Safety-Aware Human-Robot Collaborative Transportation and Manipulation with Multiple MAVs

Xinyang Liu*, Guanrui Li*, and Giuseppe Loianno

Abstract—Human-robot interaction will play an essential role in many future industries and daily life tasks, enabling robots to collaborate with humans and reduce their workload effectively. Most existing approaches for human-robot physical collaboration focus on collaboration between humans and grounded robots. In recent years, very little progress has been made in this area when considering aerial robots, which present increased versatility and mobility compared to their grounded counterparts. This paper proposes a novel approach for safe human-robot collaborative transportation and manipulation of a cable-suspended payload with multiple aerial robots. We leverage the proposed method to enable seamless and transparent interaction between the transported objects and a human worker while considering safety constraints during operations by exploiting the redundancy of the internal transportation system. The critical system components are (a) a distributed force-sensor-free payload external wrench estimator; (b) a 6D admittance controller for human-aerial-robot collaborative transportation and manipulation; (c) a safety-aware controller that exploits the internal system redundancy to guarantee the execution of additional tasks devoted to preserving the human or robot safety without affecting the payload trajectory tracking or quality of interaction. We validate the approach through extensive real-world experiments, including the robot team assisting the human in transporting and manipulating a load or the human helping the robot team navigates the environment. To our best knowledge, this work is the first to create an interactive and safety-aware pipeline for quadrotor teams to collaborate physically with a human operator to transport and manipulate a payload.

Index Terms—Aerial Robotics, Physical Human-Robot Interaction

Supplementary Material
Video: https://youtu.be/c1mj3be02cI

I. INTRODUCTION

As envisioned in the Industry 4.0 revolution, human-robot interaction will play a more important role in future industries and daily life [1]. Most research for physical human-robot interaction focuses on collaboration between humans and grounded robots. However, only a few exist for aerial robots, mostly limited to teleoperation. Compared to ground robots, collaborative Micro Aerial Vehicles (MAVs) show additional flexibility and maneuverability brought by their 3D mobility and small size. Moreover, a team of collaborative MAVs can provide increased adaptivity, resilience, and robustness during...
a task or multiple simultaneous tasks compared to a single aerial robot.

Teams of MAVs can assist humans in completing some complex or dangerous tasks. These include, but are not limited to inspection [2], mapping [4], [5], environment interaction [6], [7], surveillance [8], and autonomous transportation and manipulation [9], [10]. Specifically, in autonomous aerial transportation and manipulation, there are many possible usage scenarios. For instance, in a post-disaster response task, a team of aerial robots can cooperatively deliver emergency supplies to designated rescue locations based on the first respondent’s guidance. Or on a construction site, an aerial robot team can cooperatively manipulate over-sized construction materials with human workers to speed up the installation process and reduce their physical workload.

In this context, aerial robots such as quadrotors can carry a payload via different mechanisms, including but not limited to ball joints, robot arms, and cables [11]. As discussed in [12], cable mechanisms stand out compared to other solutions because of their lighter weight, lower costs, simpler design requirements, and zero-actuation-energy consumption. Therefore, they are particularly suited for Size, Weight, and Power (SWaP) aerial platforms.

Cables also present the right balance among the maneuverability, manipulability, and safety for physical human-aerial-robot collaboration compared to other solutions. For instance, several solutions attach the robots directly to the payloads via mechanisms like ball joints [13], magnets [14] or gripper [15]. However, these attach mechanisms present lower maneuverability and manipulability during a manipulation or physical interaction task than cables. Conversely, other solutions based on robot arms [16]–[18] can increase maneuverability and flexibility. However, this generally comes at the price of additional inertia and power requirements that may raise the human operator’s safety concern. Therefore, we believe that lightweight cable mechanisms can provide the proper trade-off among maneuverability, manipulability, and safety while executing multiple tasks, including cooperatively transporting a payload, exploring environments, changing formations to avoid obstacles, and maintaining a safe distance between the team and the human operator.

Therefore, this paper focuses on the human-aerial-robot collaborative transportation and manipulation of payload via cable mechanism using a team of aerial robots, as shown in Fig. 1. We introduce a novel control and estimation framework that allows the human operator to collaborate with a quadrotor team to transport and manipulate a rigid body payload in all 6 Degrees of Freedom (DoF). Furthermore, the proposed approach can exploit the system redundancy to enable the execution of secondary tasks such as obstacle avoidance or keeping a safe distance among the team agents and the human operator during collaboration, as shown in Fig. 1 (left).

Some existing approaches study the collaboration between humans and aerial robots but mostly with only one aerial robot [17], [19], [20] or with multiple aerial robots via teleoperation [6], [21]. Few solutions exist for human physical interaction and collaboration with several MAVs [22], [23]. However, the human operator’s physical cooperation is limited to a 2D horizontal plane, and the approaches do not consider the human operator’s safety.

In summary, the contributions of this paper are the following:

- A scalable and distributed force-sensor-free cable-suspended payload external wrench estimator.
- A 6D admittance controller for human-robot collaborative transportation and manipulation.
- A safety-aware load position and orientation controller that can exploit the additional degrees of mobility of the system introduced by using multiple agents. Specifically, compared to existing solutions, our controller considers the full nonlinear dynamics of the quadrotor team carrying a tethered rigid-body payload while offering the ability to preserve human or robot safety.

A set of extensive real-world experiments to validate the proposed solution.

To the authors’ best knowledge, this work is the first one proposing a safety-aware and interactive approach for quadrotor teams that allow seamless physical collaboration with human operators for collaborative transportation and manipulation of rigid-body payloads.

The paper is organized as follows. In Section III, we review the nonlinear system dynamics, considering the external wrench from a human operator. In Section IV, we discuss the proposed control framework that considers the nonlinear system dynamics and the safety of humans and robots. Section V presents the state estimation strategy and admittance control framework for intended human-aerial-robot collaborative manipulation. Section VI presents real-world experiments results on validating proposed framework. Section VII concludes the work and proposes multiple future research directions.

II. RELATED WORKS

Cable-suspended Aerial Transportation and Manipulation. As previously discussed, cable mechanisms have great advantages compared to other possible mechanisms. Therefore, in the following, we discuss control, planning, and estimation techniques for aerial transportation and manipulation with suspended cables.

Past literature has proposed several control and estimation methods [12], [21], [24], [25] for autonomous aerial transportation and manipulation using multiple MAVs with cables. For examples, several works [24]–[28] propose formation controllers for a team of MAVs to fly in a desired formation when carrying the suspended-payload. The carried payload is not modeled as an integrated part of the system but as an external disturbance that each MAV controller tries to compensate. Therefore, it is obvious that these solutions can struggle to transport the payload to a given position precisely. In [29], by assuming the payload is a point-mass, the authors analyze the full nonlinear dynamics of the system. Based on the dynamic model, the authors design a geometric controller to transport the payload to the desired position moving the quadrotor team to accommodate the desired load motions. However, this method, as well as the previously mentioned methods [24]–[27], only consider the payload as a point-mass and cannot manipulate the payload’s orientation.
Other approaches for autonomous aerial transportation and manipulation rely on a leader-follower paradigm [13], [30]–[32]. The leader robot follows the desired trajectory, whereas the followers maintain either a constant distance from the leader [31], or adapt to forces exerted on them when tracking their trajectory [13], [33]. However, these methods are subject to a single point of failure since they rely on the leader as a fundamental control unit for navigation. Additionally, these approaches cannot accurately guarantee the payload’s transportation to the desired location or manipulate the payload’s orientation.

Other works analyze the system’s complex nonlinear dynamics and mechanics and propose corresponding controllers to control the payload’s pose in 6 DoF [34]–[37]. For example, in [36], [37], the authors assume the system is in quasi-static state and analyze the corresponding static system mechanics. A payload pose controller assigns the quadrotors’ desired position to manipulate the payload to the desired pose. In [34], [35], the complex nonlinear dynamics in the system are thoroughly analyzed using Lagrangian mechanics. Leveraging this model, nonlinear geometric controllers enable the payload to follow the desired pose trajectory. More recently, some works also propose optimal control strategies [38], [39]. Although all these works consider the payload a rigid body, the extra redundant control degrees of freedom in the system [40] is not exploited to accommodate additional tasks like obstacle avoidance or to ensure safety distance among agents in the system. Some recent works start to investigate this aspect [21], [22]. However, they are specifically designed for a team of four quadrotors. In this work, we formulate a general safety-aware controller for any \( n \geq 3 \) quadrotors that exploit the null space of the cable tension distribution matrix, which maps the cable tension vectors to the wrench acting on the payload. By exploiting the redundancy at the control level, we allow the system to achieve some secondary tasks, such as avoiding obstacles or keeping a safe distance among robots and human operators.

