BrainBody-LLM for real robotic tasks necessitates human-curated examples and customization tailored to the specific task at hand.

6 Conclusion

This paper introduced an algorithm for robotic task planning that leverages the reasoning and dynamic error correction capabilities intrinsic to LLMs. Our approach improves both the success rate of task execution and the recall of goal conditions, positioning it favorably against current baselines within the Virtual Home Human-In-A-Household simulation environment. The design and conceptual framework of our algorithm are practical and readily adaptable for real-world implementation, as demonstrated through our experiments using the Franka Research 3 Robotic Arm in Section 5.

Future work will focus on further dissecting and mitigating the phenomena of closed-loop oscillations and hallucinations observed in LLM-generated plans. This will involve using multi-modal feedback through various sensor modalities to ensure grounded and realistic task planning. Our goal is to evaluate and refine the efficacy of LLM planning algorithms, thereby accelerating their adoption for robotics applications.

References

- Achiam, J., Adler, S., Agarwal, S., Ahmad, L., Akkaya, I., Aleman, F.L., Almeida, D., Altenschmidt, J., Altman, S., Anadkat, S., et al.: GPT-4 technical report. arXiv preprint arXiv:2303.08774 (2023)
- Ahn, M., Brohan, A., Brown, N., Chebotar, Y., Cortes, O., David, B., Finn, C., Fu, C., Gopalakrishnan, K., Hausman, K., et al.: Do as I can and not as I say: Grounding language in robotic affordances. In: arXiv Preprint arXiv:2204.01691 (2022)
- Ahn, M., Brohan, A., Brown, N., Chebotar, Y., Cortes, O., David, B., Finn, C., Gopalakrishnan, K., Hausman, K., Herzog, A., et al.: Do as I can, not as I say: Grounding language in robotic

- affordances. In: Proceedings of the Conference on Robot Learning (2022)
- Anil, R., Dai, A.M., Firat, O., Johnson, M., Lepikhin, D., Passos, A., Shakeri, S., Taropa, E., Bailey, P., Chen, Z., et al.: PaLM 2 technical report. arXiv preprint arXiv:2305.10403 (2023)
- Aimone, J.B., Parekh, O.: The brain's unique take on algorithms. *Nature Communications* **14**(1), 4910 (2023)
- Brohan, A., Brown, N., Carbajal, J., Chebotar, Y., Dabis, J., Finn, C., Gopalakrishnan, K., Hausman, K., Herzog, A., Hsu, J., et al.: Rt-1: Robotics transformer for real-world control at scale. In: arXiv Preprint arXiv:2212.06817 (2022)
- Brohan, A., Brown, N., Carbajal, J., Chebotar, Y., Chen, X., Choromanski, K., Ding, T., Driess, D., Dubey, A., Finn, C., et al.: Rt-2: Vision-language-action models transfer web knowledge to robotic control. In: arXiv Preprint arXiv:2307.15818 (2023)
- Bubeck, S., Chandrasekaran, V., Eldan, R., Gehrke, J., Horvitz, E., Kamar, E., Lee, P., Lee, Y.T., Li, Y., Lundberg, S., et al.: Sparks of artificial general intelligence: Early experiments with GPT-4. arXiv preprint arXiv:2303.12712 (2023)
- Brown, T., Mann, B., Ryder, N., Subbiah, M., Kaplan, J.D., Dhariwal, P., Neelakantan, A., Shyam, P., Sastry, G., Askell, A., et al.: Language models are few-shot learners. In: Proceedings of the Advances in Neural Information Processing Systems, vol. 33, pp. 1877–1901 (2020)
- Dalal, M., Chiruvolu, T., Chaplot, D., Salakhutdinov, R.: Plan-Seq-Learn: Language model guided rl for solving long horizon robotics tasks. In: Proceedings of the International Conference on Learning Representations (2024)
- Devlin, J., Chang, M., Lee, K., Toutanova, K.: BERT: Pre-training of deep bidirectional transformers for language understanding. CoRR **abs/1810.04805** (2018) [1810.04805](https://arxiv.org/abs/1810.04805)
- Dai, B., Khorrambakht, R., Krishnamurthy, P., Gonçalves, V., Tzes, A., Khorrami, F.: Safe navigation and obstacle avoidance using differentiable optimization based control barrier functions. *IEEE Robotics and Automation Letters* **8**, 5376–5383 (2023)
- Driess, D., Xia, F., Sajjadi, M.S.M., Lynch, C., Chowdhery, A., Ichter, B., Wahid, A., Tompson, J., Vuong, Q., Yu, T., et al.: Palm-e: An embodied multimodal language model. In: arXiv Preprint arXiv:2303.03378 (2023)
- Ding, Y., Zhang, X., Paxton, C., Zhang, S.: Task and motion planning with large language models for object rearrangement. In: Proceedings of the International Conference on Intelligent Robots and Systems (2023)
- Gao, X., Gong, R., Shu, T., Xie, X., Wang, S., Zhu, S.: Vrkitchen: an interactive 3d virtual environment for task-oriented learning. arXiv **abs/1903.05757** (2019)
- Guan, L., Valmeeekam, K., Sreedharan, S., Kambhampati, S.: Leveraging pre-trained large language models to construct and utilize world models for model-based task planning. *Advances in Neural Information Processing Systems* **36**, 79081–79094 (2023)
- Huang, W., Abbeel, P., Pathak, D., Mordatch, I.: Language models as zero-shot planners: Extracting actionable knowledge for embodied agents. arXiv preprint arXiv:2201.07207 (2022)
- Huang, W., Wang, C., Zhang, R., Li, Y., Wu, J., Fei-Fei, L.: VoxPoser: Composable 3d value maps for robotic manipulation with language models. arXiv preprint arXiv:2307.05973 (2023)
- Huang, W., Xia, F., Xiao, T., Chan, H., Liang, J., Florence, P., Zeng, A., Tompson, J., Mordatch, I., Chebotar, Y., et al.: Inner monologue: Embodied reasoning through planning with language models. In: Proceedings of The 6th Conference on Robot Learning, pp. 1769–1782 (2023)
- Jansen, P.: Visually-grounded planning without vision: Language models infer detailed plans

