# Towards Robust Aerial Co-Manipulation: Insights into Work-in-Progress[†]

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***Abstract*—The reliable operation of small teams of aerial robots used in co-manipulation tasks in public or commercial spaces is highly challenging in many ways. In this short experience report, we highlight, demonstrate (in simulation-based and physical experiments), and recapitulate five areas of our ongoing activities in this thriving area of robotic research.**

***Index Terms*—Co-manipulation, coupled multi-robotic system, multi-agent system, control, simulation, digital twinning.**

## I. Introduction

The reliable operation of small teams of aerial robots in co-manipulation tasks in public or commercial space is challenging [2]. Such teams will be deployed in a range of applications, such as flexible and eco-friendly last-mile delivery, construction automation, autonomous handling of wildfires or repair of inaccessible infrastructure, and full-pose manipulation in hazardous (e.g., polluted, extra-terrestrial) environments. Key challenges in *co-manipulation tasks* include

- precise optimal coordination under delay and input constraints (i.e., reduced uncertainty, increased robustness),
- reliable autonomy (i.e., sparse or no tele-intervention),
- obstacle-aware formation (i.e., more flexibility), and
- on-board efficiency (i.e., extended operating time).

The development of novel algorithms with correctness guarantees requires *a flexible and reliable experimental platform*.

### A. Background

For the discussion below, we introduce the following concepts, hypotheses, and assumptions about the application as well as the used control platform and technology.

By *co-manipulation*, we refer to the manipulation of a compound object (i.e., a payload) with several electro-mechanical manipulators (e.g., micro-aerial vehicles, MAVs). We speak of *coupled* co-manipulation, if it involves stable mechanical connections between several manipulators and the object (e.g., necessary for shared transport). A co-manipulation task (e.g., pick-up, transport, and drop of an object) is performed *autonomously*, if the manipulators are *agents* controlled and coordinated with scarce or no remote/operator intervention.

We assume the *co-manipulation task* to be decomposed hierarchically into co-manipulation, local manipulation, physical actuation (i.e., MAV motors), and electro-mechanics; connected via delayed feedback, estimation sub-systems, control allocation, and (differentially flat) force propagation. This hierarchy is shown in the cascaded control loop in Fig. 1.

A *co-manipulation platform* comprises computation and control (e.g., micro-controller unit, electronic servo control), sensing, mechanical (e.g., rotors, cables), and actuation (e.g., inertial measurement unit, motors) components, which execute estimation and control algorithms at all levels (e.g., task coordination, guidance, navigation, and control) to autonomously perform a given co-manipulation task.

### B. Research Objectives and Questions

Our main focus lies on two *task-related* questions:

T1) How can we perform *tracking* (e.g., payload trajectory reference) with a small but flexible number of aerial manipulators?

T2) How can we perform *robustly stable tracking* under flexible manipulator configuration, imprecise state estimation (e.g., payload location, team configuration), state abstraction (e.g., payload weight bound), and delay bounds on computation and communication cycles?

Additionally, we explore two *platform-related* questions:

P1) How do we organize (centralized) information processing for (autonomous) sensing, coordination, control, and critical operator interaction for *realistic experimentation*?

P2) How can we align (co-execute) experiments in simulators and physical settings for continuous SIM2REAL transfer, data collection, and *efficient experimentation*?

### C. Contributions

Our initial proof-of-concept encompasses three *areas of progress* worthwhile discussing in this experience report:

1) We develop a *safe, flexible, low-cost experimental indoor co-manipulation platform* (i.e., $n$ manipulators, one cable-suspended payload, locally networked remote control, passive optical tracking). This platform enables

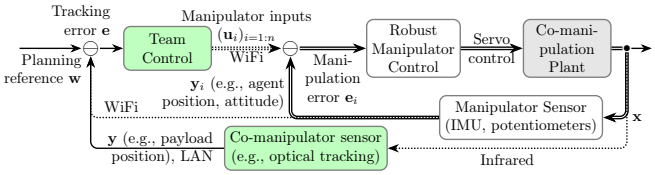



Fig. 1: Control system architecture for co-manipulation; remote (green), per agent (white).

