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REAL: Resilience and Adaptation using Large Language Models on Autonomous Aerial Robots

Andrea Tagliabue*, Kota Kondo*, Tong Zhao*, Mason Peterson*, Claudius T. Tewari, Jonathan P. How

***Abstract*— Large Language Models (LLMs) pre-trained on internet-scale datasets have shown impressive capabilities in code understanding, synthesis and in processing extended sequences of symbols, often presented in natural language. This work aims to explore new opportunities in long-term reasoning, natural language comprehension, and the available prior knowledge of LLMs for increased resilience and adaptation in autonomous mobile robots. We introduce REAL, an approach for REsilience and Adaptation using LLMs. REAL interfaces LLMs with the mission planning and control framework of an autonomous robot. The LLM employed by REAL provides (i) a source of prior knowledge to increase resilience for challenging scenarios that the system has not been explicitly designed for; (ii) a way to interpret natural language and other log/diagnostic information available in the autonomy stack, for mission planning; (iii) a way to adapt the control inputs using minimal user-provided prior knowledge about the robot. We integrate REAL in the autonomy stack of a real multirotor, querying onboard an offboard LLM at about $1.0-0.1$ Hz as part of the robot's mission planning and control feedback loops. We provide a demonstration of capabilities by showcasing in real-world experiments the ability of the LLM to reduce the position tracking errors of a multirotor, and decision-making to avoid potentially dangerous scenarios (e.g., robot oscillates) that are not explicitly accounted for in the initial prompt design.**

I. INTRODUCTION

Creating mission planning and control capabilities that are adaptive and resilient to unexpected scenarios has been a large area of research in recent years. Adaptive control has enabled exceptional performance when addressing specific failure modes, such as disturbances [1]–[3], incorrect models/parameters [4]–[6], or poor controller tuning [7]–[9]. However, these approaches work best under a pre-defined set of failure modalities, and/or leverage accurate models/prior knowledge about the robot from the designer. Similarly, complex missions for autonomous mobile robots have been successfully managed through sophisticated state machines and mission planners [10]–[15]. However, these planners often need to reason over a pre-defined set of states and/or observation models, identified through extensive efforts.

Recently, foundational models, and especially Large Language Models (LLMs) pre-trained on internet-scale datasets [16]–[18], have demonstrated impressive performance on a variety of reasoning problems, including natural language [19], [20] and mathematics [21]. This performance stems in part from the large size of their internet-scale training data,

*Equal Contribution. The authors are with the Department of Aeronautics and Astronautics, Massachusetts Institute of Technology, the corresponding authors are {atagliab, kkondo, tzhao, masonbp, cttewari, jhow}@mit.edu.

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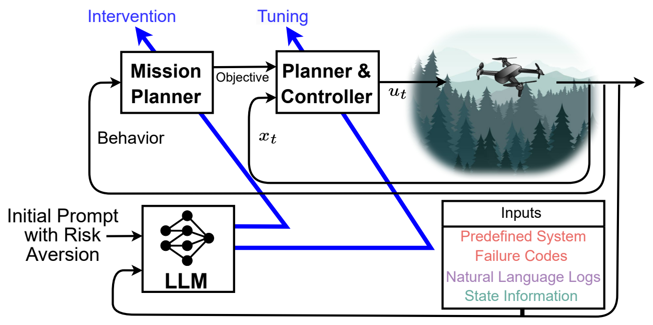


Fig. 1: REAL explores the usage of a Large Language Model (LLM) for adaptation across the different dynamics and components of an autonomous system, from low-level control to mission-scale decision-making, providing strategies to interface LLMs and existing autonomy solutions. We provide flight demonstrations and system validations, showing that an LLM queried from onboard the robot can reason about the current and desired state of the robot, selecting corrective actions at the decision-making and control level.

which embeds a vast amount of prior knowledge into the weights of the model. Additionally, their billion-of-parameters model architectures enable reasoning over long sequences of symbols, making them a natural choice for problems that involve generating a sequence of symbols.

The embedded prior knowledge and extended sequential reasoning capabilities have led to LLMs finding increased application in task planning and motion planning for robotics. In this context, the main focus of recent work has been planning for manipulation [22]–[28], using human input as a task specification and outputting calls to manipulator APIs that produce actions in a *quasi-static* regime. However, their potential has not been explored for *combined adaptive low-level control* and mission *planning/reasoning* on agile autonomous aerial robots. This new domain requires addressing important challenges, such as (a) how to *interface* the LLM with the low-level control stack, specifically accounting for the high control rates requirements typical in UAVs, and (b) how to provide information about the *fast UAV (error/mission) dynamics to the LLM*. These requirements are in contrast with the high latency and slow inference speed of LLMs (1.0-10.0s). Last, open questions remain (c) on the level of performance achievable under *limited domain-specific prior knowledge and human inputs*, as required in uncertain autonomous missions.