- from high-level instructions. In: Findings of the Association for Computational Linguistics: EMNLP 2020, pp. 4412–4417. Association for Computational Linguistics, Online (2020)
- Korteling, J.E.H., Boer-Visschedijk, G., Blankendaal, R., Boonekamp, R., Eikelboom, A.: Human- versus artificial intelligence. *Frontiers in Artificial Intelligence* **4**, 622364 (2021)
- Lin, K., Agia, C., Migimatsu, T., Pavone, M., Bohg, J.: Text2Motion: from natural language instructions to feasible plans. *Autonomous Robots* (2023)
- Liu, F., Fang, K., Abbeel, P., Levine, S.: Moka: Open-vocabulary robotic manipulation through mark-based visual prompting. arXiv preprint arXiv:2403.03174 (2024)
- Liang, J., Huang, W., Xia, F., Xu, P., Hausman, K., Ichter, B., Florence, P., Zeng, A.: Code as policies: Language model programs for embodied control. In: Proceedings of the IEEE International Conference on Robotics and Automation, pp. 9493–9500 (2023). <https://doi.org/10.1109/ICRA48891.2023.10160591>
- Liu, P., Orru, Y., Paxton, C., Shafullah, N.M.M., Pinto, L.: OK-Robot: What really matters in integrating open-knowledge models for robotics. arXiv preprint arXiv:2401.12202 (2024)
- Luo, X., Xu, S., Liu, C.: Obtaining hierarchy from human instructions: an llms-based approach. In: CoRL 2023 Workshop on Learning Effective Abstractions for Planning (2023)
- Micheli, V., Fleuret, F.: Language models are few-shot butlers. In: Proceedings of the Conference on Empirical Methods in Natural Language Processing, pp. 9312–9318 (2021)
- Minderer, M., Gritsenko, A., Stone, A., Maxim Neumann, D.W., Dosovitskiy, A., Mahendran, A., Arnab, A., Dehghani, M., Shen, Z., Wang, X., Zhai, X., Kipf, T., Houlsby, N.: Simple open-vocabulary object detection with vision transformers. ECCV (2022)
- Mu, Y., Zhang, Q., Hu, M., Wang, W., Ding, M., Jin, J., Wang, B., Dai, J., Qiao, Y., Luo, P.: Embodiedgpt: Vision-language pre-training via embodied chain of thought. *Advances in Neural Information Processing Systems* **36** (2024)
- Parakh, M., Fong, A., Simeonov, A., Gupta, A., Chen, T., Agrawal, P.: Human-assisted continual robot learning with foundation models. In: CoRL 2023 Workshop on Learning Effective Abstractions for Planning
- Puig, X., Ra, K., Boben, M., Li, J., Wang, T., Fidler, S., Torralba, A.: Virtualhome: Simulating household activities via programs. In: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pp. 8494–8502 (2018). <https://doi.org/10.1109/CVPR.2018.00886>
- Padmakumar, A., Thomason, J., Shrivastava, A., Lange, P., Narayan-Chen, A., Gella, S., Piramithu, R., Tur, G., Hakkani-Tür, D.Z.: Teach: Task-driven embodied agents that chat. In: AAAI Conference on Artificial Intelligence (2021). <https://api.semanticscholar.org/CorpusID:238253352>
- Ren, A.Z., Dixit, A., Bodrova, A., Singh, S., Tu, S., Brown, N., Xu, P., Takayama, L., Xia, F., Varley, J., et al.: Robots that ask for help: Uncertainty alignment for large language model planners. In: Proceedings of the Conference on Robot Learning (2023)
- Rana, K., Haviland, J., Garg, S., Abou-Chakra, J., Reid, I., Suenderhauf, N.: SayPlan: Grounding large language models using 3d scene graphs for scalable task planning. In: 7th Annual Conference on Robot Learning (2023)
- Rajvanshi, A., Sikka, K., Lin, X., Lee, B., Chiu, H.-P., Velasquez, A.: Saynav: Grounding large language models for dynamic planning to navigation in new environments (2024)
- Singh, I., Blukis, V., Mousavian, A., Goyal, A., Xu, D., Tremblay, J., Fox, D., Thomason, J., Garg, A.: Progprompt: Generating situated robot task plans using large language models. In: Proceedings of the IEEE International Conference on Robotics and Automation, pp. 11523–11530 (2023). <https://doi.org/10.1109/ICRA48891.2023.10160591>