[†]All authors contributed equally and are partially supported by the Chair "Architecture des Systèmes Complexes" of the Institut Polytechnique de Paris.

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a: Crazyflie™ 2 b: DJI Tello c: Customized MAV

Fig. 2: MAV platforms used in our experiments, equipped with reflective markers for passive optical tracking.

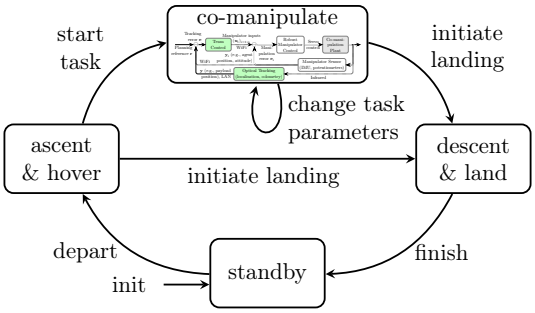



Fig. 3: Control system architecture: example of a task automaton with event-triggered (e.g., operator interaction) switches between tasks, each task using multi-threaded signal processing for sensing and control (cf. Fig. 1).



Fig. 4: Customized MAV, tracked and manually controlled.

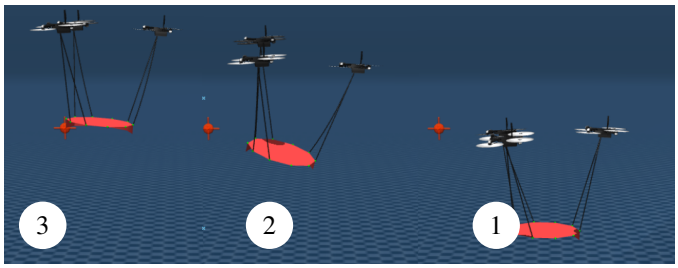



Fig. 5: Triple-agent co-manipulator under centralized model-predictive control (MPC), with payload and flexible cable dynamics. Simulation in MUJOCO showing the tracking of a waypoint (red dot) in three snapshots.

several *critical areas of experimentation* in aerial co-manipulation (e.g., payload tracking, obstacle-aware formation flight, task switching) in simulation, physical, and digital twin (DT) modes.

2) We replicate and evaluate recent technological advances in this domain, with a current focus on simulation.
3) We identify current strengths, limitations, and critical next steps in the development of our platform.

In Sec. II, we present five areas of our ongoing research. We provide a brief reflection of these areas in Sec. III, closing with an outlook beyond these areas.

## II. Five Work-in-Progress Areas

In this section, we describe five areas in our road-map for tackling the research questions in Sec. I-B. In each area, we provide snapshots of our experiments in the simulator, accompanied with first impressions of the envisaged physical setting. Our experiments are built on recent advances (cited below) in aerial co-manipulation.

### A. Task-based Platform-in-the-Loop Experimentation (P1)

The basis of the ongoing series of experiments is a lightweight and flexible coordination and control concept capable of running a range of scenarios side by side. The experiments are performed on three MAV hardware platforms (Figs. 2 and 4) and a simplified, robot operating system (ROS)-less, remote control architecture according to Fig. 3. Inspired by [4], we employ a conventional hybrid automaton for event-triggered task switching (Fig. 3). Depending on the platform, task-level control in each mode of this automaton can be organized into sensing, control, and event monitoring (e.g., operator interaction) threads, all sharing memory and running at appropriate frequencies. The control loop is closed over a multi-channel network (Wi-Fi 802.11 and Ethernet 802.3).

