

# Planning and Coordination for Unmanned Aerial Vehicles

Doctoral Consortium

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## ABSTRACT

Unmanned Aerial Vehicles (UAVs) are a versatile platform that can be used for many data collection applications including emergency response, environmental monitoring, and military intelligence collection, among many others. This extended abstract summarizes our recent advancements in the field of single and multi-UAV route planning and cooperation, with a focus on quadrotors. We first look at how to plan efficient paths and adapt vehicle speed to minimize mission completion time in the presence of energy constraints of UAVs in problems where a single UAV must visit a series of waypoints and then rendezvous with a moving ground vehicle. We then look at a holistic approach for route planning and deploying a team of UAVs to collect data from wireless sensors while minimizing data collection latency. The abstract concludes with a summary of future research directions.

## KEYWORDS

UAV Path Planning; Cooperative Vehicle Routing; Data Collection

### ACM Reference Format:

Jonathan Diller. 2023. Planning and Coordination for Unmanned Aerial Vehicles: Doctoral Consortium. In *Proc. of the 22nd International Conference on Autonomous Agents and Multiagent Systems (AAMAS 2023), London, United Kingdom, May 29 – June 2, 2023*, IFAAMAS, 3 pages.

## 1 INTRODUCTION

Unmanned Aerial Vehicles (UAVs) are commonly proposed as a solution for various data collection and monitoring problems due to their versatility and commercial availability. In particular, quadrotors have seen a lot of attention in recent research due to their mobility and affordable price. Quadrotors can take off vertically, travel long distances, stop and hover over areas of interest and carry payloads. A lot of research has studied how to use quadrotors for surveillance [10, 17, 18], environmental monitoring [21, 22], data collection in wireless networks [1, 6], package delivery [12, 14] and disaster response [15, 20], among many others. In this doctoral dissertation research, we will look at problems relevant to UAVs with a focus on quadrotors, hereafter referred to as drones.

A common method for planning and coordinating drone actions is to transform the scenario into a traditional graph theory problem then solve it using mathematical optimization or heuristic-based algorithms. Many works transform the problem into the Traveling Salesman Problem (TSP) [11, 19, 22, 24], a well studied problem with both optimal and near optimal algorithms [4, 16]. Other popular graph theory problems seen in drone planning research include

the Vehicle Routing Problem (VRP) [10] and the orienteering problem [21]. Researchers often make assumptions about the physical characteristics of drones to fit these problems into well studied graph theory algorithms. However, these assumptions are often too optimistic and do not accurately account for real-world behavior.

Although versatile, drones have limitations such as limited on-board energy or limited communication capabilities. Most drones are powered by on-board batteries that can quickly be depleted. When the assigned task requires the drone to operate beyond its energy limitations, the drone must stop to recharge or have its batteries swapped out during mission execution. Due to limited carrying capacities and energy, drones are normally equipped with low-grade wireless communication equipment. Communication limitations can restrict the communication distance and data transfer bandwidth. These requirements must be considered when planning actions for both single and multi-drone applications.

In this extended abstract, we summarize our recent work on planning and coordination for drones while adhering to realistic energy and communication constraints. Our work asks the question: Can we improve how we model the physical world in planning algorithms and does updating these models lead to better algorithms?

## 2 UAV PLANNING WITH ADAPTIVE SPEED

Traditional energy models are usually based off of flight time or travel distance. However, recent works have shown that drone power consumption is determined by drone speed, creating the velocity-based drone energy model [7, 23]. Using this model, we showed that there is a trade-off between extending the total travel distance of the vehicle and maximizing the speed of the vehicle.

We exploited the relationship between velocity and power consumption in a routing problem where a drone must visit a series of waypoints before rendezvousing with a moving ground vehicle while minimizing mission completion time [3]. In many drone applications, the objective is to use the drone to gather information as fast as possible. In applications such as maritime search and rescue or military reconnaissance the user deploying a drone may need to continue moving and cannot wait in a single location for the drone to return. An example of this is a ship that cannot stop and wait for the drone to complete its mission. In these scenarios, high-level route planning algorithms must account for user movements in addition to traditional constraints such as limited on-board energy. Adding our realistic energy model to this scenario requires the drone to periodically return to the moving user to swap-out batteries, incurring a time penalty. We termed this problem the *Minimum-Time while On-The-Move* problem.

To solve our Minimum-Time while On-The-Move problem, we designed an iterative algorithm that simplifies the problem by fixing

*Proc. of the 22nd International Conference on Autonomous Agents and Multiagent Systems (AAMAS 2023), A. Ricci, W. Yeoh, N. Agmon, B. An (eds.), May 29 – June 2, 2023, London, United Kingdom. © 2023 International Foundation for Autonomous Agents and Multiagent Systems (www.ifaamas.org). All rights reserved.*

or estimating parts of the larger problem. We first fix the number of times the drone must rendezvous with the ground vehicle then estimate the total mission time. This allows us to formulate the problem into a variation of the multiple depot, multiple terminal, Hamiltonian path problem with fixed start and stop points. Using the results of this Hamiltonian path problem variation, we update our predicted total mission time and repeat the process until we find a consistent solution.

We proposed two approaches to solve the multiple depot, multiple terminal, Hamiltonian path problem with fixed start and stop points: a mathematical optimization-based approach and a heuristics-based approach. For the optimization-based approach, we formulated a Mixed-Integer Non-Linear Program (MINLP), using a variation of the Miller-Tucker-Zemlin formulation [5, 13] that minimizes the total mission completion time while optimizing the vehicle’s speed. In the heuristics-based approach, we first use Lloyd’s  $k$ -means cluster algorithm [8] to form subtours between stops with the ground vehicle. This turns the problem into a TSP instance, which we solve using commercial solvers. We then select speeds for each subtour that minimize the completion time.

We evaluated our approach on a variety of simulations and a physical testbed. For the simulations, we compared our two approaches against a baseline adapted from [9] on inputs with waypoints ranging from five up to 80, at increments of five. Fig. 1 shows an abbreviated version of our results. We found an average improvement of 23.8% and 14.5% for the MINLP and heuristics-based approaches, respectively, in mission completion time over the baseline approach (Fig. 1 top). We further evaluated how scheduling speed improved mission completion time while using the heuristics-based approach (Fig. 1 bottom). We found an average of 11.9% compared to moving at max speed,  $v_{max}$ , 31.9% compared to moving at max-distance speed,  $v_{opt}$ , and 47.1% compared to moving at best endurance speed (i.e the speed the maximizes flight time),  $v_{be}$ .

To demonstrate how our solution can be applied on real-world scenarios, we prototyped our problem and solution on our own custom physical testbed [2]. More details on our physical experiments as well as more simulation results can be found in the full publication [3].

### 3 MULTI-UAV PLANNING FOR DATA COLLECTION

In ongoing research, we are looking at how to deploy a team of drones to collect data from wireless-enabled sensors. In environmental monitoring scenarios, sensors are often deployed in remote locations to record natural phenomena such as air quality or water samples from streams. We propose using a team of drones to periodically collect data from the sensors via wireless data transfer (e.g. IEEE 802.11).

We are taking a holistic approach to this problem, where we first plan data collection routes using an offline algorithm then look at online strategies for adapting drone behavior during mission execution. For offline planning, we have been looking at ways to adapt the capacitated Vehicle Routing Problem to our data collection problem. For an online algorithm, we have been motivated by the following question: what should a drone do if it stops at a

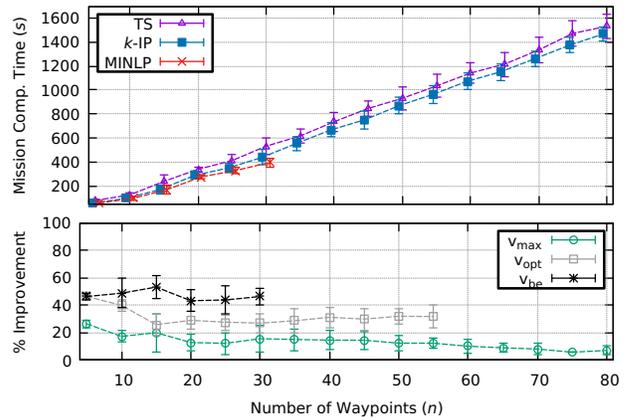


Figure 1: Mission completion time for MINLP and heuristics-based approach ( $k$ -IP) versus baseline (top) and percent improvement with speed scheduling compared to fix speeds (bottom).

waypoint assigned offline but cannot communicate with the wireless sensor? We have been considering hybrid approaches for this problem where we derive a plan prior to deployment then adapt that plan as needed online.

### 4 FUTURE DIRECTIONS

In future research, we plan to investigate decision making in hybrid centralized-decentralized systems. A centralized machine can make real time decisions for connected agents but not all agents in the system are guaranteed to be connected to a centralized system and must operate with what information is available to them. A hybrid-connected system creates unique challenges in decentralized decision making for autonomous agents. There is a trade-off in performance at a given task when operating in a disconnected state compared to moving to reconnect to the larger system to update state knowledge.

We would like to further investigate this trade-off, determine how this trade-off impacts decision making for autonomous agents, and apply our solutions on physical drone testbeds to validate their feasibility in the real world. We are particularly interested in decision making where an all-knowing oracle could make an optimal decision for each agent but the agents themselves do not have enough information to make these decisions and must balance accomplishing their task with staying informed by a central computer.

### ACKNOWLEDGMENTS

I would like to thank my advisor, Dr. Qi Han, for supporting and guiding me in my research. I would also like to thank the various research assistants at the Pervasive Computing Systems (PeCS) research group at Colorado School of Mines. Specifically, I would like to thank Peter Hall and Corey Schanker for putting in extra hours and long weekends over the last two years to help me move my research forward.

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