- Shinn, N., Cassano, F., Gopinath, A., Narasimhan, K., Yao, S.: Reflexion: Language agents with verbal reinforcement learning. Proceedings of the Advances in Neural Information Processing Systems (2024)
- Silver, T., Dan, S., Srinivas, K., Tenenbaum, J.B., Kaelbling, L., Katz, M.: Generalized planning in PDDL domains with pretrained large language models. In: Proceedings of the AAAI Conference on Artificial Intelligence (2024)
- Silver, T., Hariprasad, V., Shuttleworth, R.S., Kumar, N., Lozano-Pérez, T., Kaelbling, L.P.: PDDL planning with pretrained large language models. In: NeurIPS 2022 Foundation Models for Decision Making Workshop (2022)
- Shah, D., Osiński, B., Ichter, B., Levine, S.: LM-Nav: Robotic navigation with large pre-trained models of language, vision, and action. In: Proceedings of the 6th Conference on Robot Learning (2023)
- Shridhar, M., Thomason, J., Gordon, D., Bisk, Y., Han, W., Mottaghi, R., Zettlemoyer, L., Fox, D.: ALFRED: A Benchmark for Interpreting Grounded Instructions for Everyday Tasks. In: The IEEE Conference on Computer Vision and Pattern Recognition (CVPR) (2020). <https://arxiv.org/abs/1912.01734>
- Song, C.H., Wu, J., Washington, C., Sadler, B.M., Chao, W.-L., Su, Y.: LLM-planner: Few-shot grounded planning for embodied agents with large language models. In: Proceedings of the IEEE/CVF International Conference on Computer Vision, pp. 2998–3009 (2023)
- Sun, H., Zhuang, Y., Kong, L., Dai, B., Zhang, C.: Adaplanner: Adaptive planning from feedback with language models. arXiv preprint arXiv:2305.16653 (2023)
- Todorov, E., Erez, T., Tassa, Y.: MuJoCo: A physics engine for model-based control. In: Proceedings of the IEEE/RSJ International Conference on Intelligent Robots and Systems, pp. 5026–5033 (2012). <https://doi.org/10.1109/IROS.2012.6386109>
- Touvron, H., Martin, L., Stone, K., Albert, P., Almahairi, A., Babaei, Y., Bashlykov, N., Batra, S., Bhargava, P., Bhosale, S., et al.: Llama 2: Open foundation and fine-tuned chat models. arXiv preprint arXiv:2307.09288 (2023)
- Valmecikam, K., Marquez, M., Sreedharan, S., Kambhampati, S.: On the planning abilities of large language models - a critical investigation. Proceedings of the Advances in Neural Information Processing Systems (2023)
- Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A.N., Kaiser, L.u., Polosukhin, I.: Attention is all you need. In: Proceedings of the Advances in Neural Information Processing Systems, vol. 30 (2017)
- Wu, J., Antonova, R., Kan, A., Lepert, M., Zeng, A., Song, S., Bohg, J., Rusinkiewicz, S., Funkhouser, T.A.: Tidybot: Personalized robot assistance with large language models. 2023 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), 3546–3553 (2023)
- Wake, N., Kanehira, A., Sasabuchi, K., Takamatsu, J., Ikeuchi, K.: GPT-4V(ision) for robotics: Multimodal task planning from human demonstration. arXiv preprint arXiv:2311.12015 (2023)
- Wei, J., Wang, X., Schuurmans, D., Bosma, M., Ichter, B., Xia, F., Chi, E., Le, Q.V., Zhou, D.: Chain-of-thought prompting elicits reasoning in large language models. In: Proceedings of the Advances in Neural Information Processing Systems (2022)
- Xie, Y., Yu, C., Zhu, T., Bai, J., Gong, Z., Soh, H.: Translating natural language to planning goals with large-language models. arXiv preprint arXiv:2302.05128 (2023)
- Yao, S., Zhao, J., Yu, D., Du, N., Shafran, I., Narasimhan, K., Cao, Y.: ReAct: Synergizing reasoning and acting in language models. In: Proceedings of the IEEE International Conference on Learning Representations (2023)
- Zhou, G., Hong, Y., Wu, Q.: Navgpt: Explicit