### B. Constrained Optimal Payload Reference Tracking (T1)

For payload reference tracking, we replicate and test a recent centralised MPC (CMPC) for aerial co-manipulation [7] in a simulation (Fig. 5). We allow full-state feedback (via an optical tracking system) on the payload location and attitude. To obtain a *simpler prediction model*, all cables are assumed tight, reducing the cost function (minimizing, e.g., state error, control input, and cable tension) and hard constraints (including, e.g., manipulator separation, obstacle avoidance, and state/input limits) to a multi-rigid-body predictive setting, which runs at frequencies between 10 and 20 Hz. Fig. 6 shows one of our physical settings for the SIM2REAL transfers, here using preliminary PID position control.

### C. Delay-robust Payload Tracking (T2)

Next, we develop and test a delay-aware controller inspired by [5], [6], whose gains are optimized to maximize the decay rate of the tracking error, in a simulation setting equivalent to the one in Fig. 5 (see Fig. 7). The controller guarantees asymptotic tracking of the payload reference trajectory in the presence of input delays arising from control computation, communication, and actuation. It consists of a *feedforward* term combined with a *proportional-derivative-acceleration* (FF+PDA) feedback law, with the gains selected to achieve the fastest decay rate. The resulting total force is allocated

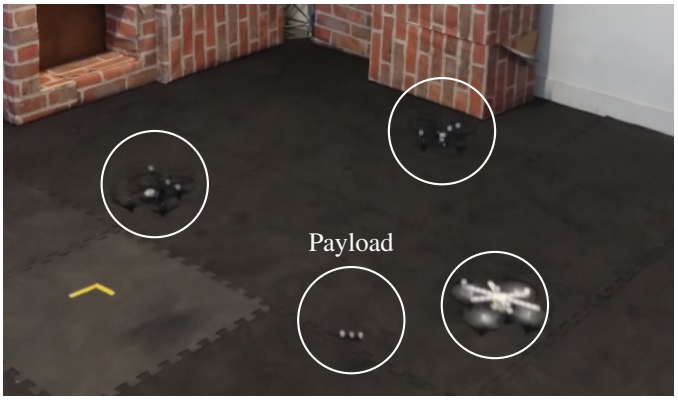
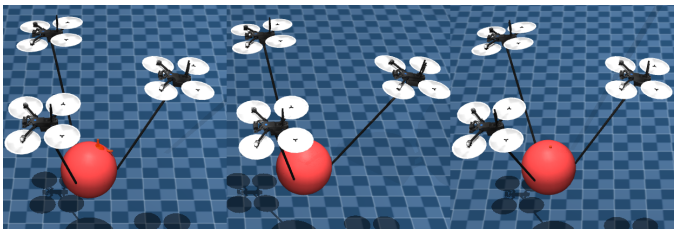
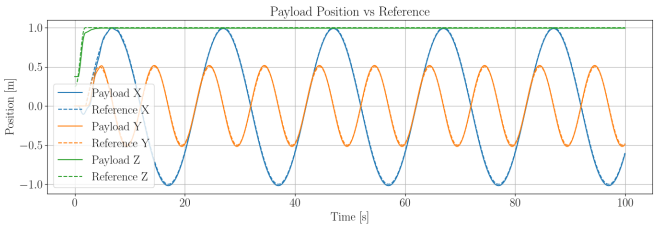



Fig. 6: Three Tellos attached to a cable-suspended $\approx 10$ g-payload, hovering at stable PID-based MAV-position control.



a: Simulation of three agents co-manipulating a spherical payload in MUJOCO under a 0.1 s control input delay.




b: Stable tracking (solid) of a 2D sine-wave reference (dashed).

Fig. 7: Triple-agent co-manipulator (similar to Fig. 5 except for a single cable per agent) under delay.