Towards addressing these questions, this paper presents REAL (Resilience and Adaptation using LLMs), a method that explores the capabilities of LLMs for mission planning and low-level adaptive control of an agile mobile robot, a multirotor UAV. Our work studies strategies to use the LLM's embedded prior knowledge of the UAV's controller to create adaptation throughout the stack, including altering low-level parameters, producing commands to better track trajectories, and making mission-level decisions. REAL uses human-crafted prompts (zero-shot prompting) to define minimal robot specifications and task/controller API available to the LLM. Then, during real-time deployment, REAL receives as input a set of natural-language and numerical signals available onboard the multirotor which capture mission-relevant information at different timescales, including information about the dynamics of the robot and its high-level mission objectives. Then, based on these automatically generated robot prompts, REAL chooses the most suitable control/mission planning APIs that are executed by the robot. This feedback loop operates at about $1.0-0.1$ Hz, while the prompts are processed remotely using the `OpenAI GPT-4 API`. We showcase the feasibility of REAL via hardware demonstrations, exposing our multirotor to a variety of performance-lowering conditions. Some of these conditions require low-level adaptation (e.g., by adjusting the commanded thrust), while others require mission-level adaptation (e.g., by improving controller tuning or conducting an emergency landing). Through these demonstrations, we also highlight that the behavior of an LLM as an adaptive controller can be modified by the use of natural language cues (e.g. using stronger language when the instructions given to the LLM are safety-related and important to follow). Additionally, we show that although the LLM cannot be queried at a high rate (up to 1 Hz), it can still process and make suggestions in response to high-frequency information by making use of algorithmically pre-processed information.

Contributions:

- We present REAL, an approach to integrate LLMs in the autonomy stack of an aerial robot, specifically for *mission planning* and *low-level control*, addressing how to *interface a slow, high-latency LLM with the fast control rates required on a UAV*. REAL enables us to investigate the potential and benefits of leveraging LLMs' internet-scale priors for adaptation and resilience on a UAV. We leverage zero-shot prompting, and we show that our prompt requires minimal knowledge of the robot's model/dynamics and mission specifications.
- We validate our system design choices via hardware demonstrations, showcasing adaptation and decision-making capabilities using LLMs. To the best of our knowledge, this is the first time that such capabilities have been demonstrated on an *aerial* robot.

II. RELATED WORKS

A. Adaptation at Mission-Scale and Low-Level Control

Adaptive Control. There are two broad categories of methods used for adaptive control: direct and indirect methods. Indirect methods aim at explicitly estimating models or parameters, which are leveraged in model-based controllers, such as MPC [29], to improve performance. Model/parameter identification include filtering techniques [30], [31], disturbance observers [32]–[34], set-membership identification methods [35], [36] or learning-based methods [5], [37]. Direct methods, instead, develop policy updates that improve a certain performance metric. These updates are often done to drive the behavior of the system towards that of a reference model, with the updates themselves involving changing the shallow layers of the DNN policy [1], [38], [39]. Other strategies include learning a policy update strategy offline using meta-learning [2], [40], or using parametric adaptation laws such as $\mathcal{L}_1$ adaptive control [3].

While many adaptive control strategies are able to improve low-level performance in real-world systems, these strategies often fail when mission-level adaptation is required. LLMs, like the one employed by REAL, provide opportunities to simultaneously reason at low-level and mission-level scale.

Uncertainty-Aware Mission Planning. Mission-level adaptation is usually achieved with robot autonomy. State-of-the-art approaches to autonomy have involved the use of finite-state machines and uncertainty-aware planners [13], [15], [41], enabling autonomy on many systems, from a single autonomous car [10] to multiple heterogeneous robots [11], [12]. While these methods achieve impressive performance in the coordination of multiple autonomous systems, they do not leverage the internet-scale prior knowledge in LLMs that may be helpful in making decisions under natural language-based observations that are available at the system level (e.g., log), nor they require to specify observations models/mission states.

