Towards a Stable 3D Physical Human-Drone Interaction

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ABSTRACT

Key requirements of physical human-drone interactions are that the system is stable, safe, and expressive. The user should be free to interact with the drone in 3D space, and the drone should react appropriately and stably to the physical touch from the user. These requirements are necessary for both single-drone interactions and even more so for the interactions with swarms required to realize a holodeck. The majority of previous physical human-drone interaction systems that have been created use a simple PID controller. Our prior work has shown that these PID controllers are effective at vertical interactions but can quickly become during lateral interactions. However, recent control strategies, such as nonlinear model predictive control (NMPC) and incremental nonlinear dynamic inversion control (INDI) showed improvement in performance in agile flight and handling uncertainties. In this paper, we present the lessons learned from our prior work and discuss implications of these advancements and limitations for physical human-drone interaction. We speculate on how the integration of these advanced control strategies could overcome current limitations, enhancing interaction capabilities. We conclude with suggestions for future research directions, including the exploration of new adaptive methods and their potential integration into human-drone interaction frameworks.

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1 MOTIVATION

1.1 Physical Human-Drone Interaction

In the rapidly evolving field of robotics, physical human-drone interaction (HDI) has emerged as a pivotal area of research, offering a myriad of applications ranging from appropriate virtual objects [2, 11, 13], to rendering virtual stiffness [1, 7, 11]. Physical human-drone interaction can be categorized by the display methods: interaction requiring a head-mounted display (HMD) [1, 2, 13] or interaction that is self-illuminated [6, 7, 11]. For VR-incorporated systems, VRHapticDrones [13] implemented the presence of a virtual object using a drone installed with different shaped cages, the system by Abtahi et al. [2] rendered texture and grab-and-pull interactions, and HapticDrone [1] simulated virtual stiffness and weights for virtual objects. For self-illuminated systems, GridDrone [6] and BitDrone [11] demonstrated using swarms of drones installed with LED to render 3D objects. Our system [7] is currently a single LED installed drone. These results expand the possibilities of intuitive human-drone interaction and interaction with virtual systems such as VR [1, 2, 13], design[6], or communication [11]. Our past implementation of virtual stiffness rendering simulated different stiffness levels given 0.21 N of thrust [7].

Recent advancements have been made in control strategies, particularly in nonlinear realms. This paper gives special attention to nonlinear model predictive control (NMPC) [12, 14, 18] and non-predictive control such as Differential Flatness Based Control (DFBC) [8] or incremental nonlinear dynamic inversion (INDI) [17]. These advanced control methods have demonstrated superior performance in agile flight scenarios and in managing uncertainties, a key requirement in dynamic HDI environments. We examine the efficacy of differential flatness-based control and adaptive NMPC in addressing model mismatches and external disturbances through a past comparative study, challenges that are quintessential in real-world HDI applications.

The implications of these advancements are profound for the future of HDI. We hypothesize that the integration of advanced control strategies, such as NMPC and INDI, could significantly enhance the capabilities of drones in interactive environments, enabling complex interactions such as 3D force feedback or trajectory based stiffness rendering. The improvements in handling disturbance could potentially enable drones to provide force feedback given close formation, handling the disturbance from other close-by drone's air turbulence or downwash effects [16]. The implementation of such controllers could enable more complex systems towards the realization of an interactive swarm display, such as Flying Light Specks (FLS) [3, 4, 9, 10]. Each drone would act as a proxy for a part of the point cloud which represents the virtual object to render within a holodeck. These improvements could lead to more robust, efficient, and safer human-drone collaborations. Finally, we chart potential future research directions, emphasizing the need for exploring novel adaptive methods and integrating these advancements into comprehensive human-drone interaction frameworks. Our goal is to contribute to the development of more intelligent, responsive, and intuitive HDI systems that can adapt to the complexities of real-world applications. Our contribution in this abstract is: 1. We analyzed the limitation of using PID controller with a Crazyflie drone to render force feedback, and identified that it has limited capabilities responding to lateral and orientation errors. 2. We survey recent advancement of controlling techniques, identify their strengths and limitations, and propose that nonlinear

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Figure 1: A user interacting with our implementation of Flying Light Speck

predictive controller could improve the performance in physical human-drone interaction.

2 PRELIMINARY WORK WITH CRAZYFLIE SYSTEMS AND LIMITED LATERAL FORCE FEEDBACK RESPONSE

Our initial attempts at implementing a single Flying Light Speck (FLS) utilized the Crazyflie 2.1 quadcopters [7]. These compact drones, measuring 92mm x 92mm x 29mm, are equipped with features suitable for our study, such as a responsive accurate position control system and miniature size. Their 45mm propellers can generate up to 0.59 N of instantaneous thrust, providing ample power for their lightweight frames. We rendered different stiffness by choosing the PID controller gain (KPz) in the position controller, and conducted a user study with 12 participants. Our results showed that while the available thrust is only 0.21 N, users are able to perceive various stiffness levels based on the choice of KPz.

During technical evaluations, we analyzed the performance of the Crazyflie with a PID controller using a Vicon camera system to track the drone's position. We focused on vertical and lateral interactions where the drone hovered at a fixed height. Fig. 1 shows a typical vertical interaction, during which the user presses the drone downward. An example trajectory of a vertical interaction is shown in Fig. 2, in which the drone drifts 18.7 cm along the x-axis and 14.0 cm along the y-axis. The rendered stiffness is followed by a Hookes-law relationship by converting the distance that the user disturbs the drone away from its setpoint location to the thrust output of the drone:

$$-K(\hat{X}_d - \hat{X}_r) = f + mg, \tag{1}$$

where K is the stiffness constant, and X is the translation of the drone. The total force output of the drone is equal to its body weight plus the rendered force f.

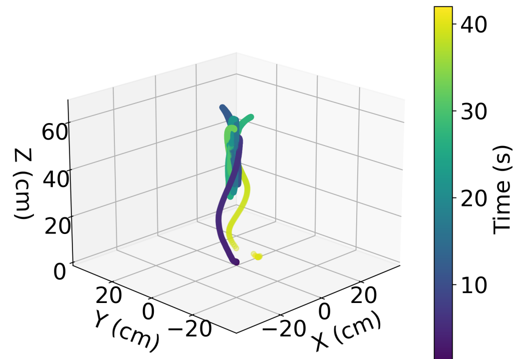

Figure 2: 3D trajectory of vertical Interaction in Crazyflie Study

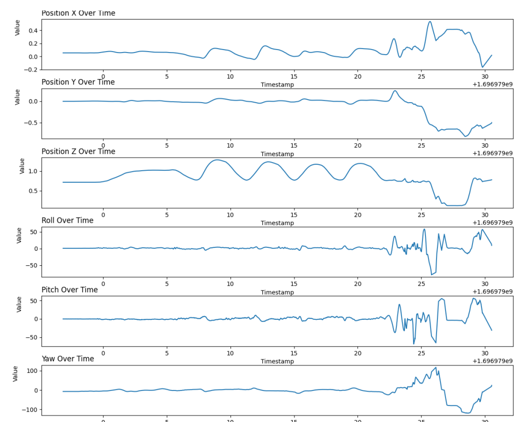

Figure 3: A flight log for a Crazyflie drone during interaction. At 23 seconds (x axis), the drone started to show roll and pitch error. Although the PID controller tried to adjust, the drone ended up oscillating and crashed.

In our experiment, we conducted analysis on vertical stiffness rendering. Using a PID controller, our drone completed 72 trials of user interaction with only 8 crashes. Among those crashes, we found that the drone usually underwent an oscillation in orientation before the crash. We analyzed the flight log which confirmed our findings. We conduced further studies to look into details of the flight control. One of the flight logs is shown in Fig. 3, where the user interacted with the drone four times and crashed on the fifth interaction. The log in roll and pitch showed that the drone experienced negative orientation and oscillated after a roll error of 15 degree and 25 degree pitch error. Such an error could be due to the limitation of the linear controller, as linear PID falls under small angle assumption to maintain stability.

Our experiments highlighted critical limitations in the flying stability of Crazyflie drones with non-predictive control such as a PID controller, especially in the lateral x and y planes. These limitations are particularly evident in scenarios involving user touch, where the drone often struggles to regain balance after disturbance.

The observed challenges in maintaining stability and responding adequately to user interactions are a critical challenge in realizing the full potential of the FLS system.

3 QUADCOPTER CONTROLLER WITH UNCERTAINTY

In the context of implementing FLS systems to realize holodecks using quadcopters like Crazyflie, handling uncertainty becomes a crucial aspect. The field has seen significant progress in recent years, particularly in managing unexpected uncertainties in drone control.

3.1 Non-Predictive Control

Non-predictive control utilizes sensor feedback to adjust for actions or account for external disturbances. Control techniques such as PID, incremental nonlinear dynamic inversion (INDI), differential flatness based control (DFBC), and admittance control. INDI offers a robust solution for quadcopter control, particularly in environments with significant external disturbances [17]. Unlike traditional control methods that rely on pre-determined models, INDI dynamically adjusts the control inputs in real-time based on immediate feedback from the drone's accelerometers. This approach allows for a more responsive and adaptable control system, capable of compensating for unexpected changes in the drone's dynamics, such as those caused by wind gusts or sudden shifts in payload. INDI's real-time responsiveness and adaptability make it well-suited for complex and unpredictable environments, enhancing the drone's stability and overall performance. DFCB utilizes the concept of differential flatness, which allows for the transformation of a quadcopter's inherently nonlinear dynamics into a more manageable linear form [8]. This transformation facilitates precise trajectory tracking, making DFCB particularly effective in controlled environments where external disturbances are minimal or predictable. However, its reliance on a disturbance-free assumption can be a limitation in real-world scenarios where unpredictable environmental factors are present. Federico et al. [5]. presented a non-learning approach to drone control in 2013, employing a high-level controller in addition to the usual position and attitude controllers. It successfully estimated forces from the lateral X-direction, demonstrating the effectiveness of admittance control in managing drone uncertainties.

3.2 Model Predictive Control

Learning methods to handle uncertainty have also been popular in recent years, since using physics approach to model the uncertainty in quadcopter systems are intrinsically hard due to the complex dynamics. Learning approach can utilize data from real flight or simulation, train a policy that could address some the uncertainty within the state space. Research from Wu [18] introduced an L1 adaptive control augmentation for geometric tracking control of quadrotors. It handles nonlinear uncertainties in quadrotor dynamics without enforcing parametric structures. The experimental results demonstrated a significant improvement in trajectory tracking errors compared to the geometric controller alone under various uncertainties and disturbances. Hanover et al. proposes an L1-NMPC [12], a hybrid adaptive Nonlinear Model Predictive Control for quadrotors. This approach is designed to handle model uncertainties online and immediately compensate for them, thereby enhancing performance significantly over non-adaptive methods. The architecture is evaluated in various environments, demonstrating over 90% tracking error reduction under large unknown disturbances and the ability to fly highly agile racing trajectories at top speeds of 70 km/h. The adaptive controller is shown to be effective in real-time damage adaptation, transitioning to fault-tolerant modes, and maintaining performance in uncertain environments. Saviolo [15] discussed uncertainty-aware model predictive control (MPC) for quadrotor systems. It leveraged an advanced neural network-based approach to estimate and actively compensate for uncertainties, thus enhancing drone control effectiveness. The experimental results demonstrated superior model training efficiency and faster convergence due to the continual optimization loop created by the system.

4 ADDRESSING THE UNCERTAINTY

One constraint in realizing future physical human-drone interaction systems is the difficulty in managing unmodeled uncertainties. These uncertainties arise from various factors, such as high-speed air friction, human touch input, or air disturbances caused by nearby drones. Our initial implementation used PID (Proportional-Integral-Derivative) control, which, while effective in managing disturbances in the Z direction, proved inadequate in the face of the non-linear dynamics typical of quadcopter systems. The linear nature of PID control is suited for scenarios involving small angle deviations, but it falls short when dealing with larger, more complex disturbances.

To overcome these challenges, we propose the adoption of a more complex controller, such as nonlinear model predictive controller (NMPC). Recent advancements in NMPC have shown significant improvements in robust handling of unmodeled disturbances. MPC, unlike PID control, is designed to anticipate future system states, allowing for more effective management of the complex dynamics inherent in drone swarms.

Implementing NMPC in the FLS system could address many of the current limitations. By enhancing response robustness, NMPC could enable drones to maintain stability even under the influence of high-speed disturbances or direct user interactions. This would not only improve flying stability but also reduce the minimal distance between drones, enhancing the rendering resolution of smooth and safe human-drone interaction.

Our vision for the next generation of human-drone interaction system incorporates NMPC-based control algorithms to significantly improve overall system performance. By leveraging NMPC, we aim to create a more responsive, stable, and precise system, capable of delivering richer and more immersive haptic and visual experiences. This advancement would mark a significant step forward in the realization of fully interactive and responsive immersive systems, bringing us closer to the full potential of the smooth and intuitive human-drone interaction.

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