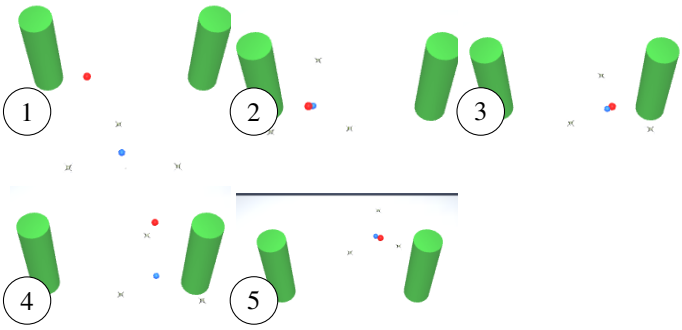
among the UAVs using a simple optimization algorithm,[1] from which the corresponding position, velocity, and acceleration references are constructed.[2]

### D. Obstacle-aware Formation Control (T1+P2)

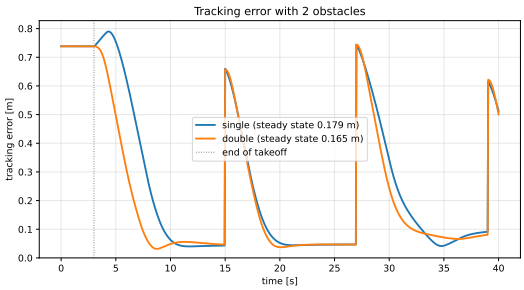
Furthermore, we investigate formation flight using single- and double-integrator, leader-less and leader-follower consensus laws [1, Secs. 3.1 and 4.4]. Unlike the two previous algorithms (Secs. II-B and II-C), this one includes *(possibly delayed) information sharing* between the manipulator control laws. To focus on obstacle-aware formation control, we apply this algorithm to uncoupled MAV dynamics without payload but with potential-field-based avoidance of static obstacles [4] and intra-team collisions (Figs. 8a and 8b). We ran first

[1]We impose a constraint on the force applied by each UAV to ensure that all forces remain positive and the cables remain in tension.

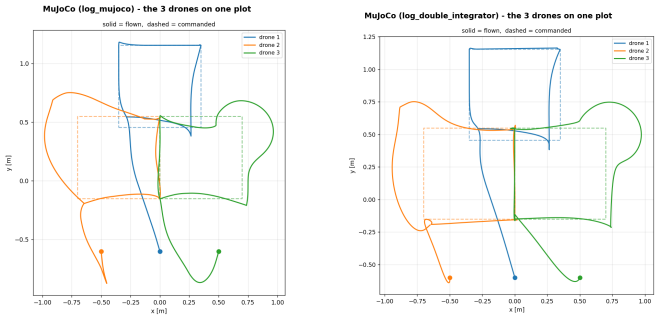
[2]Demo videos: https://tinyurl.com/PhysCollaBot2026




a: The center of formation (blue dot) is following three consecutive way-points (red dot) while avoiding two obstacles.




b: Tracking error decay in the simulation with two obstacles, comparison of the single- and double-integrator laws.




c: 2D tracking error from data captured in a triple-Tello setting for single- (left) and double- (right) integrator laws.

Fig. 8: Formation simulation aside the physical experiment.

tests of the two leader-less consensus variants with three Tellos (both with markers and using its internal state) in a *detached/uncoupled* DT mode (Fig. 8c) indicated in Sec. II-A: Data from the physical environment is compared a-posteriori with the data from the same 2D scenario in the simulation.

### E. Autonomous Payload Tracking (T1+T2)

One way to increase the degree of *team autonomy* is to reduce dependencies on remote automatic control as well as the frequency of operator interaction. Thus, we replicate and test a recent quasi-decentralized non-linear MPC (NMPC) [3] in a simulation setting that improves the one in Sec. II-B. Fig. 9 illustrates how the step impulses from supplying new 3D way-points are compensated with little overshoot while the manipulators avoid oscillations along any of the axes.