B. Foundational Models in Robotics

Foundational models have quickly found a variety of applications in robotics, with a focus on planning from natural language instructions. [42] develops a holistic foundational model that performs perception, planning, and control using internet-scale datasets to train a multi-modal foundational model that, given a goal described in natural language, can use video feed to plan and execute a sequence of commands to achieve that goal. [22] decodes an LLM weighted by skill affordances [43] from value functions to generate feasible plans for robots. [23]–[25] all translate a high-level instruction into a plan expressed in code, which is then executed by the robot. [26] uses an LLM to translate a natural language planning problem into a domain-specific language, then runs a classical planner to solve the problem. [28] uses an LLM to generate a plan in natural language, then uses a similarity measure to translate the plan from natural language into one executable by the robot. [27] uses closed-loop environmental feedback to improve the performance of using an LLM for planning and control in manipulation tasks. While existing methods focus on task-level planning for functioning in quasi-static scenarios (especially for manipulation), our work uniquely leverages LLMs for low-level adaptation combined with high-level mission management on an agile aerial robot, demonstrating a new domain of possible deployment of LLM-based reasoning.

III. APPROACH

A. Approach Overview

The objective of our work is to explore a decision-making and adaptation mechanism that uses LLM reasoning to enable successful and resilient mission execution in autonomous systems despite the presence of uncertainties and potentially unplanned/unexpected failures that may happen across different levels of the autonomy stack. The considered autonomous system is a multirotor, whose objective consists in reaching a desired position. During the mission, the robot is subject to uncertainties, such as model errors or wind, that may cause a critical mission failure. The robot needs to understand how to mitigate the effect of those uncertainties and autonomously decide whether to abort the mission if the effects of those uncertainties cannot be corrected, based on a natural-language specified risk tolerance. Our approach, summarized in Fig. 1, leverages an LLM to trigger adaptive/resilient behaviors in the mission planning and control stack using the following inputs: available signals, pre-defined error codes, and natural-language-based logs and error messages. In the following sections, we define in detail the interface between an existing autonomy stack and the LLM.

B. Autonomy Stack

1) Controller: We consider a multirotor controlled by a cascaded position and attitude controller. The employed position controlled is based on a Linear-Quadratic Regulator (LQR) that uses a hover-linearized model of an attitude-controlled robot. The model is described in detail in [44], and has the form:

$$\mathbf{x}_{t+1} = \mathbf{A}\mathbf{x}_t + \mathbf{B}\mathbf{u}_t, \tag{1}$$

where $\mathbf{x} \in \mathbb{R}^8$ is the state and $\mathbf{u} \in \mathbb{R}^3$ is the control input. The state is:

$$\mathbf{x} = [{}_W\mathbf{p}^\top, {}_W\mathbf{v}^\top, {}_I\phi, {}_I\theta]^\top, \tag{2}$$

where ${}_W\mathbf{p}^\top \in \mathbb{R}^3$ and ${}_W\mathbf{v}^\top \in \mathbb{R}^3$ represent, respectively, the position and velocity expressed in a world frame W. The quantities ${}_I\phi$ and ${}_I\theta$ denote the attitude of the robot, expressed as roll and pitch Euler angles in a gravity-aligned, yaw-fixed frame I, whose x-axis is aligned with the world reference frame W.

Following [44], the control input $\mathbf{u}$ is:

$$\mathbf{u} = [{}_I\phi_{\text{cmd}}, {}_I\theta_{\text{cmd}}, \delta f_{\text{cmd}}]^\top, \tag{3}$$

where δf_{cmd} denotes the linearized commanded thrust, and ${}_I\phi_{\text{cmd}}$ and ${}_I\theta_{\text{cmd}}$ are the commanded roll and pitch. These commands are executed by a cascaded attitude controller, whose dynamics are assumed to correspond to a first-order dynamical system. Yaw is controlled via a separate cascaded PD controller, not shown here for brevity.

The control input is computed via:

$$\mathbf{u}_t = \bar{\mathbf{u}}_t + \mathbf{K}(\mathbf{x}_t - \mathbf{x}_t^{\text{ref}}) + \delta\mathbf{u}_t, \tag{4}$$

where $\bar{\mathbf{u}}_t$ represents the nominal command at hover and $\mathbf{x}_t^{\text{ref}}$ a desired reference trajectory computed by the mission-level planner. $\mathbf{K}$ is a linear gain matrix, obtained by solving the Discrete Algebraic Riccati Equation (DARE) using the linearized model $\mathbf{A}$, $\mathbf{B}$ and given positive-definite tuning matrices $\mathbf{R}$ and $\mathbf{Q}$. Key to this work, the additive control input $\delta\mathbf{u}_t$ represents an adaptive term that will be controlled by the LLM based on descriptions of the state of the system (error codes, logs), enabling adaptation at low-level control.