reasoning in vision-and-language navigation with large language models. arXiv preprint arXiv:2305.16986 (2023)

A Prompt Examples for VirtualHome Experiments

Planning prompt of Brain-LLM for VirtualHome Experiments

You are in the command of a virtual agent... Some examples of High-level Instruction - Step-by-step Plans pairs are given below.

High-level Instruction: refrigerate the salmon

Step-by-step Plans:

- 0: I would go to the kitchen and find the salmon.
- 1: I would take the salmon and put it in the fridge.
- 2: I would close the fridge.
- 3: Done.

High-level Instruction: turn off the table lamp

Step-by-step Plans:

- 0: walk to the table lamp.
- 1: find the switch.
- 2: turn off the switch.
- 3: Done.

... (More examples) ...

You have the following objects in scene: {object_list}. The list of available actions are - walk, run, walktowards, walkforward, turnleft, turnright, sit, standup, grab, open, close, put, putin, switchon, switchoff, drink, touch and lookat.

...

Feedback prompt of Brain-LLM for VirtualHome Experiments

You are in the command of a virtual agent... Some examples of high level tasks, generated subtasks, error step and error message are given below...

Initial Plan:

- 0: Walk to the radio.
- 1: Look at the radio.
- 2: Grab the radio.
- 3: Switch off the radio.
- 4: Done.

Error Step: 2

Feedback: '0': 'message': 'ScriptExecutor 0: execution_general: Script is impossible to execute'

Explanation: Radio is an object that cannot be grabbed. You can either turn it off or turn it on.

New Plan:

- 2: Switch off the radio.
- 3: Done.

... (More examples) ...

You were given task: {input}, a generated Initial Plan was: {init_plan}. The robot received the following feedback message: {feedback_message}

You have the following objects in scene: object list. The list of available actions are - walk, run, walktowards, walkforward, turnleft, turnright, sit, standup, grab, open, close, put, putin, switchon, switchoff, drink, touch and lookat.

...

Execution prompt of Body-LLM for VirtualHome Experiments

You are in control of a virtual agent...
Some examples of plan - action program pairs are given below -
Description: walk to laundry room
Action Plan: <char0>[walk] <laundry-room>
Explanation: Since there exists a walk action that is executable by the simulator and a bathroom in the simulator, this action plan will satisfy the given description.