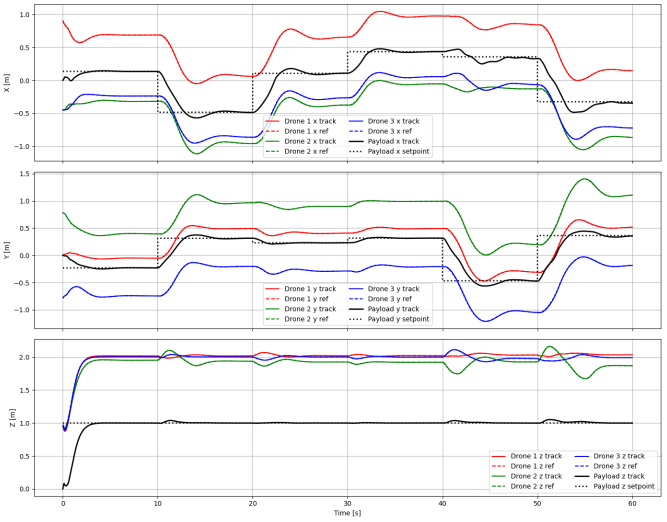



Fig. 9: Payload position (solid black) tracking via decentralized NMPC; simulation in MUJOCO, using a triple-manipulator/cable setting similar to the one in Fig. 5.

Each agent performs NMPC while accessing the payload trajectory predictions of the other agents and computing its own prediction based on consensus. The predicted payload states computed by each agent are shared with its neighbors, with whom a (communication-driven) consensus step is performed to facilitate convergence to the optimal solution. As opposed to the setting in Sec. II-B, the cost function does not minimize cable tension and the hard constraints include the co-manipulator kinematics instead of its dynamics as well as no manipulator separation.

## III. Discussion

Below, we reflect on our insights so far, organized into strengths, limitations, and a final outlook on our next steps.

### A. Strengths

- Our initial experiments operate in the context of challenging ratios of payload/cable weight to co-manipulation strength (e.g., Crazyflie™ setting in Fig. 2a: $\approx 10/15$).
- The manipulators are fragile enough in the coupled, delayed, and non-uniform sampled-data control setting to pose realistic algorithmic challenges (e.g., narrow region of attraction or stability margins with respect to the tracking precision of occasionally jittering markers).
- Our setting indicates moderate robustness to non-real-time scheduling (no RTOS), control prototyping in high-level languages (e.g., Python), numerically ill-conditioned computations, and lossy multi-channel networking.

### B. Limitations

- Higher levels of control (e.g., guidance, navigation, task switching) are still computed remotely.
- Our experimental settings do not yet support full-pose payload control, and they are not geared towards payloads of practical dimensions (i.e., shape, weight, or size).
- The fidelity of the dynamical and prediction models is not yet matured, and many loop parameters (e.g., delays, sampling and input rates, their stochasticity, estimation and control gains) are not precisely identified.

### C. Next Steps

From the research areas and experiments highlighted in Sec. II, we identified several areas in which to develop and refine our research. In particular, on the *task side* we want to

- implement an MPC scheme for precise full-pose payload tracking (i.e., position and attitude),
- enhance robustness to a variety of computation (e.g., MPC cycle time) and signaling delays and non-monitored disturbances (e.g., wind),
- handle varying-parameter (e.g., non-rigid) payloads, and
- focus on decentralized information processing, GPS-denied environments, and the treatment of fault events to increase the degree of autonomy.

On the *platform side*, we aim to

- reduce on-agent algorithmic complexity and efficiency as well as energy consumption and
- refine our co-manipulation platform to support mixed-reality and high-precision experimentation (e.g., by connecting distributed sensing and control components to simulated or physical platforms, or both).

The latter—a type of DT—allows us to provide control inputs to multiple plants simultaneously and combine the feedback from these plants.

The previously described areas are being investigated from a more fundamental viewpoint with the aim of developing novel mathematical and algorithmic contributions.

*Acknowledgments:* We thank our colleagues Julien Alexandre dit Sandretto, Alexandre Chapoutot, and Thibault Toralba for their guidance in getting to know the lab infrastructure including the off-the-shelf MAVs and tracking equipment, setting up and adjusting the tracking system, as well as using the various machine tools and 3D printing facilities.

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