2) Mission Planner: The mission is managed by a finite state machine (FSM) that contains desired initial/terminal position setpoints, and timed transitions between the desired states. Once a desired position is selected, the FSM generates reference trajectories (position, velocity) that are tracked via the position controller Eq. (4). Every state inside the FSM is connected to an `emergency_landing` action that leads to a safe state (on the ground below the robot), which can be triggered by the LLM upon seeing what it determines is sufficient cause to terminate the mission.

C. Prompt Design And Interface with the Autonomy Stack

In this section, we present the strategy to interface the control and mission/trajectory planning stack with the LLM. We use an approach inspired by [23], i.e., we leverage Python-based syntax to define the possible failure modes in the autonomy stack, as well as the description of a set of function callbacks (API) in our control framework available to execute corrective actions. However, our approach differs from [23], as we provide additional natural language instructions to express mission-level goals and trade-offs, i.e., the willingness to risk to continue the mission when complications arise, versus aborting the mission. Additionally, we limit the potentially dangerous execution of automatically generated Python code by providing the LLM with the instruction to call a set of pre-defined Python APIs. Last, in our experiments, the LLM is connected in a closed feedback loop with the rest of the autonomy stack, without human intervention beyond the initial prompt design.

Code Color Convention: Note that throughout this work we use the following convention: green denotes the initial prompt to the LLM; this prompt is hand-crafted by a human and is loaded at the start of the mission; grey denotes the query automatically generated by the autonomous system, and blue denotes the reply from the LLM, closing the feedback loop.

Our prompt begins with the following sentence:

Initial Prompt (Part 1)
```
# Inside the codebase of my multirotor I found
the following python code:
```

This sentence introduces the LLM to the Python-based syntax that will be used next to list possible mission failures/issues, requirements, and actions available, and additionally introduces the LLM to the type of platform it needs to control. Next, we introduce a list of possible, easy-to-monitor, state-based errors and failures:

Initial Prompt (Part 2)
```
# list of possible issues/failures in mission planner/controller:
NO_ISSUE = 0
FLYING_TOO_HIGH = 3
FLYING_TOO_LOW= 4
FLYING_TOO_LARGE_POSITIVE_POSITION_ERROR_X = 7
FLYING_TOO_LARGE_NEGATIVE_POSITION_ERROR_X = 8
FLYING_TOO_LARGE_POSITIVE_POSITION_ERROR_Y = 5
FLYING_TOO_LARGE_NEGATIVE_POSITION_ERROR_Y = 6
```

These failures can be easily detected, and their corresponding number is fed as input to the LLM. Additionally, we found that the LLM is more easily able to interpret failures expressed in natural language than failures expressed in numerical signals (i.e., current trajectory tracking errors). The corresponding error codes are generated by comparing the current trajectory tracking error $\mathbf{p}_t - \mathbf{p}_t^{\text{des}}$, and by triggering an issue on the corresponding axis if the error exceeds a predefined threshold.

Next, we define a new fictitious Python variable and function call that computes the possible failures:

```
Initial Prompt (Part 3)
# check current failure using check_failure.
# outputs a list of possible failures, for example [2, 3],
# and a string with additional information.
# The string may be empty.
# Example current_failure:
# ([2, 3], 'position error = [0.1, -0.1, 1.5]')
current_failures = check_failures()
```

As in [23], we make use of Python comments to provide contextual information on the output of the function call and describe additional inputs that we will be feeding into the LLM, using the second term in tuple of `current_failure`. This extra input can be used to provide descriptive error messages or other information that is not known/does not need to be specified a priori, providing additional flexibility in the type of information that we can feed to the LLM.

Next, we provide the LLM with information about the system-level actions (APIs) that the LLM can select:

```
Initial Prompt (Part 4)
# possible failure mitigation strategies
from controller import (
  # modify control input
  increase_thrust,
  decrease_thrust,
  accel_positive_x,
  accel_negative_x,
  accel_positive_y,
  accel_negative_y,
  # Mission-level decisions
  emergency_landing,
  do_nothing,
  # Controller tuning - we use a LQR
  tune_controller_by_decreasing_the_cost_of_actuation_usage,
  tune_controller_by_increasing_the_cost_of_actuation_usage,
  tune_controller_by_increasing_penalty_on_position_errors,
  tune_controller_by_decreasing_penalty_on_position_errors,
)
```

Controller API	Parameter/Change (Units)
`increase_thrust`	δf_{cmd}+=$0.5(m/s^2)$
`decrease_thrust`	δf_{cmd}-=$0.5(m/s^2)$
`accel_positive_x`	${}_I\theta_{\text{cmd}}$+=0.3(rad)
`accel_negative_x`	${}_I\theta_{\text{cmd}}$-=0.3(rad)
`accel_positive_y`	${}_I\phi_{\text{cmd}}$-=0.3(rad)
`accel_negative_y`	${}_I\phi_{\text{cmd}}$+=0.3(rad)
`tune_controller_by_...` `decreasing_cost_actuation_usage`	$\mathbf{R}_{\text{diag}}$*=0.8
`tune_controller_by_...` `increasing_cost_actuation_usage`	$\mathbf{R}_{\text{diag}}$*=1.2
`tune_controller_by_...` `increasing_penalty_pos_errors`	$\mathbf{Q}_{\text{diag}}[0:3]$*=1.2
`tune_controller_by_...` `decreasing_penalty_pos_errors`	$\mathbf{Q}_{\text{diag}}[0:3]$*=0.8

TABLE I: Mapping of specific control actions to parameter/amount changes. Note that the parameter changes is expressed with the compact Python syntax, e.g., δf_{cmd}+=0.5 corresponds to $\delta f_{\text{cmd},k+1} = 0.5 + \delta f_{\text{cmd},k}$.

These actions correspond to pre-defined changes in the control inputs or to events in the mission planner. More specifically, `increase_thrust` and `decrease_thrust` increase/decrease an adaptive term in the control input, while `accel_positive_...` and `accel_negative_...` produce accelerations along an axis by increasing/decreasing the extra roll/pitch setpoints by a pre-specified amount. Additionally, `tune_controller_...` updates the corresponding part of the weight matrices $\mathbf{R}$ and $\mathbf{Q}$ of the position controller Eq. (4); the corresponding DARE is solved onboard and the resulting gain matrix updates $\mathbf{K}$. The amount by which each parameter is changed is fixed and is a hyperparameter of the approach. The values used in our experiments are shown in Table I.

Towards the end of the prompt, we switch back to natural language, and we provide task/mission specifications:

```
Initial Prompt (Part 5)
From now on, I provide you with the value of the variable
"current_failure", and your output needs to be your best guess of
the function names in the python list
"list_of_function_names_to_be_executed_right_now".
For instance, your output: ["emergency_landing"],
"low_battery_voltage",
"because the drone can hardly move it is safer to land"
Try to think like a drone control engineer.
```

This prompt specifies the output that we expect from the LLM (a list of names of functions the controller can execute). It additionally includes two elements that can help the LLM reason about its choice of actions, and a brief and long explanation of the issue. Following best prompting practices, we also encourage the LLM to role-play, i.e., thinking like a "drone control engineer".

In addition, we discourage the LLM from outputting planned future actions and encourage brevity in its explanations, by adding the following lines in the initial prompt:

```
Initial Prompt (Part 6)
DO NOT output function names to be called in the future, but
account for past problems to come up with your guess of the functions
in "list_of_function_names_to_be_executed_right_now".
```

Last, we include sentences to further make the LLM aware of the possibility of taking emergency landings.

```
Initial Prompt (Part 7)
If problems persist, do not hesitate to emergency land. if your actions
do not take the desired effect, you must perform an emergency landing.
```

We note that omitting these sentences was making the LLM less prone to trigger an emergency landing, while exaggerating the need to emergency land (e.g., using "MUST" instead of "must") made the LLM more prone to immediately trigger an emergency landing, potentially providing a natural-language avenue to specify willingness to take risks in an autonomous system.

Last, to provide information on rapidly changing signals to the LLM, onboard the drone we implement a module that stores a buffer of positions and uses a Fast Fourier Transform (FFT) to evaluate the maximum amplitude of any frequency content. If the maximum frequency content is above a threshold, this information is outputted to the log received by the LLM, which can take decision accordingly.

IV. EVALUATION

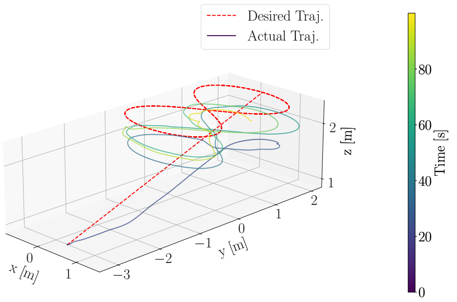
This section validates in real-time hardware demonstrations the proposed architectural choices.

A. Implementation Details

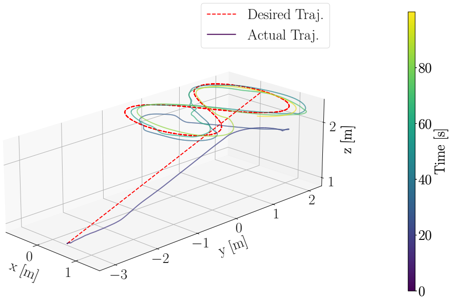
REAL is deployed on the MIT-ACL multirotor. Control and state estimation (IMU data fused with poses from a motion capture system) are executed onboard. The LLM is queried from onboard and receives replies via the `OpenAI GPT-4 API`. The UAV connects to the internet over Wi-Fi and queries the LLM at the highest possible rate, about $1.0 - 0.1$ Hz, depending on network latency and API usage.

B. Low-Level Adaptation and Controller Auto-Tuning

We begin by demonstrating the LLM's ability to perform low-level adaptive control and decision-making by adjusting the UAV's control inputs based on issues reported to the LLM. To introduce tracking error, we deliberately use an incorrect mass parameter during controller synthesis, deviating by $15\,\%$ from the UAV's true mass. This deviation results in a significant altitude error. We then deploy the UAV in a mission that consists of taking off, following a figure-eight trajectory, and then landing. We repeat the experiment two times, with the difference that in the first experiment, to study the choice that the LLM would make absent this parameter, we removed the `tune_controller_by_..` in `Initial Prompt (Part 4)` that API call.



(a) Trajectory Tracking **without** Control Gain $\mathbf{K}$ Tuning



(b) Trajectory Tracking **with** Control Gain $\mathbf{K}$ Tuning.

Fig. 2: REAL's successful altitude (z-axis) adaptation during a figure eight ($0.25\,\mathrm{m/s}$) with an incorrect mass parameter in the controller ($15\,\%$ error from nominal). *Top*: experiment performed when the API calls `tune_controller_by_...` removed from the initial prompt. *Bottom*: same experiment with the `tune_controller_by_...` APIs added back. REAL successfully interprets the system-provided error messages, and calls useful APIs. Specifically, in the first scenario (top) REAL achieves adaptation by calling the `increase_thrust` API, successfully converging to the desired altitude. In the second scenario (bottom), REAL calls a combination of `tune_controller_by_...` and `increase_thrust` APIs, triggering changes in the controller matrix $\mathbf{K}$. This results in faster/better convergence to the desired trajectory.

Fig. 2 (top) shows the result without tuning the API call `tune_controller_by_..` in `Initial Prompt (Part 4)`, highlighting that throughout the mission, REAL succeeds at improving the altitude through the duration of the experiment (about $100\,\mathrm{s}$) by repeatedly calling the `increase_thrust` in `Initial Prompt (Part 4)`, obtaining an altitude tracking error within $30\,\mathrm{cm}$. Fig. 2 (bottom) shows the results on the same trajectory, but with the `tune_controller_by_..` in `Initial Prompt (Part 4)` added back to the prompt. In this experiment, the LLM calls both commands, as shown by the conversation (Conversation 1) between the LLM and the robot during the experiment:

Conversation 1

```
t = 3.92s: Prompt ([0], ")
t = 3.92s: Response list_of_function_names_to_be_executed_right_now:
           ["do_nothing"], "no_issue", "Since there are currently
           no issues detected with the drone, no corrective
           actions are needed at this time."
t = 8.47s: Prompt ([4, 6], 'z error is -0.14, y error is -0.44, ')
t = 8.47s: Response list_of_function_names_to_be_executed_right_now:
           ["increase_thrust", "accel_positive_y"],
           "flying_too_low_and_negative_y_position", "The drone
           is currently flying too low and also has a negative
           error in the Y-axis. Increasing thrust will correct
           the altitude issue, and accelerating in the positive Y
           direction will correct the positional error."
t = 14.03s: Prompt ([4, 6], 'z error is -0.63, y error is -1.18, ')
t = 14.03s: Resp. list_of_function_names_to_be_executed_right_now:
            ["increase_thrust", "accel_positive_y",
            "tune_controller_by_increasing_penalty_on_position_
            errors"], "flying_too_low_and_large_negative_y
            _position", "The drone is flying significantly too low
            and has a large negative error on the Y-axis. It's
            necessary to increase thrust and accelerate in the
            positive Y direction to correct these issues.
            Additionally, the large errors suggest it may be
            beneficial to tune the controller to penalize
            position errors more severely."
t = 19.0s: Prompt ([4, 5, 7], 'z error is -0.30, y error is 0.15, x
           error is 0.12, ')
t = 19.0s: Resp. list_of_function_names_to_be_executed_right_now:
           ["increase_thrust", "accel_negative_y",
           "accel_negative_x"], "flying_too_low_and_positive_
           position_errors", "The drone is below the desired
           altitude and has minor positive errors in both X and Y
           axis. To correct these, it should increase thrust to
           gain altitude, and decelerate in Y and X directions."
```

The altitude tracking error resulting from this experiment is within only 10 cm. This shows that the LLM is capable of selecting multiple mission-relevant low-level control APIs, without providing detailed prior instructions on its choice, and whose usage is beneficial at improving the outcome of the mission.

Now, we consider a more challenging scenario that highlights REAL's ability to correct for unmodeled dynamics. To test this, we place a large extra mass on the end of one of the multirotor's arms, creating an unmodeled torque disturbance. For brevity, the prompt is not shown, but adaptation is triggered by repeatedly selecting the expected API calls: `increase_thrust`, `accel_negative_y` and `accel_negative_x`. Fig. 3 shows the hardware experiment results of the LLM successfully reasoning how to eliminate error along each of its axes. Note that in this earlier experiment, roll and pitch torque function names were used in the prompt to control acceleration along the y

and x axes respectively. We later found that the LLM was more consistent when using the commands for requesting acceleration in x and y directions directly.

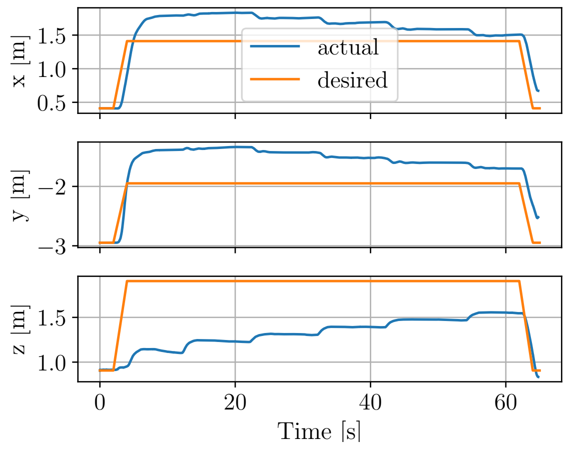


Fig. 3: REAL reduces position errors across the x, y, and z axes under unmodeled dynamics. In this experiment, an additional weight of 210 g was added to one of the UAV's arms, representing a 15 % increase in mass, which introduced a significant unmodeled external torque, affecting both attitude and position control. REAL successfully identifies the appropriate APIs to mitigate this error, although convergence is slowed due to the limited frequency at which the API can be invoked.

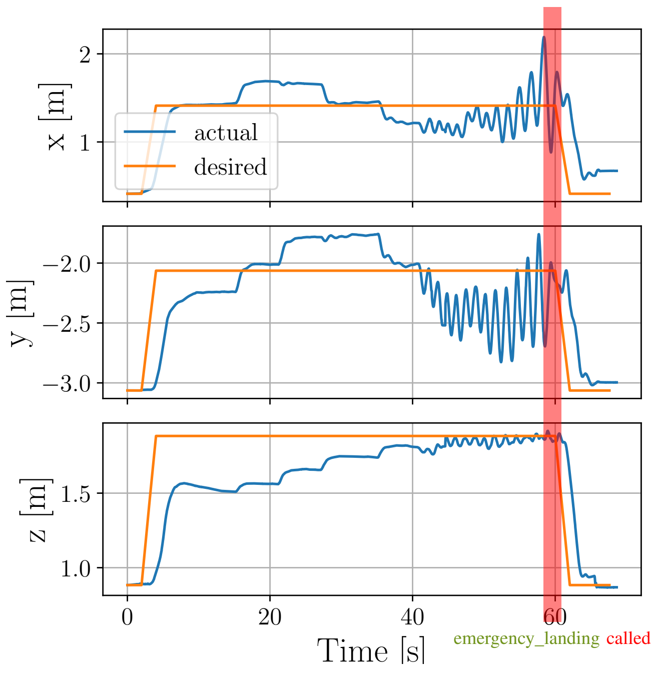


Fig. 4: REAL's position adaptation combined with its ability to trigger emergency landing automatically. In this experiment, the UAV was configured with a 15 %-less mass model. Initially, REAL successfully adjusted its control inputs to this discrepancy. Subsequently, we artificially introduced oscillations by pulling a cable attached to the UAV. Upon receiving a natural-language log that informs REAL of these oscillations, the LLM invokes the `emergency_landing` API. This experiment highlights REAL's ability to handle both lower-level control adaptations and higher-level mission-critical decisions such as terminating the mission for safety reasons.

C. Mission-scale Decision Making via Unsafe State Detection and Automatic Mission Termination

The purpose of this demonstration is two-fold: (1) show the LLM's ability to make critical mission-level decisions in the event that unforeseen circumstances cause the UAV to lose control and (2) show the LLM's ability to process additional information that was not in the original prompt.

Since the LLM is only able to make adaptive corrections at a slow rate, we would expect it to call for an emergency landing in the event of loss-of-control. To simulate a loss-of-control event, we apply large external disturbances to the robot by pulling it via a rope, causing large oscillations along the y axis, as seen in Fig. 4. The information warning provided by the onboard FFT tool are shown in the conversation history in Conversation 2. Although the LLM was not told it would receive any information about oscillations nor what to do if it did receive this information, it was able to make the critical decision to select the `emergency_land` API when it recognized that the UAV was in a dangerous condition via the provided log message "`DANGEROUS oscillations...`". Fig. 4 additionally highlights the LLM's ability to correct the altitude errors of the UAV, caused by an additional 15% mass mismatch, as visible before the interaction begins.

Conversation 2

```
t = 6.07s: Prompt ([0], ”)
t = 6.07s: Response list_of_function_names_to_be_executed_right_now:
           ["do_nothing"] reason: The reported information indicates
           that there are currently no discernible issues with the
           drone. Therefore, no actions are necessary at this time.
t = 13.95s: Prompt ([4, 6, 8], 'z error is -0.69, y error is -0.62,
            x error is -0.40, ')
t = 13.95s: Response list_of_function_names_to_be_executed_right_now:
            ["increase_thrust", "tune_controller_by_decreasing_the_
            cost_of_actuation_usage", "accel_positive_y",
            "accel_positive_x"] reason: The drone is flying too low
            and has negative position errors in both X and Y
            directions, hence, increasing thrust is the first step,
            along with acceleration in positive X and Y directions
            to correct the position errors. Besides, the cost of
            actuation usage should also be decreased to ensure a
            higher rate of control input changes for faster
            response. It's preferable to decrease the cost of
            actuation usage to make the drone respond more swiftly
            to the control inputs, as there are multiple issues
            happening simultaneously.
t = 57.48s: Prompt ([6, 8], 'y error is -0.65, x error is -0.28, VERY
            DANGEROUS oscillations on y-axis. Frequency is 0.67 [Hz],
            amplitude is 0.19 [m].')
t = 57.48s: Response list_of_function_names_to_be_executed_right_now:
            ["emergency_landing"] reason: The drone has large errors
            in both X and Y directions, and additionally, is
            exhibiting dangerous oscillations on the Y-axis. This
            indicates unstable flight dynamics which could be
            detrimental to the safety of the operation. An immediate
            emergency landing should be executed to prevent potential
            damage or hazards.
```

V. DISCUSSION

This work has presented a strategy to interface an LLM with different parts of the autonomy stack of an UAV, specifically focusing on control and decision making, and has explored new opportunities in terms of low-level adaptation and mission-level decision making on UAVs provided by LLMs. Although our demonstrations of capability focused on simple mission scenarios, within the capabilities of existing state-of-the-art adaptive controllers and decision making algorithms, REAL has show for the first time that LLMs can be successfully integrated and deployed within critical components of the autonomy stack. This capability enables access to LLM's prior knowledge and ability to process long sequences, providing new opportunities for decision making and control.

In addition, while our work has leveraged the general purpose `OpenAI GPT-4.0` LLM, requiring ad-hoc prompt design strategies, it has demonstrated that an *off-the-shelf* LLM can correctly identify relevant functions, obtaining interesting behaviors, without requiring human inputs, unlike prior existing work. In the future, we believe that improvements in performance and simplifications in prompt design can be further obtained by fine-tuning the LLM on mission-specific data.

Last, despite the high latency and the slow inference speed of existing LLMs, we have demonstrated techniques that successfully parse high-frequency signals (such as fast oscillations) into LLM-usable inputs, and strategies that enable the slow LLM output to alter control signals that require fast rates.

VI. CONCLUSIONS

We have presented REAL, a method that explores the usage of LLMs for zeros-shot cross-stack adaptation and autonomy on agile aerial robots. The method works by leveraging the LLM's natural language understanding, its ability to reason over long sequences, and its embedded prior knowledge of the robot's model/dynamics. Our evaluation in hardware experiments has validated our system design, and has demonstrated promising first steps towards low-level adaptation and improvements in mission-level resilience. In the future, we would like to further extend this framework to more complex, multi-robot autonomous systems, where more advanced reasoning is required to diagnose and recover from failures.

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