Description: put clothes in washing machine
Action Plan: <char0>[putin] <clothespile><washingmachine>
Explanation: Since there exists a putin action that is executable by the simulator, and a washing machine and clothespile in the simulator, this action plan will satisfy the given description.

Description: add detergent
Action Plan: <pass>
Explanation: There exists detergent in the scene but there is no action add that is executable by the simulator so I should not generate an action plan but simply pass it.

... (*More examples*) ...

You have the following objects in scene: {object_list}. The list of available actions are: walk, run, walktowards, walkforward, turnleft, turnright, sit, standup, grab, open, close, put, putin, switchon, switchoff, drink, touch, lookat. Return a suitable action program for the provided plan...

Description: {input}
Action Plan:

B Prompt Examples for Franka Arm Experiments

Planning Prompt of Brain-LLM for Franka Arm Experiments

You are in the command of the Franka Arm...
Some examples of High-level Instruction - Step-by-step Plan pairs are given below -

High-level Instruction: separate the blue cubes from the others.

Step-by-step Plans:

- 0: grasp blue cube
- 1: move blue cube to location_A
- 2: grasp aqua cube
- 3: move aqua cube to location_B
- 4: grasp azure cube
- 5: move azure cube to location_C
- 6: grasp yellow cube
- 7: move yellow cube to location_D
- 8: grasp beige cube
- 9: move beige cube to location_E
- 10: return to base

High-level Instruction: order the rainbow colors on the table

Step-by-step Instructions:

- 0: grasp red cube
- 1: move red cube to location_A
- 2: grasp orange cube
- 3: move orange cube to location_B
- 4: grasp yellow cube
- 5: move yellow cube to location_C
- 6: grasp green cube
- 7: move green cube to location_D
- 8: grasp blue cube
- 9: move blue cube to location_E
- 10: grasp indigo cube
- 11: move indigo cube to location_F
- 12: grasp violet cube
- 13: move violet cube to location_G
- 14: return to base

... (*More examples*) ...

You have the following objects in scene: {object_list}. The list of available actions are - grasp, move, return to base.

...

Feedback prompt of Brain-LLM for Franka Experiments

You are in the command of a virtual agent...

Some examples of high level tasks, generated subtasks, error step and error message are given below...

High-level Instruction: move 2 of the blueish cubes to the right of the table.

Initial plan: 0: grasp blue cube

1: move blue cube to location_A

2: grasp aqua cube

3: move aqua cube to location_B

4: return to base

Error step: 2

Feedback: aqua_cube is out of the workspace of the robot.

New plan:

2: grasp azure cube

3: move azure cube to location_B

4: return to base

High-level Instruction: order the rainbow colors in the table.

Initial plan:

0: grasp red cube

1: move red cube to location_A

2: grasp orange cube

3: move orange cube to location_B

4: grasp yellow cube

5: move yellow cube to location_C

6: grasp yellow cube

7: move green cube to location_D

8: grasp blue cube

9: move blue cube to location_E

10: grasp indigo cube

11: move indigo cube to location_F

12: grasp violet cube

13: move violet cube to location_G

14: return to base

Error step: 13

Feedback: location_G is out of the workspace of the robot.

New plan:

13: move violet cube to location_H

14: return to base

... (*More examples*) ...

You were given task: {input}, a generated Initial Plan was: {init_plan}. The robot received the following feedback message: {feedback_message}

You have the following objects in scene: object list. The list of available actions are - grasp, move, return to base.

...

Body-LLM prompt for Franka Arm Experiments

You are in control of a virtual agent...
Some examples of plan - action program pairs are given below -

Description: grasp the white cube
Action Plan: <rob0>[grasp] <white_cube>
Explanation: Since there exist a grasp action in the repertoire of the controller and white_cube in the environment, this action plan will satisfy the given description.

Description: hold the black tube
Action Plan: <rob0>[grasp] <black_tube>
Explanation: Since there exist a grasp action in the repertoire of the controller and black_tube in the environment, this action plan will satisfy the given description.

... (More in-context examples) ...

You have the following objects in scene: {object_list}. The list of available actions are: grasp, move, return to base.

Return a suitable action program for the provided plan...

Description: {input}

Action Plan: