Laboratory of Sustainability Robotics

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Student Project Task Agreement

Student:	**Name:** ____________	
	Student ID: ____________	**Department:** TBD
	University: EPFL	
Thesis:	**Title:** Model Predictive Control for Tooltip Stabilisation of a Coaxial Tricopter with a 6 DoF Stewart Parallel Manipulator	
	Kind of thesis: MSc	**Semester:** TBD
Supervisor:	Prof. Dr. Mirko Kovac	
Advisor:	Yusuf Furkan Kaya	
Co-Advisor:	Visnusuthan Vairavipillai	

Start of the project:	TBD
Final report deadline:	TBD

1 Introduction

Aerial manipulation extends drones from pure flight into direct physical interaction with a target surface, using an end effector mounted on the airframe rather than the airframe itself [1]. On our platform, a coaxial tricopter hosts an end effector: a six-degree-of-freedom Stewart platform actuated by six Dynamixel servos, which has already deployed across the group's aerial additive manufacturing and inspection demonstrations [2, 3, 4]. Across all of these tasks, it is the tool tip's precision relative to the target surface, not the drone's own flight precision, that determines the quality of the result.

The existing control stack keeps the tool tip on target with a state machine that plans a drone body trajectory and a tooltip trajectory together, then tracks them through two separate loops: a standard cascaded controller for the body, and a node that recomputes the platform's setpoint, every time a new body pose estimate arrives, by combining the tooltip's world-frame target with the body's currently measured pose. This is a real feedback loop, but a purely kinematic, instantaneous one, with no model of where the body is moving next, no accounting for loop latency, and no awareness of the platform's joint limits or singularities. The vehicle's own tracking error and vibration therefore reach the tool tip as an unrejected disturbance.

This thesis replaces that reactive compensation with a model predictive controller built around the coupled dynamics of the airframe and the platform, one that predicts the body's disturbance motion over the loop's latency and enforces the platform's constraints directly, in the style already established for trajectory tracking on other aerial vehicles [5], drawing on the wider literature comparing model-based and learning-based control for agile flight [6, 7, 8, 9] to define the metrics a later, learning-based comparison will need. The outcome will be a validated predictive controller and a shared benchmark, in simulation and on hardware, that a follow-up thesis can use to bring in a learning-based controller for a fair comparison.

2 Objectives

This project aims to:

- Model the coupled dynamics of the coaxial tricopter body and the Stewart platform tooltip, including the platform's effect on the vehicle's centre of mass and inertia, and extend the group's existing Gazebo simulation, currently a generic PX4 quadrotor with the platform represented only kinematically, to include this coupling and a physically simulated platform.
- Design a model predictive tooltip stabilisation controller or a whole-body controller that predicts the body's disturbance motion over the sensing-and-actuation latency and computes corrective platform commands that respect the platform's joint limits and avoid singular configurations, replacing the existing reactive, kinematic compensation node.
- Quantify tooltip tracking accuracy against the existing kinematic baseline under representative disturbances, such as hover drift, wind-like perturbations, aerodynamic proximity effects (wall, ground, and ceiling) and rotor vibration, using tooltip pose error, settling behaviour, and actuator effort as the comparison metrics.
- Validate the controller on the real hardware in bench and flight tests, and document the disturbance profiles, metrics, operational efficiency, and test procedure so a follow-up project can implement and fairly compare a learning-based controller against the same benchmark.

3 Work breakdown

The project will be structured into the following clearly defined tasks:

1. **Literature review and system characterisation:** Review model predictive control for aerial vehicles [5] and for parallel mechanisms [10], aerial manipulation [1], and the group's own aerial additive manufacturing platform [2, 3, 4]. Review recent comparisons between model-based and learning-based control for agile flight [6, 7, 8, 9, 11, 12, 13] to inform the metrics the follow-up comparison will need.
2. **Coupled dynamics modelling:** Derive the coupled rigid-body model of the Y6 airframe and the Stewart platform, including the platform's reaction on the vehicle's centre of mass and inertia, using conservative estimates of the platform's mass distribution and actuator response.
3. **Simulation extension:** Extend the existing Gazebo and PX4 SITL simulation, currently a generic quadrotor with the platform represented only kinematically, to include a physically simulated platform and the coupling derived in Task 2. Set up the numerical tooling (e.g. CasADi or acados [14]) that will provide the controller's internal model.
4. **MPC controller design and implementation:** Implement a predictive tooltip stabilisation controller using the model from Tasks 2–3, integrated into the existing ROS architecture, including explicit handling of the platform's joint limits and singularities and a chosen approach to disturbance prediction, whether from the state estimator, direct inertial feedback, or both.
5. **Bench and simulation validation:** Validate the controller in simulation against the existing kinematic baseline, using a repeatable disturbance profile, either recorded or synthetic body motion, and the accuracy metrics defined in the objectives. Iterate on controller tuning and

constraint handling.

6. **Flight validation and reporting:** Validate the chosen controller in real flight against the same baseline and metrics. Consolidate the disturbance profiles, test procedure, and results so they can be reused directly by a follow-up comparison project, and compile the final report together with the code and model changes.

The work will take place in the Laboratory of Sustainability Robotics at EPFL and will be conducted in collaboration with Empa, building directly on the group's existing ROS and Gazebo codebase and the BuilDrone hardware. The project start date will be agreed with the advisor.

4 Deliverables and assessment

The student is expected to deliver:

- A written report following the host university's guidelines, submitted by the deadline stated above.
- A final presentation to the laboratory (15 min plus questions).
- A documented code repository, comprising the extended simulation, the MPC controller implementation, and the raw bench and flight validation data, structured so it can be reused directly by a follow-up learning-based control project.

Assessment follows the host university's regulations, with weight on the scientific quality of the work, the independence shown during the project, the quality of the documentation and the reproducibility of the results.

5 Bibliography

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