However, as the methods above are designed to control the payload’s pose explicitly, it is essential to have a reasonable estimation of the payload’s states (i.e., pose and twists) to be fed back into the controller to have a good tracking performance of the payload’s pose. Some estimation approaches can recover the payload pose in [21], [42], but they rely on GPS and, therefore, cannot be employed in indoor environments or areas where the GPS signal is shadowed. Conversely, in our previous work [12], we tackled the payload pose inference problem using onboard vision sensors and IMU to obtain closed-loop control of the payload pose. However, estimating the payload pose using vision might be subject to onboard visual inertial odometry drift errors, resulting in inaccurate pose estimation and tracking. If potential control or state estimation errors happen, an autonomous aerial transportation and manipulation pipeline might require extra guidance to maneuver the payload to the desired pose. As shown in the proposed work, a human operator can provide additional guidance by collaboratively transporting and manipulating the payload with the quadrotor team, correcting the payload path.

**Human-Robot Interaction with Aerial Robots.** As mentioned above, the human operator’s additional guidance or collaboration with the robot team can help the overall task. Human-robot interaction can be achieved in several complementary ways. The first approach is human-robot interaction through teleoperation. In [21], [43], a state machine is designed for a human operator to command the entire quadrotor team to transition among hover, move, land, and take off. A similar approach is also proposed in [6], where the authors propose a shared control structure such that the human operator can remotely send the payload’s desired pose via a joystick. After obtaining the desired payload pose, the framework would generate desired position and velocity from the robot team to track based on an inverse kinematic controller in [44]. In [45], the human operator employs a remote controller to control the leader quadrotor. The remaining quadrotors in the team will follow the leader to transport the payload collaboratively. However, the “teleoperation approach” does not remove the system’s dependency on the onboard controller and state estimation to maintain high precision tracking and may not provide a suitable human operator’s interaction in certain tasks.

An appealing alternative solution is human-robot interaction through human-robot physical collaboration. In [22], the authors propose a framework for physical human-robot collaborative transportation of cable-suspended payload with a team of quadrotors. The proposed approach models the payload as a point mass and assumes external forces applied on the payload to be constrained in 2D. Leveraging their previous work [31], the designed controller assigns three quadrotors as leaders and the remaining robots as followers in the team. When an external force is applied to the payload, a fixed step is given to the leaders’ positions along the estimated force direction. In [23], five quadrotors collaborate with a human operator to transport a point mass payload. The force applied by a human on the payload is estimated by summing the cable tension forces and subtracting the gravity. The human-applied force is fed into an admittance controller, which updates the desired quadrotor position and velocity in the formation. However, compared to our work, the cable tension magnitude is measured by a custom tension measurement module and its direction by a motion capture system. In addition, in the works above, the authors assume that the human operator can only apply a force in 2D and limit their approach to a point-mass load. On the other hand, in the proposed work, we model the payload as a rigid body with 6 DoF, and our framework allows estimation of the full 6-DoF wrench acting on the payload, which increases the ranges of possible physical interactions between the human operator and the payload. Furthermore, we do not use any tension measuring device (except as ground truth during testing to validate our inference approach), or require any sensors to be installed on the payload.

### III. System Dynamics

In this section, we introduce the overall system dynamics modeling. We consider a team of \( n \) MAVs cooperatively transporting a rigid body payload. Each MAV has one massless cable attached from it to the payload, as depicted in Fig. 3.
Without loss of generality, the system’s world frame $I$ fixes at a location on the ground. The payload frame, $L$, is located at the center of mass of the payload and initially coincides with $I$. The relevant variables in our problem are stated in Table I. The system dynamics models are developed based on the following assumptions.

1) Aerodynamic interactions with the ground and other effects caused by high robot velocity are ignored due to its insignificant effect at a low moving speed that’s achieved by this system;

2) Each cable is assumed to be attached at the center of mass of each robot, each robot’s center of gravity coincides with its geometrical center, and all cables are assumed to be massless with no dynamic effects on the system;

3) Wind disturbances are ignored, the human operator would only interact with the payload, and all external forces on the payload and each robot are considered to be exerted by a human operator.

Assumption 1 is made based on the operational velocity, as well as based on the fact that, with our proposed framework, we can specify a spatial distance among agents to minimize these effects. This can also be enforced in our safe aware controller presented in Section IV-B. Assumption 2 is considered valid as a result of the symmetrical design of the MAV and the lightweight nature of all the cables used. Assumption 3 is based on the fact that in this work, we tackle indoor operating conditions.

### A. Quadrotor Dynamics

As shown in Fig 1, the cable attached to the $k^{th}$ quadrotor is attached to the payload at point $k$. The location of the attach point $k$ with respect to $L$ is represented by constant vector $\rho_{k} \in \mathbb{R}^3$. Based on assumptions 2 and 3, we consider the translational and rotational dynamics of the $k^{th}$ quadrotor as follows.

$$m_{k}\ddot{x}_{k} = F_{k} - \mu_{k} - m_{k}g,$$  \hspace{1cm} (1)

$$J_{k}\dot{\Omega}_{k} = M_{k} - \Omega_{k} \times J_{k}\Omega_{k},$$  \hspace{1cm} (2)

where $g = ge_3$, $g = 9.81 \text{m/s}^2$, $e_3 = [0 \ 0 \ 1]^\top$, $F_{k} = f_kR_k e_3$, and $\mu_{k} = -\mu_k\rho_k$.

### B. Payload Dynamics

Consider the payload suspended by $k$ MAVs, the net force $F_{L}$ and moment $M_{L}$ on the payload is determined by all the cable tension forces $\mu_{k}$, gravitational pull, and external wrench $F_{H}, M_{H}$ applied by the human operator.

$\begin{bmatrix} \dot{F}_{L} \\ \dot{M}_{L} \end{bmatrix} = \begin{bmatrix} \dot{F}_{H} \\ \dot{M}_{H} \end{bmatrix} + P\mu - \begin{bmatrix} m_{L}g \\ 0 \end{bmatrix}$,  \hspace{1cm} (3)

$$\mu = \begin{bmatrix} \mu_1 \\ \vdots \\ \mu_n \end{bmatrix},$$

where $P$ maps tension vectors of all $n$ MAVs in $I$ to the wrench on the payload with force in $I$ and moments in $L$.

$$P = \begin{bmatrix} I_{3\times3} & \cdots & I_{3\times3} \\ \rho_1 R_L^{-T} & \cdots & \rho_n R_L^{-T} \end{bmatrix},$$  \hspace{1cm} (4)

where the hat map $\hat{a}b : \mathbb{R}^3 \rightarrow so(3)$ is defined such that $\hat{a}b = a \times b, \forall a, b \in \mathbb{R}^3$. Through eq. (3), the translational and rotational dynamics of the payload are obtained

$$m_{L}\ddot{x}_{L} = F_{L},  \hspace{1cm} J_{L}\dot{\Omega}_{L} = M_{L} - \Omega_{L} \times J_{L}\Omega_{L}.$$  \hspace{1cm} (5)
IV. CONTROL

In this section, we describe the 6 DoF load controller considering a rigid-body load suspended by cables from \( n \) quadrotors. The controller is formulated based on the system dynamics presented in Section III. As shown in Fig. 2, we employ a hierarchical formulation for the controller like our previous work [12]. The formulation starts from a payload wrench \( \mathbf{W} \) that generates the desired wrenches \( \mathbf{F}_{L, \text{des}}, \mathbf{M}_{L, \text{des}} \) to control the position and orientation of the payload. Then the desired wrench is distributed to obtain desired cable tension vectors for each robot.

As discussed in Section IV-B compared to existing control solutions, the proposed approach allows, for \( n \geq 3 \) number of robots, to control the payload’s full pose explicitly while concurrently exploiting the system redundancy to execute the additional tasks. As we will present in Section IV-C, the key idea is to exploit the additional system redundancy to increase system safety by guaranteeing a spatial separation between the robots and some objects in the environments. To achieve this goal, we propose and discuss two different approaches. Overall, the system will distribute the wrench to the desired cable tension forces by considering

1) Minimizing the total cable tension forces to save the robot’s energy.

2) Exploiting the null space of the cable distribution matrix \( \mathbf{P} \) to achieve secondary tasks such as keeping safety distance between robots and possible human operators in the team.

Finally, the robot controller will input the desired tension vector to generate the corresponding thrust and moment as presented in Section IV-C.

A. Payload Controller

We present a payload controller that enables the load to follow the desired trajectory in a closed loop. The subscript *\( \text{des} \) denotes the desired value given by the trajectory planner. The desired forces and moments acting on the payload are designed as

\[
\mathbf{F}_{L, \text{des}} = m_l \mathbf{a}_{L, \text{des}},
\]

\[
\mathbf{a}_{L, \text{des}} = \mathbf{K}_p \mathbf{e}_x L + \mathbf{K}_d \mathbf{e}_d L + \mathbf{K}_i \int_0^t \mathbf{e}_x L \, dt + \mathbf{x}_L, \quad \mathbf{g}_L,
\]

\[
\mathbf{M}_{L, \text{des}} = \mathbf{K}_R \mathbf{e}_R L + \mathbf{K}_\Omega \mathbf{e}_\Omega L + \mathbf{J}_L \mathbf{R}^T L, \mathbf{O}_L, \mathbf{O}_L, \mathbf{O}_L
\]

\[
+ \left( \mathbf{R}^T L, \mathbf{O}_L, \mathbf{O}_L \right) \mathbf{O}_L, \mathbf{O}_L, \mathbf{O}_L,
\]

where \( \mathbf{K}_p, \mathbf{K}_d, \mathbf{K}_i, \mathbf{K}_R, \mathbf{K}_\Omega \in \mathbb{R}^{3 \times 3} \) are diagonal positive constant matrices, and

\[
\mathbf{e}_x L = \mathbf{x}_{L, \text{des}} - \mathbf{x}_L, \quad \mathbf{e} x L = \mathbf{x}_{L, \text{des}} - \mathbf{x}_L,
\]

\[
\mathbf{e}_R L = \frac{1}{2} \left( \mathbf{R}^T L, \mathbf{R}_{L, \text{des}} - \mathbf{R}_{L, \text{des}} \mathbf{R}_L \right),
\]

\[
\mathbf{e}_\Omega L = \mathbf{R}^T L, \mathbf{R}_{L, \text{des}} - \mathbf{R}_L, \mathbf{O}_L - \mathbf{\Omega}_L.
\]

B. Safety-Aware Controller

Once obtained the desired payload wrench \( \mathbf{F}_{L, \text{des}}, \mathbf{M}_{L, \text{des}} \), these can be distributed to the desired tension force \( \mathbf{\mu}_{k, \text{des}} \) along each cable as

\[
\mathbf{\mu}_{\text{des}} = \begin{bmatrix} \mathbf{\mu}_{1, \text{des}} \\ \vdots \\ \mathbf{\mu}_{n, \text{des}} \end{bmatrix} = \mathbf{P}^\dagger \begin{bmatrix} \mathbf{F}_{L, \text{des}} \\ \mathbf{M}_{L, \text{des}} \end{bmatrix},
\]

where \( \mathbf{P}^\dagger = \mathbf{P}^T (\mathbf{P} \mathbf{P}^T)^{-1} \) is the Moore-Penrose inverse of \( \mathbf{P} \) for full-column-rank matrices. The above solution can be directly used as the desired cable tension vector for the robot, like in our previous work [9], [12]. However, the above solution does not exploit the possibility for the quadrotor team’s needs to accomplish secondary tasks, for example, avoiding obstacles or, as shown in this paper, increasing human operator safety during physical collaboration when transporting or manipulating a rigid-body payload.

In the following, we propose two methods that allow each of the MAVs to maintain a minimum safe distance from an object, meanwhile still applying the original \( \mathbf{F}_{L, \text{des}} \) and \( \mathbf{M}_{L, \text{des}} \) from the Section IV-A therefore not influencing the original load configuration. The proposed methods exploit the redundancy introduced by using more than three MAVs. Moreover, as the number of rigid body DoF of the payload is 6, and each cable provides control force on the payload in 3 DoF, for any number of robots \( n \geq 3 \), \( n \in \mathbb{N}^+ \), we can exploit the additional system redundancy in \( \mathbb{R}^{3n-6} \). Specifically, the null space of \( \mathbf{P}, \mathcal{N}(\mathbf{P}) \in \mathbb{R}^{3n-6} \), quantifies such redundancy.

Let us assume to find a tension modifier, \( \mathbf{\tilde{\mu}} \in \mathbb{R}^{3n} \), that modifies \( \mathbf{\mu}_{k, \text{des}} \) in \( \mathbf{P} \), and \( \mathbf{\tilde{\mu}} \in \mathcal{N}(\mathbf{P}) \), then we have

\[
\mathbf{P} \mathbf{\tilde{\mu}} = \mathbf{0}, \quad \mathbf{\tilde{\mu}} = \begin{bmatrix} \mathbf{\tilde{\mu}}_1 \\ \vdots \\ \mathbf{\tilde{\mu}}_n \end{bmatrix}.
\]
and the updated desired cable tension force in the $k^{th}$ robot is
\[ \mathbf{\mu}_{k,des} = \mathbf{\mu}_{k,des} + \mathbf{\hat{\mu}}_k. \] (11)

Intuitively, $\mathcal{N}(\mathbf{P})$ provides all the possible combinations of $n$ cable tension vectors that can generate internal motions of the structure (i.e., variations of the cables’ directions) that do not affect the load configuration controlled by the method presented in Section IV-A. This is confirmed by eq. (3) and eq. (11), as $\mathbf{\mu}_{k,des}$ would create a nonzero net wrench on the payload while $\mathbf{\hat{\mu}}_k$ creates zero net wrench. Moreover, $\mathbf{\hat{\mu}}_k$ can be related to the position of each robot
\[ \mathbf{p}_{att,k} + \mathbf{l}_k \mathbf{\hat{\xi}}_k = \mathbf{x}_k, \] (12)
where
\[ \mathbf{\hat{\xi}}_k = \frac{\mathbf{\hat{\mu}}_{k,des} + \mathbf{\hat{\mu}}_k}{\|\mathbf{\hat{\mu}}_{k,des} + \mathbf{\hat{\mu}}_k\|}. \] (13)

The advantage is that we can exploit $\mathbf{\hat{\mu}}_k$ to enforce the $k^{th}$ robot to maintain a safe distance between the other agents in the system and other objects in the environments, like a potential human operator. Therefore, the safety controller needs to find the aforementioned tension modifier, $\mathbf{\tilde{\mu}} \in \mathcal{N}(\mathbf{P})$, and use eq. (11) to move MAVs based on eq. (12) without affecting payload. We propose the following two approaches for finding $\mathbf{\tilde{\mu}}$.

1) **Gradient-Based Safety Controller**: Find a $\mathbf{\tilde{\mu}}$ such that each MAV maximizes the distance between itself and the object using a gradient ascent method.

2) **Optimization-Based Safety Controller**: Find a $\mathbf{\tilde{\mu}}$ such that each MAV guarantees a predetermined minimal safe distance between all its neighboring drones and the object by using nonlinear optimization.

In the following, we can describe the obstacle or human operator as a particular object of interest in the environment. The corresponding point position with respect to $\mathcal{I}$ is denoted as $\mathbf{p}_O$ in the following controller formulation.

**Gradient-Based Safety Controller**: Inspired by strategies used for redundant rigid link robot in [46], we introduce a gradient-based method to compute $\mathbf{\tilde{\mu}}$. Specifically, a pseudo-tension-modifier, $\mathbf{\mu}^0$, is found by maximizing the distance between objects in the environment and each drone. $\mathbf{\mu}^0$ is then projected into $\mathcal{N}(\mathbf{P})$ to become the tension modifier $\mathbf{\tilde{\mu}}$. To update the pseudo-tension-modifier, we propose
\[ \mathbf{\mu}^0 = \mathbf{Q} \frac{\partial \mathbf{w}(\mathbf{\tilde{\mu}})}{\partial \mathbf{\tilde{\mu}}}, \] (14)
where $\mathbf{Q} \in \mathbb{R}^{3n \times 3n}$ is a diagonal positive-definite matrix with variable and tunable coefficients on its diagonal. And $\mathbf{w}(\mathbf{\tilde{\mu}})$ is the cost function and is defined as the squared distance between each drone and the object from which the system is required to keep a safe distance
\[ \mathbf{w}(\mathbf{\tilde{\mu}}) = \sum_{i=1}^k \| \mathbf{p}_O - (\mathbf{p}_{att,k} + \mathbf{l}_k \mathbf{\tilde{\xi}}_k) \|^2, \] (15)
where $\mathbf{l}_k = \mathbf{l}_k \mathbf{I}_{3 \times 3}$. Note that $\mathbf{\tilde{\xi}}_k$ points from the $k^{th}$ attach point to the $k^{th}$ robot. Computing the partial derivative of the cost function for the $k^{th}$ robot using eq. (15), we have
\[ \frac{\partial \mathbf{w}(\mathbf{\tilde{\mu}}_k)}{\partial \mathbf{\tilde{\mu}}_k} = -2 \mathbf{l}_k [\mathbf{p}_O - \mathbf{p}_{att,k}] \mathbf{^\top} \frac{\partial \mathbf{\tilde{\xi}}_k}{\partial \mathbf{\tilde{\mu}}_k} = -2 \mathbf{l}_k [\mathbf{p}_O - \mathbf{p}_{att,k}] \mathbf{^\top} \left( \mathbf{I}_{3 \times 3} \mathbf{\tilde{\xi}}_k \mathbf{\tilde{\xi}}_k \mathbf{^\top} \right)/\|\mathbf{\tilde{\mu}}_{k,des} + \mathbf{\tilde{\mu}}_k\|. \] (16)

For each control step, we update $\mathbf{\mu}^0$ based on eq. (14), performing gradient ascent to maximize the distance between each robot and the objects in the environment. To regulate the effect of gradient on each robot when the object is far away, we propose each element of $\mathbf{Q}$ as a function of the robot-to-object distance of exponential decay type
\[ \mathbf{Q} = \text{diag}(\mathbf{Q}_1, \ldots, \mathbf{Q}_n), \quad \mathbf{Q}_k = a e^{-b\|\mathbf{p}_O - \mathbf{x}_k\| \mathbf{I}_{3 \times 3}}, \] (17)
where $a, b \in \mathbb{R}$ are tunable coefficients. With this varying coefficient, distance limit is achieved to ensure the effect of gradient is particularly significant when $k^{th}$ robot is close to the object, $\mathbf{\mu}^0$ from eq. (14) is not yet in $\mathcal{N}(\mathbf{P})$. We consider the following optimization problem
\[ \min_{\mathbf{\tilde{\mu}}} \| \mathbf{\mu}^0 - \mathbf{\tilde{\mu}} \|^2 \quad \text{s.t.} \quad \mathbf{P} \mathbf{\tilde{\mu}} = 0 \] (18)

The closed-form solution [47] for this quadratic programming problem is
\[ \mathbf{\tilde{\mu}} = \mathbf{B} \mathbf{\mu}^0 = (\mathbf{I} - \mathbf{P}^\mathbf{\dagger} \mathbf{P}) \mathbf{\mu}^0 \] (19)
where $\mathbf{P}^\mathbf{\dagger}$ is the pseudoinverse as in eq. (9). $\mathbf{P}$ will be full-column-rank if we have redundancy (i.e., $n \geq 3$). $\mathbf{B}$ is a particular null space projector that projects any $\mathbf{\mu}^0$ orthogonally into the null space of $\mathbf{P}$. We project $\mathbf{\mu}^0$ into $\mathcal{N}(\mathbf{P})$ with eq. (19), ensuring zero payload movement when each robot is maximizing distance from the object. Finally, we update the desired tension vector as
\[ \mathbf{\mu}_{des} = \mathbf{\tilde{\mu}}_{des} + \mathbf{B} \mathbf{\mu}^0. \] (20)

**Optimization-Based Safety Controller**: In this section, we directly formulate an optimization problem to solve for a tension vector $\mathbf{\tilde{\mu}}$ in $\mathcal{N}(\mathbf{P})$ that guarantees safety distance among the objects and the robots. The nonlinear optimization problem is to minimize the total square norm of the resulting cable tension vector. Furthermore, we formulate predetermined robot-to-object distance constraints. Additionally, another $(\frac{n(n+1)}{2})$ constraint is added between each pair of robots to prevent robot collision. Consider the following nonlinear optimization problem
\[ \min_{\mathbf{c}} \| \mathbf{\mu}_{des} + \mathbf{Gc} \|^2 \quad \text{s.t.} \quad \|\mathbf{p}_O - \mathbf{x}_k\|^2 \geq h_{r}^2, \quad 0 < k \leq n \]
\[ \|\mathbf{x}_i - \mathbf{x}_j\|^2 \geq h_{r}^2, \quad 0 < i < j < n \] (21)

where $\mathbf{G}$ spans $\mathcal{N}(\mathbf{P})$ and $\mathbf{c} \in \mathbb{R}^{3n-6}$ is the vector to be optimized. $r$ and $h_r$ are two scalar values denoting the predetermined safe minimum distance allowed between robots and between the object and each robot, respectively. The $k^{th}$ robot’s position is expressed in terms of $\mathbf{G}_k \mathbf{c}$ and $\mathbf{\tilde{\mu}}_{k,des}$
\[ \mathbf{x}_k = \mathbf{p}_{att,k} + \mathbf{l}_k \mathbf{\tilde{\mu}}_{k,des} + \mathbf{G}_k \mathbf{c} \|\mathbf{\tilde{\mu}}_{k,des} + \mathbf{G}_k \mathbf{c}\| \] (22)
where $\mathbf{G}_k$ represents the three rows of the null space basis matrix $\mathbf{G}$ for the $k^{th}$ MAV. Since eq. (21) is a nonlinear op-
timization problem with quadratic cost function and quadratic constraints, we use sequential quadratic programming solver for nonlinearly constrained gradient-based optimization [48] in NLOPT [49] to solve eq. (21) and obtain c. After obtaining c, the desired cable tension forces can be obtained as follows:

\[ \mu_{des} = \mu_{des} + Gc. \]  \hspace{1cm} (23)

**Discussion:** The proposed methods are both effective for the quadrotor team to keep a safe distance away from a given object, as we also experimentally verify in Section VI. However, from the perspective of computation, the gradient-based method requires fewer resources than the optimization-based method since the solution of the gradient-based method is in the closed form. In contrast, the optimization-based method needs to solve a nonlinear optimization problem. The advantage of the optimization-based method is that we can specify the desired distance we would like the quadrotor to stay away from each other and the given objects, while the gradient-based way tries to maximize the distance till it reaches some boundaries. The users can decide their preferable policy based on the robots, tasks, and available computational resources. In the Fig. 2, we show how we can feed the human operator’s position in NLOPT [49] to solve eq. (21) and obtain c, and use sequential quadratic programming solver for nonlinearly constrained gradient-based optimization [48] for application to safe human-robot interaction. We want to remind the readers again the same safety controller can be applied in other contexts to other secondary tasks like obstacle avoidance.

**C. Robot Controller**

Once we obtain the desired tension forces \( \mu_{des} \) from eq. (20) or eq. (23), the tension input of each cable of the individual quadrotor is selected as the projection of desired tension on the corresponding cable

\[ \mu_k = \xi_k \xi_k^T \mu_{k,des}, \]  \hspace{1cm} (24)

The desired direction \( \xi_{k,des} \) and the desired angular velocity \( \omega_{k,des} \) of the \( k^{th} \) cable link can be obtained as

\[ \xi_{k,des} = \frac{\mu_{k,des}}{\| \mu_{k,des} \|}, \omega_{k,des} = \xi_{k,des} \times \dot{\xi}_{k,des}, \]

where \( \dot{\xi}_{k,des} \) is the derivative of \( \xi_{k,des} \). The thrust \( f_k \) and moments \( \mathbf{M}_k \) acting at the \( k^{th} \) quadrotor are

\[ f_k = \mathbf{u}_k \cdot \mathbf{R}_k \mathbf{e}_3 = (\mathbf{u}_k^\parallel + \mathbf{u}_k^\perp) \cdot \mathbf{R}_k \mathbf{e}_3, \]  \hspace{1cm} (25)

The orientated control force is therefore,

\[ \mathbf{F}_k = f_k \mathbf{R}_k \mathbf{e}_3, \]  \hspace{1cm} (26)

where \( \mathbf{e}_3 = [0 \hspace{0.5cm} 0 \hspace{0.5cm} 1]^T \).

\[ \mathbf{M}_k = \mathbf{K}_{\Omega} \mathbf{e}_k \mathbf{R}_k + \mathbf{K}_\omega \mathbf{e}_\omega \mathbf{R}_k + \mathbf{R}_k \mathbf{K}_\Omega \mathbf{e}_\Omega, \]

\[ = -\mathbf{J}_k \left( \mathbf{R}_k \mathbf{R}_k^\top \mathbf{M}_{k,des} - \mathbf{R}_k^\top \mathbf{R}_k \mathbf{M}_{k,des} \hat{\mathbf{R}}_k \right), \]  \hspace{1cm} (27)

where \( \mathbf{K}_{\Omega} \) and \( \mathbf{K}_\omega \) are diagonal positive constant matrices, \( \mathbf{e}_k \) and \( \mathbf{e}_\omega \) are the orientation and angular velocity errors similarly defined using \( \theta \). The inputs \( \mathbf{u}_k^\perp \) and \( \mathbf{u}_k^\parallel \) are designed as

\[ \mathbf{u}_k^\perp = m_k l_k \mathbf{e}_k - \mathbf{K}_\omega \mathbf{e}_\omega \mathbf{e}_\omega - \xi_k^2 \omega_{k,des} - (\mathbf{e}_k \cdot \omega_{k,des}) \mathbf{e}_\omega - m_k \xi_k \mathbf{R}_k \mathbf{e}_c, \]

\[ \mathbf{u}_k^\parallel = \mu_k + m_k l_k \left( \beta \xi_k + m_k \xi_k \mathbf{e}_k^T a_{k,c,c} \right), \]  \hspace{1cm} (28)

where

\[ a_{k,c} = a_{L,c} = -\mathbf{R}_L \mathbf{p}_k \mathbf{R}_L \mathbf{L}_L \mathbf{p}_k + \mathbf{R}_L \mathbf{R}_L^2 \mathbf{p}_k, \]  \hspace{1cm} (29)

where \( \mathbf{K}_{\xi} \) and \( \mathbf{K}_{\omega} \) are diagonal positive constant matrices, \( \mathbf{e}_\xi_k \) and \( \mathbf{e}_\omega_k \) are the cable direction and cable angular velocity errors respectively

\[ \mathbf{e}_\xi_k = \xi_k \mathbf{e}_k - \xi_k, \mathbf{e}_\omega_k = \mathbf{e}_\omega - \mathbf{e}_\omega \]

Readers can refer to [40] for a stability analysis.

**V. HUMAN-ROBOT PHYSICAL INTERACTION**

**A. State Estimation**

In this section, we present a method of state estimation based on an Unscented Kalman Filter (UKF). The estimation design is fully distributed. We included unit cable direction and cable tension magnitude as part of the state estimation, which enables us to estimate the amount of external force applied on the payload by the human operator through eq. (3).

State estimation is performed fully onboard each MAV. The distributed nature of our method allows the entire system to be scaled easily. Since the estimation algorithm runs onboard, the computation cost per robot does not increase as the swarm gets larger. The distributed design also reduces possible interference among robots as estimation algorithms are running independently in a parallel fashion. Below, we will discuss the UKF-based MAV state estimation in Section V-A1 and how we estimate payload external wrench in Section V-A2.

1) Robot State Estimator: We consider the \( k^{th} \) MAV to have the following state \( \mathbf{S}_k \)

\[ \mathbf{S}_k = [x_k \hspace{0.5cm} x_k \hspace{0.5cm} y_p \hspace{0.5cm} \mathbf{e}_k \hspace{0.5cm} \xi_k \hspace{0.5cm} \mathbf{\dot{\xi}}_k \hspace{0.5cm} \mathbf{\mu}_k]^T, \]  \hspace{1cm} (30)

where \( \mathbf{y}_p \) are the robot orientation Euler angles expressed according to the ZYX convention and the input are defined as

\[ \mathbf{U}_k = [f_k \hspace{0.5cm} \mathbf{M}_k]^T, \]  \hspace{1cm} (31)

where \( f_k \) is the known motor constant, \( \omega_{m,j} \) is the motor speed of the \( j^{th} \) motor. Denote the current time step as \( s \) and the previous time step as \( s - 1 \). Now we will present the nonlinear process model and the linear measurement model of the UKF.

a) Process Model: Based on MAV equations of motion presented in eq. (3), discretizations of quadrotor states are performed by assuming each control step moves forward in time by \( \Delta t \). The discrete-time nonlinear process model is, therefore, on each robot

\[ \mathbf{S}'_k = g(\mathbf{S}_{k-1}^t, \mathbf{U}_k), \]  \hspace{1cm} (33)

where

\[ g(\mathbf{S}_{k-1}^t, \mathbf{U}_k) = \begin{bmatrix} x_{k-1}^t + x_{k-1}^t \delta t + x_{k-1}^t \delta t^2/2 \\ \dot{x}_{k-1}^{t-1} + \dot{x}_{k-1}^t \delta t \\ \dot{x}_{k}^{t-1} + \dot{x}^{t-1}_k \delta t^2/2 + n_{\xi_k,k} \\ \xi_k^{t-1} + \dot{\xi}_k \delta t + \dot{\xi}_k \delta t^2/2 + n_{\xi_k,k} \\ \dot{\xi}_k^{t-1} + \dot{\xi}_k \delta t + n_{\xi_k,k} \\ \mu_k^{t-1} + n_{\mu_k,k} \end{bmatrix}, \]  \hspace{1cm} (34)
For updating the Euler angle, a few nonlinear mappings are used as in \[50\]

1) $[*]$ that maps $* \in SO(3)$ to $\text{ypr} \in \mathbb{R}^3$.
2) $\exp[*]$ that maps $* \in \mathbb{R}^3$ to $SO(3)$; or maps axis-angle $\mathfrak{so}(3)$, to rotation matrix $SO(3)$.

In eq. (34), $\Omega^\top$ is rotated into $I$. After stepping $dt$, the new robot angular position in $I$ represented in $\mathfrak{so}(3)$ is mapped into $SO(3)$. This new angular position in $SO(3)$ is then added to the previous orientation. The resultant orientation is mapped to the Euler angle with $[*]$. The noise terms $n_{\xi_{k},k}, \Omega_{k}, k \in \mathbb{R}^3$, and $n_{\mu,k} \in \mathbb{R}$ are assumed to be additive zero-mean Gaussian white noise to each specific state according to the subscript. Additive Gaussian white noise is also considered as process noise for linear and angular acceleration. Additionally, the equations of motion for unit cable direction are presented in $[12]$. Here, we provide the result. Gaussian white noise, $N_k$, is added as process noise

\[
\begin{bmatrix} \xi_{k}^l \\ \xi_{k}^r \end{bmatrix} = \begin{bmatrix} \xi_{k}^{l-1} \\ \xi_{k}^{r-1} \end{bmatrix} \frac{1}{m_{k}k} \begin{bmatrix} u_{n} - m_{k}k \Delta_k \end{bmatrix} - \left\| \xi_{k}^{l-1} \right\| \xi_{k}^{l-1} + N_k. \tag{35}
\]

To predict with the process model, the UKF algorithm calls eq. (34). Since measurement does not necessarily arrive at every control time step, nonlinear prediction with zero process noise is used.

b) Measurement Model: Using an indoor MOCAP system, we can measure everything in the state except tension magnitude. The measured states for $k^{th}$ robot therefore are

\[
Z_k = [x_k \ x_k^{\text{ypr}} \ \Omega_k \ \xi_k \ \hat{\xi}_k]^\top. \tag{36}
\]

We also want to note that using onboard Visual Inertial Odometry and vision-based methods from our previous work $[12]$ can provide the exact measurements and make measurements fully onboard.

Denoting the time step when UKF measurement update is triggered as $m$, the UKF finds the state prior to $m$, $S_k^{m-1}$. A nonlinear propagation through eq. (34) is performed by propagating sigma points around $S_k^{m-1}$ through the system model in eq. (34) as shown in $[51]$. The linear measurement model is

\[
H = \begin{bmatrix} I_{18 \times 18} & 0_{18 \times 1} \\ 0_{18 \times 1} & 0_{1 \times 1} \end{bmatrix}.
\]

The system state prediction is compared to the actual measurement using the above model

\[
S_k^m = K_k(HS_k^{m-1} - Z_k), \tag{37}
\]

where $\bar{S}^m_k$ is the averaged state after sigma point propagation and $K_k$ is the Kalman gain. Kalman gain is computed based on the standard UKF update as in $[51]$.

2) Payload Wrench Estimator: Rearranging eq. (3), we obtain

\[
\begin{bmatrix} m_L \dot{x}_L \\ J_L \dot{\Omega}_L \end{bmatrix} = \begin{bmatrix} F_H \\ M_H \end{bmatrix} + P \begin{bmatrix} \mu_1 \\ \mu_2 \end{bmatrix} - \begin{bmatrix} m g \\ 0_{1 \times 1} \end{bmatrix}. \tag{38}
\]

Considering quasi-static operating conditions, we can assume payload linear and angular accelerations are small. Therefore, leveraging this assumption and rearranging based on eq. (38)

\[
\begin{bmatrix} F_H \\ M_H \end{bmatrix} = -P \begin{bmatrix} \mu_1 \\ \mu_2 \end{bmatrix} + \begin{bmatrix} m g \\ 0_{1 \times 1} \end{bmatrix}. \tag{39}
\]

Extracting tension values from each robot’s state allows us to compute external wrench on the payload.

B. Payload Admittance Controller

The admittance controller is a high level controller that updates $x_{L,\text{des}}$ and $R_{L,\text{des}}$ in eq. (3) for the payload controller (Section IV-A) based on the external force applied on the payload. When interacting with the payload, it allows the human operator to experience a virtual mass-spring-damper system instead of the actual mass. By setting the admittance controller’s tunable parameters to the desired values, the payload can be either sensitive or insensitive to external forces regardless of the payload’s actual property.

The admittance controller treats the payload as a virtual mass-spring-damper system as the external force applied to the payload. The input is a payload external wrench, $F \in \mathbb{R}^{6 \times 1}$. The output includes payload twist, $\dot{X}_{\text{des}} \in \mathbb{R}^{6 \times 1}$, and payload linear and angular position, $X_{\text{des}} \in \mathbb{R}^{6 \times 1}$, with angular position represented by Euler angle. Admittance controller also computes payload linear and angular acceleration, $\ddot{X}_{\text{des}} \in \mathbb{R}^{6 \times 1}$, but the lower level payload controller does not use this output. The controller assumes the following dynamics for the payload,

\[
M(\ddot{X}_{\text{des}} - \ddot{X}_{\text{traj}}) + D(\dot{X}_{\text{des}} - \dot{X}_{\text{traj}}) + K(\dot{X}_{\text{des}} - \dot{X}_{\text{traj}}) = F, \tag{40}
\]

where $M$, $D$, and $K$ in $\mathbb{R}^{6 \times 6}$ are tunable positive semidefinite matrices denoting the desired mass, damping, and spring property of the payload. Based on the initial starting condition of the payload, $\dot{X}_{\text{traj}}, \ddot{X}_{\text{traj}},$ and $\dot{X}_{\text{traj}}$ can be set accordingly. We choose to set them to be the planned trajectory. Closed form solutions exist for eq. (40) with the assumption that $F$ is a predetermined function (e.g., linear function). However, such assumption is not ideal for our use case. Thus, we choose to solve $X_{\text{des}}, \dot{X}_{\text{des}}, \ddot{X}_{\text{des}}$ with Runge-Kutta $4^{th}$ order approximation.
Fig. 5: Wrench estimation experiment results. Comparison between the wrench estimation algorithm results and the wrench measurements from the force measurement device in all 6 DoF.

Fig. 6: We test the admittance controller together with wrench estimation in all 6 DoF. Payload pose, desired pose from the admittance controller, and estimated wrench are plotted. On the top: translation tests in $x$, $y$, $z$ in $I$. On the bottom: rotation tests in roll, pitch, yaw in $L$.

VI. EXPERIMENTAL RESULTS

The experiments are conducted in an indoor testbed with a flying space of $10 \times 6 \times 4$ m$^3$ of the ARPL lab at the New York University. We use three quadrotors to carry a triangular payload via suspended cables. The quadrotor platform used in the experiments is equipped with a Qualcomm® Snapdragon™ board for on-board computing [52]. The framework has been developed in ROS\textsuperscript{1}. The mass of the payload is 310g, which exceeds the payload capacity of every single vehicle as well as of our previous system [14]. The odometry of the payload and quadrotors, the position and velocity of attachment points, and the human operator’s position are estimated using a Vicon\textsuperscript{2} motion capture system at a frequency of 100 Hz. The unit vector of each cable direction $\xi_k$ and the corresponding velocity $\dot{\xi}_k$ are estimated by

$$\xi_k = \frac{p_{att,k} - x_k}{\|p_{att,k} - x_k\|}, \quad \dot{\xi}_k = \frac{\dot{p}_{att,k} - \dot{x}_k}{l_k},$$

where $p_{att,k}, \dot{p}_{att,k}$ are position and velocity of the $k^{th}$ attach point in $I$ and $x_k, \dot{x}_k$ are position and velocity of the $k^{th}$ robot in $I$, all of which are estimated by the motion capture system.

A. Wrench Estimation

In this section, we validate our wrench estimation algorithm by comparing the estimation results obtained using the approach presented in Section V-A2 with the ground truth from the wrench measurement device as shown in Fig. 4. During the experiment, we hover the system with the regular payload controller without the admittance controller. Then, the human
Fig. 7: Human-robot collaborative transportation experiment results. Payload Position vs. Desired Position from Admittance Controller. Transnational results when optimization-based human-safety-aware method is used (top row). Transnational results when gradient-based human-safety-aware method is used (bottom row).

The force measurement device is connected to the payload via a lightweight cable. Its goal is to obtain a ground truth wrench, i.e., the ground truth force and torque acting on the payload. We identify the ground truth force by measuring the force direction and force magnitude separately. As the ground truth force direction is along the cable between the measurement device and the payload, it is measured by computing the difference between the load cell’s position and the attach point position on the payload using the Vicon motion capture system. The ground truth force magnitude is measured via a Phidget micro load cell\(^3\) as shown in the Fig. 4. The measured cable direction and tension magnitude are post-processed to yield the ground truth force acting on the payload. After that, the ground truth external torque is obtained by crossing the attached point position vector in \(\mathcal{L}\) and the measured ground truth force vector from the measurement device. The payload is pulled so that the external wrench is non-zero in all six DoF, as shown in Fig. 4.

The results are shown in Fig. 5. In the plots, we compare the measured wrenches to the estimated wrenches in all 6 DoF. The estimated wrenches track measured ground truth quite accurately. In the \(z\) direction, however, the estimation deviates from measurement. We believe this is caused by the hybrid dynamics switching when the payload is pulled in the positive \(z\) direction. The root mean squared errors in all six directions are also reported in Table II, confirming a good accuracy.

| Force (N) | Moment (N·m) |
|----------|--------------|
| \(x\)    | \(y\)        | \(z\)    | roll | pitch | yaw |
| 0.0185   | 0.0117       | 0.0564   | 0.0088| 0.0066| 0.0045|

Fig. 8: Human-robot collaborative transportation tasks. The human operator to translate the payload in three Cartesian directions to reach the final location with the quadrotor team.

B. Admittance Control with Wrench Estimation

After validating the wrench estimation module, we test the admittance controller jointly with the external wrench estimator in this experiment. We conduct six tests involving all 6 DoF of the admittance controller. The human operator manipulates the payload by translating the payload in \(x\), \(y\), and \(z\) and rotating the payload in roll, pitch, and yaw, respectively, to show that the load can be fully manipulated. At the end of
Fig. 9: Human-robot collaborative transportation experiment results. Top down view of human operator and the team of drones. *On the top:* trajectory when optimization-based human-safety-aware method is used. *On the bottom:* trajectory when gradient-based human-safety-aware method is used.

Fig. 10: Human-robot collaborative transportation experiment results. Drone to drone distance and human to drone distance when gradient-based human-safety-aware method is used. Each experiment, the human operator releases the payload. The square gain matrices in the admittance controller have a block-diagonal structure as $M = \text{diag}(0.25I_{3\times3}, 0.1I_{3\times3})$, $D = \text{diag}(1.25I_{3\times3}, 5.0I_{3\times3})$, $K = \text{diag}(0_{3\times3}, 0_{3\times3})$.

The experiment results are shown in the Fig. [6] As shown in the plots, the human operator translates the payload approximately 1 m in x and y direction, 0.4 m in the z direction. In the rotation part of the experiment, the human operator rotates the payload approximately 30° in the roll and pitch direction and 60° in the yaw direction. The tests show that the admittance controller, coupled with the wrench estimator, can successfully update the payload’s desired position or orientation according to the human operator’s interactive force as input. As the human operator releases the payload, the wrench estimation outputs $[0_{6\times1}]$ as wrench estimation. Since $K$ in the admittance controller is $[0_{6\times6}]$ in this set of experiments, the payload remains at the position or orientation released by the human operator without returning to its original reference position or orientation. It further confirms the effectiveness of the wrench estimation and admittance controller pipeline in assisting object transportation and manipulation.

C. Safety-Aware Human-Robot Collaborative Transportation

In this section, we show that our system enables human-robot collaboration by challenging the robot team and the human operator to the following two tasks:

1) The robot team and the human operator collaboratively transport the payload to a goal location.

2) Human operator corrects the payload trajectory to avoid an obstacle in an existing trajectory.
The gradient-based and optimization-based human-safety-aware controllers are tested for each of the two tasks. For the optimization-based method, the drone-to-drone distance is set to be 0.75 m, and the human-to-drone distance is set to be 1.0 m. The gradient-based method does not require a predetermined distance.

In addition, as we show in Fig. 2 and discuss in Section IV-B, we feed the human operator’s position $p_H$ from the Vicon in $L$ as $p_O$ to the eq. (16) and eq. (21) for application to safe human-robot interaction. We would also like to note that by using deep-learning based human pose estimation techniques [53], the robots can also use onboard camera to estimate $p_H$ but we will refer this as future works.

1) Human-robot collaborative transportation: In this experiment, the robot team and the human operator collaborate together to move a payload from the starting location to the final location via direct force interaction. Payload translates in all three axes, as shown in Fig. 8. The square gain matrices are selected block-diagonal as $M = \text{diag}(0.25I_{3 \times 3}, 0.1I_{3 \times 3})$, $D = \text{diag}(5.0I_{3 \times 3}, 5.0I_{3 \times 3})$, $K = \text{diag}(0_{3 \times 3}, 0_{3 \times 3})$.

Note that the spring constant coefficient for the admittance controller is set to zero so that the payload stays at the position/orientation once the human operator releases the payload. The experimental results are shown in Fig. 7 where we compare the actual payload position with desired payload position from the admittance controller. The results demonstrate the pipeline can confidently update the desired payload position to satisfy the human operator’s intention of moving the payload under both gradient-based and optimization-based human safety methods. Furthermore, the movement introduced by the null-space-based safety controller does not affect the performance of the payload wrench estimation or admittance controller. In Fig. 7, the effects of the two human-safety-aware controllers are shown with a top view of the entire payload manipulation task. In Fig. 10, distances between each drones with human operator and one another are plotted. Both optimization-based and gradient-based methods perform similarly when it requires keeping a safe distance between the human and each drone. Both methods generate a safe distance of 1 m between the human and drone when the human approaches. The optimization-based method, however, differs from the gradient-based method in that it allows safety distance to be implemented between drones. In the top plot in Fig. 11 all three drones are keeping a 0.75 m safe distance from each other. However, such behavior is not observed in the top plot in Fig. 10. Both methods generate sufficient distance between the human operator and drones to give the human operator confidence and a sense of security when interacting with the payload.

2) Human-assisted Payload Trajectory Tracking: In this experiment, the payload follows a straight trajectory from the starting location to the final location, as the robot team is unaware of the obstacle. The human operator corrects the payload trajectory to avoid the obstacle, as shown in Fig. 12. Both gradient-based and optimization-based methods are also applied here. The square gain matrices for the admittance controller have a block-diagonal structure as $M = \text{diag}(0.25I_{3 \times 3}, 0.1I_{3 \times 3})$, $D = \text{diag}(5.0I_{3 \times 3}, 5.0I_{3 \times 3})$, $K = \text{diag}(1.2I_{3 \times 3}, 0_{3 \times 3})$.

Note that the constant spring coefficient for the admittance controller is no longer zero. The payload will now return to the position/orientation commanded by the trajectory when the human operator releases the payload.
As we can see from Fig. 13, the correction takes effects according to the admittance controlled trajectory. Once the human operator stops the correction, the non-zero $K$ constant starts to allow the corrected trajectory to converge with the original trajectory. As expected, such behavior is present in both the gradient-based and optimization-based methods.

VII. Conclusion

In this paper, we presented a safety-aware human-robot collaborative transportation and manipulation approach considering a team of aerial robots with a cable-suspended payload. We validate that our control and state estimation approaches allow a human operator to interact in 6 DoF with a rigid structure transported through the cable by a MAV team. Additionally, the system incorporates important safety requirements by exploiting the additional system redundancy. We demonstrated, through real-world experiments, our system’s capability to keep a safe distance from the human operator and between each agent without affecting the quality or accuracy of the interactive experience. The system can assist the human during a complex and heavy manipulation task and enable the human operator to complement the load navigation presented in the obstacle avoidance experiment.

Future works include distributing the gradient-based human-safety-aware method to utilize computing power onboard each MAV, making the proposed framework an even-more-scalable solution. We would also like to introduce an obstacle detection module. As a result, the robot team can identify potential hazardous volume in space using onboard computation. And then they can utilize the null space to autonomously avoid any drone getting close to such volume without affecting payload trajectory tracking. Finally, another potential future work will be applying deep-learning-based methods with the robots’ onboard cameras to estimate the human operator’s pose as input to the proposed safety-aware controller.

REFERENCES

[1] K. Schwab, The fourth industrial revolution. London, England: Portfolio Penguin, 2017.
[2] S. S. Mansouri, C. Kanellakis, E. Fresk, D. Kominiak, and G. Nikolakopoulos, “Cooperative coverage path planning for visual inspection,” Control Engineering Practice, vol. 74, pp. 118–131, May 2018.
[3] K. Shah, G. Ballard, A. Schmidt, and M. Schwager, “Multidrone aerial surveys of penguin colonies in antarctica,” Science Robotics, vol. 5, no. 47, p. eabc3000, 2020.
[4] G. Loianno, Y. Mulgaonkar, C. Brunner, D. Ahuja, A. Ramanandand, M. Chari, S. Diaz, and V. Kumar, “Autonomous flight and cooperation control for reconstruction using aerial robots powered by smartphones,” The International Journal of Robotics Research, vol. 37, no. 11, pp. 1341–1358, 2018.
[5] N. Michael, S. Shen, K. Mohta, Y. Mulgaonkar, V. Kumar, K. Nagatani, Y. Okada, S. Kiriyabashi, K. Otake, K. Yoshida, K. Ohno, E. Takeuchi, and S. Tadokoro, “Collaborative mapping of an earthquake-damaged building via ground and aerial robots,” Journal of Field Robotics, vol. 29, no. 5, pp. 832–841, 2012.
[6] A. E. Jiménez-Can, D. Sanalitro, M. Tognon, A. Franchi, and J. Cortés, “Precise Cable-Suspended Pick-and-Place with an Aerial Multi-robot System: A Proof of Concept for Novel Robots-Based Construction Techniques,” Journal of Intelligent & Robotic Systems, vol. 105, no. 3, p. 68, Jul. 2022.
[7] D. Sanalitro, M. Tognon, A. J. Cano, J. Cortés, and A. Franchi, “Indirect force control of a cable-suspended aerial multi-robot manipulator,” IEEE Robotics and Automation Letters, vol. 7, no. 3, pp. 6726–6733, 2022.
[8] M. Saska, V. Vonásek, J. Chudoba, J. Thomas, G. Loianno, and V. Kumar, “Swarm Distribution and Deployment for Cooperative Surveillance by Micro-Aerial Vehicles,” Journal of Intelligent & Robotic Systems, vol. 84, no. 1, pp. 469–492, Dec. 2016.
[9] G. Li and G. Loianno, “Design and experimental evaluation of distributed cooperative transportation of cable suspended payloads with micro aerial vehicles,” in Experimental Robotics, B. Siciliano, C. Laschi, and O. Khatib, Eds. Cham: Springer International Publishing, 2021, pp. 28–36.
[10] B. E. Jackson, T. A. Howell, K. Shah, M. Schwager, and Z. Manchester, “Scalable cooperative transport of cable-suspended loads with uavs using distributed trajectory optimization,” IEEE Robotics and Automation Letters, vol. 5, no. 2, pp. 3368–3374, 2020.
[11] A. Ollero, M. Tognon, A. Suarez, D. Lee, and A. Franchi, “Past, present, and future of aerial robotic manipulators,” IEEE Transactions on Robotics, vol. 38, no. 1, pp. 626–645, 2022.
[12] G. Li, R. Ge, and G. Loianno, “Cooperative transportation of cable suspended payloads with MAVs using monocular vision and inertial sensing,” IEEE Robotics and Automation Letters, vol. 6, no. 3, pp. 5316–5323, 2021.
[13] A. Tagliabue, M. Kanel, S. Verling, R. Siegwart, and J. Nieto, “Collaborative transportation using mavs via passive force control,” in IEEE International Conference on Robotics and Automation (ICRA), 2017, pp. 5766–5773.
[14] G. Loianno and V. Kumar, “Cooperative transportation using small quadrotors using monocular vision and inertial sensing,” IEEE Robotics and Automation Letters, vol. 3, no. 2, pp. 680–687, April 2018.
[15] D. Mellinger, M. Shomin, N. Michael, and V. Kumar, Cooperative Grasping and Transport Using Multiple Quadrotors, Berlin, Heidelberg: Springer Berlin Heidelberg, 2013, pp. 545–558.
[16] J. Thomas, G. Loianno, J. Polin, K. Sreenath, and V. Kumar, “Toward autonomous avian-inspired grasping for micro aerial vehicles,” Bioinspiration & biomimetics, vol. 9, no. 2, p. 025010, 2014.
[17] A. Affifi, M. van Holland, and A. Franchi, “Toward physical human-robot interaction control with collaborative manipulators: Compliance, redundancy resolution, and input limits,” in IEEE International Conference on Robotics and Automation (ICRA), 2022, pp. 4855–4861.
[18] G. Corsini, M. Jacquet, H. Das, A. Affifi, D. Sidobre, and A. Franchi, “Nonlinear Model Predictive Control for Human-Robot Handover with Application to the Aerial Case,” in The 2022 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS 2022), Kyoto, Japan, Oct. 2022.
[19] M. Tognon, R. Alami, and B. Siciliano, “Physical human-robot interaction with a tethered aerial vehicle: Application to a force-based human guiding problem,” IEEE Transactions on Robotics, vol. 37, no. 3, pp. 723–734, 2021.
[20] J. Lee, R. Balachandran, Y. S. Sarkisov, M. De Stefano, A. Coelbo, K. Shinde, M. J. Kim, R. Triebel, and K. Kondak, “Visual-inertial telepresence for aerial manipulation,” in IEEE International Conference on Robotics and Automation (ICRA), 2020, pp. 1222–1229.
[21] J. Geng and J. Langelaan, “Cooperative transport of a sling load using load-leading control,” Journal of Guidance, Control, and Dynamics, vol. 43, no. 7, pp. 1313–1317, 2020.
[22] H. Rastgoftar and E. M. Atkins, “Cooperative Aerial Payload Transport Guided by an In Situ Human Supervisor,” IEEE Transactions on Control Systems Technology, vol. 27, no. 4, pp. 1452–1467, Jul. 2019.
[23] M. Romano, A. Ye, J. Pye, and E. Atkins, “Cooperative Multilift Sling Load Transportation Using Haptic Admittance Control Guidance,” Journal of Guidance, Control, and Dynamics, vol. 1–14, Jul. 2022.
[24] K. Klausen, C. Meissen, T. F. Fossen, M. Anvik, and T. A. Johansen, “Cooperative control for multirotorso transporting an unknown suspended load under environmental disturbances,” IEEE Transactions on Control Systems Technology, vol. 28, no. 2, pp. 653–660, 2020.
[25] M. Bernard, K. Kondak, I. Maza, and A. Ollero, “Autonomous transport and deployment with aerial robots for search and rescue missions,” Journal of Field Robotics, vol. 28, no. 6, pp. 914–931, 2011.
[26] V. P. Tran, F. Santoso, M. Garratt, and S. Anavatti, “Distributed artificial neural networks-based adaptive strictly negative imaginary formation control for unmanned aerial vehicles in time-varying environments,” IEEE Transactions on Industrial Informatics, pp. 1–1, 2020.
[27] X. Zhang, F. Zhang, P. Huang, J. Gao, H. Yu, C. Pei, and Y. Zhang, “Self-triggered control based coordination with low communication for tethered multi-uav collaborative transportation,” IEEE Robotics and Automation Letters, vol. 6, no. 2, pp. 1559–1566, 2021.
Y. Liu, F. Zhang, P. Huang, and X. Zhang, “Analysis, planning and control for cooperative transportation of tethered multi-rotor uavs,” Aerospace Science and Technology, vol. 113, p. 106673, 2021.

T. Lee, K. Sreenath, and V. Kumar, “Geometric control of cooperating multiple quadrotor uavs with a suspended payload,” in 52nd IEEE Conference on Decision and Control, 2013, pp. 5510–5515.

M. Gassner, T. Cieslewski, and D. Scaramuzza, “Dynamic collaboration without communication: Vision-based cable-suspended load transport with two quadrotors,” in IEEE International Conference on Robotics and Automation (ICRA), 2017, pp. 5196–5202.

H. Rastgoftar and E. M. Atkins, “Continuum deformation of a multiple quadcopter payload delivery team without inter-agent communication,” in International Conference on Unmanned Aircraft Systems (ICUAS), 2018, pp. 539–548.

H. Xie, K. Dong, and P. Chirarattananon, “Cooperative transport of a suspended payload via two aerial robots with inertial sensing,” IEEE Access, vol. 10, pp. 81 764–81 776, 2022.

A. Tagliabue, M. Kamel, R. Siegwart, and J. Nieto, “Robust collaborative object transportation using multiple MAVs,” The International Journal of Robotics Research, vol. 38, no. 9, pp. 1020–1044, 2019.

T. Lee, “Geometric control of quadrotor uavs transporting a cable-suspended rigid body,” IEEE Transactions on Control Systems Technology, vol. 26, no. 1, pp. 255–264, 2018.

G. Wu and K. Sreenath, “Geometric control of multiple quadrotors transporting a rigid-body load,” in 53rd IEEE Conference on Decision and Control. IEEE, 2014, pp. 6141–6148.

J. Fink, N. Michael, S. Kim, and V. Kumar, “Planning and control for cooperative manipulation and transportation with aerial robots,” The International Journal of Robotics Research, vol. 30, no. 3, pp. 324–334, 2011.

N. Michael, J. Fink, and V. Kumar, “Cooperative manipulation and transportation with aerial robots,” Autonomous Robots, vol. 30, no. 1, pp. 73–86, Jan 2011.

R. C. Sundin, P. Roque, and D. V. Dimarogonas, “Decentralized model predictive control for equilibrium-based collaborative uav transport,” in IEEE International Conference on Robotics and Automation (ICRA), 2020, pp. 4915–4921.

G. Tartaglione, E. D’Amato, M. Ariola, P. S. Rossi, and T. A. Johansen, “Model predictive control for a multi-body slung-load system,” Robotics and Autonomous Systems, vol. 92, pp. 1–11, Jun. 2017.

T. Lee, “Geometric control of multiple quadrotor uavs transporting a cable-suspended rigid body,” in 53rd IEEE Conference on Decision and Control, 2014, pp. 6155–6160.

J. Geng, P. Singla, and J. W. Langelaan, “Load-distribution-based trajectory planning and control for a multilift system,” Journal of Aerospace Information Systems, vol. 0, no. 0, pp. 1–16, 0.

H. Butika, C. He, J. Webbeh, and I. Sharf, “Experiments on collaborative transport of cable-suspended payload with quadrotor uavs,” in 2022 International Conference on Unmanned Aircraft Systems (ICUAS), 2022, pp. 1465–1473.

J. Geng and J. W. Langelaan, “Implementation And Demonstration Of Coordinated Transport Of A Slung Load By A Team Of Rotorcraft,” in AIAA Scitech 2019 Forum. San Diego, California: American Institute of Aeronautics and Astronautics, Jan. 2019.

D. Sanalitro, H. J. Savino, M. Tognon, J. Cortés, and A. Franchi, “Full-pose manipulation control of a cable-suspended load with multiple uavs under uncertainties,” IEEE Robotics and Automation Letters, vol. 5, no. 2, pp. 2185–2191, 2020.

P. Prajapati, S. Parekh, and V. Vashista, “On the human control of a multiple quadcopters with a cable-suspended payload system,” in IEEE International Conference on Robotics and Automation (ICRA), 2020, pp. 2253–2258.

B. Siciliano, L. Sciavicco, L. Villani, and G. Oriolo, Robotics Modelling, Planning and Control. Springer London, 2009.

D. Bertsekas, Nonlinear Programming. Athena Scientific, 1999.

D. Kraft, “Algorithm 733: Tomp–fortran modules for optimal control calculations,” ACM Trans. Math. Softw., vol. 20, no. 3, p. 262–281, sep 1994.

S. G. Johnson, The NLopt nonlinear-optimization package, 2011. [Online]. Available: [http://ab-initio.mit.edu/nlopt](http://ab-initio.mit.edu/nlopt)

J. Sola, “Quaternion kinematics for the error-state kalman filter,” arXiv preprint arXiv:1711.02508, 2017.

S. Thrun, W. Burgard, and D. Fox, Probabilistic Robotics. MIT Press, 2005.

G. Loianno, C. Brunner, G. McGrath, and V. Kumar, “Estimation, control, and planning for aggressive flight with a small quadrotor with a single camera and imu.” IEEE Robotics and Automation Letters, vol. 2, no. 2, pp. 404–411, April 2017.

S. Ren, K. He, R. Girshick, and J. Sun, “Faster r-cnn: Towards realtime object detection with region proposal networks,” in Advances in Neural Information Processing Systems, C. Cortes, N. Lawrence, D. Lee, M. Sugiyama, and R. Garnett, Eds., vol. 28. Curran Associates, Inc., 2015.