ANALYSIS OF OPTIMAL ROUTE PATH PROBLEM OF UNMANNED AERIAL VEHICLE

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Abstract

Abstract Over the past few years, Unmanned Aerial Vehicles (UAVs) have become more and more popular. The complexity of routing UAVs has not been fully investigated in the literature. In this paper, we provide a formal definition of the UAV Routing and Optimal route path problem of unmanned aerial vehicle (ORPPUAV). Next, we introduce Issue with UAV Path Planning, UAV routing and Problem with UAV task assignment addressing these problems, and their variants, simultaneously. We conclude with the identification of future research opportunities.

Keywords: *unmanned aerial vehicles, routing, trajectory optimisation, literature review,*

Introduction

Unmanned aerial vehicle (UAV) use for data collection and measurement has grown in popularity in recent years. UAV use frequently enables cost savings and enhancements to other performance standards. The academic routing community is aware that businesses and organizations are interested in using UAVs in their operations. However, restrictions brought on by UAV flight dynamics are frequently disregarded. It is difficult to find feasible UAV trajectories in a routing problem, yet it is essential to guarantee the viability of the routes. We introduce the Optimal Route Path Issue of Unmanned Aerial Vehicle (ORPPUAV) in this study. This problem involves maximizing the routes and trajectories of a fleet of UAVs while taking into account limitations imposed by flight dynamics.

Drones' primary environmental impact is likely to be the noise pollution they produce, especially when they have rotary wing systems (helicopters, quadcopters, etc.). In heavily populated regions, this additional noise can be a problem, especially if several NGOs are using drones simultaneously.

Motivation

Unmanned aerial vehicles (UAVs) are planes that can fly without a human pilot. These vehicles are typically either piloted using a remote control or by an embedded computer. UAVs include drones, remote-controlled helicopters, and unmanned gliders. Gliders are distinct from other varieties since they don't have on-board propulsion (e.g., an electric or combustion engine). This thesis investigates the viability of replacing physical inspection with drones for data collection.

Drone technologies and types of drones

Unmanned aerial systems are typically split into three categories: hybrid drones, multirotor UAVs, and fixed-wing UAVs (which is a combination of the first two). These categories each have a number of benefits and drawbacks. Ideally, a user should decide on the best drone platform based on the organisational requirements, mission requirements, and environmental factors. The price of each system is typically so high that NGOs cannot afford to purchase and run multiple systems. In order to complete as many distinct missions as possible, a compromise is frequently made, even if the results are less than ideal.

- Fixed-wing drones
- Drones with rotor blades
- Fusion Drones

Objectives

- Examine the study on UAV trajectory and routing optimization.

Reviews

The literature on aeronautical engineering and optimum control has extensively examined the computation of UAV trajectories (Yang et al., 2016). The search for a control history for a vehicle that minimizes a scalar performance index (like flight time or fuel consumption) while satisfying constraints on the kinematics (position, velocity, and acceleration) and dynamics (forces and moments) of the vehicle is known as the trajectory optimization (TO) problem. A trajectory is often associated with a set of Equations of Motion (EOM) that describe the interrelationships between the spatial and temporal changes in a system. The TO problem is closely related to the Optimal Control (OC) problem (Betts, 2001).

Zhang et al. (2012) take into account a situation when a UAV needs to visit a number of targets. The UAV must adjust its flight attitude after getting near enough to a target to deliver a payload. The UAV must execute an escape manoeuvre after the delivery and get ready for the following delivery. Zhang et al. (2012) claim that in order to assure both the vehicle's safety and the viability of trajectories, routing and trajectory optimization must be linked.

The Optimal route path problem of unmanned aerial vehicle

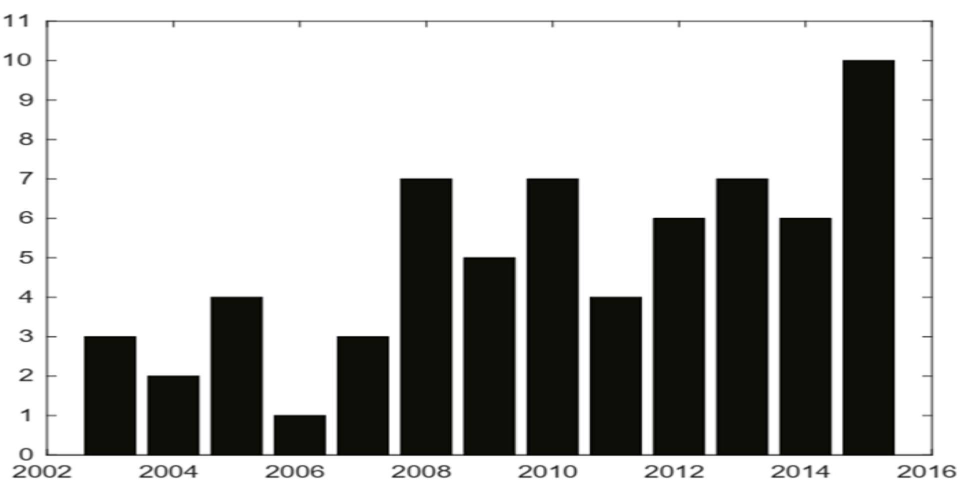
The ORPPUAV, or optimal route path problem of unmanned aerial vehicle, is explicitly defined in this section. It is a problem in which a fleet of UAVs must go to a set of waypoints while assuming a range of kinematic and dynamical constraints. Additionally, the model may take into account obstacles to avoid, wind conditions, and UAV collision avoidance.

The Issue with UAV Path Planning

Following is a definition of the fundamental PP problem using the notation established by Latombe (1991).For example, in a Euclidean space, S = Rn, where n = 2 or 3, let A stand in for a moving item (a robot) in workspace S. The distribution of a set of obstacles over S is assumed to be B1,..., Bm. Given the initial and final configurations (position and orientation) for A, the task is to construct a path in S that avoids running into the objects B1,..., and Bm. If the velocity of object A is unbounded and rotation is disregarded, it has been determined that this problem is NP-hard (Reif and Sharir, 1994). A path planning problem, according to Gasparetto et al., seeks a collision-free route through an environment from a starting point to a destination (2015). For instance, a three-dimensional path planning problem with obstacles is studied by YongBo et al. (2017). In literature, the terms "PP" and "motion planning" are frequently and essentially interchanged (Barraquand and Latombe, 1991). The popularity of both problems has increased over time.

The issue with vehicle routing

A particularly well-known issue in operational research and combinatorial optimization is the vehicle routing problem (VRP). Routes must be assigned to a set of vehicles that must service a set of clients in order to maintain operational costs in the VRP to a minimum. The typical variant of the issue, in which each vehicle is assigned a load capacity, is called the Capacitated Vehicle Routing Problem (CVRP).



Problem with UAV task assignment

Finding the best way to allocate UAVs to a collection of tasks is known as the UAV Task Assignment Problem (UAVTAP). The activities frequently provide specific requirements, and the UAVs frequently have different characteristics. This problem has been demonstrated to be NP-hard (Alidaee et al., 2010). Numerous algorithms have been created to solve the new obstacles brought on by the swift development of UAV technology, which has led to the daily emergence of new challenging assignment problems. Figure 2.2's y-axis displays the number of publications by year in UAVTAPs, which is connected with the number of papers discovered in the Science Direct and Web of Knowledge databases. One can see that the scientific community is paying more attention to this area of study. Khamis et al. provide a thorough literature overview on methods for multi-robot TA challenges (2015).

Unmanned Aerial Vehicles Routing

We build a virtual network to operate UAVs by modelling two realistic environments that UAVs may confront during deliveries. Based on the network, we find optimal roundtrip routes of UAVs by minimizing total costs for delivery. In this process, we determine the number of UAVs in service. Furthermore, we eliminate sub tours using a flow variable. Moreover, we dispatch UAVs to customers to satisfy demand considering the maximum range and loading capacity of UAVs.

UAVs must deliver goods to all customers after they depart from their depots without reloading goods. However, a single-depot system is not suitable for UAVs as the maximum range of UAVs can be less than the round-trip distance between the depot and customer. Thus, customers located further than the maximum range from the depot cannot receive goods. Furthermore, UAVs cannot move in straight lines between customers because buildings or trees might block the flight path of UAVs. Therefore, we build a network having multiple depots organized by region to serve all customers. We also utilize intermediate vertices that UAVs can visit to avoid large obstacles when traveling between customers.

The network is composed of vertices, which include multiple depots, customers and intermediate vertices, and edges. The blue square markers represent locations of different UAV depots. The yellow triangle markers represent the location of each customer. The gray points represent intermediate vertices for routing UAVs. The gray lines represent edges, and UAVs can only move from vertex to vertex along edges. The network-related notations are as follows:

- The vertices set is $N = \{1, 2, ..., n\}$ denoted by i, j, where $i, j \in N$, and $i \neq j$.

- The depots set is $P = \{1, 2, ..., m\}$ denoted by p, where $p \in P$, $P \subset N$.

- The customers set is $D = \{1, 2, ..., l\}$ denoted by d, where $d \in D$, $D \subset N$.

- The set of UAVs belonging to depot p is $K_p = \{1, ..., h\}$ denoted by k_p, where $k_p \in K_p$.

- The set of all UAVs is K denoted by k, where $K_p \subset K$, $K = \{1, ...,s\}$, $k \in K$.

- The set of edges is $(i, j) \in \{(i, j), ...,(s, t)\}$, where $i \in \{1, ..., n\}$, $j \in \{1, ..., n\}$, $i \neq j$.

Based on the network, our objective minimizes total costs for UAVs as follows:

$$\min \sum_{k=1}^{s} \sum_{j=1}^{n} \sum_{i=1}^{n} c_{ij} \times x_{ijk} + \sum_{k=1}^{s} \gamma \times \delta_k , \quad (1)$$

where the integer variable x_{ijk} decides the number of trips between a vertex i and a vertex j for the kth UAV. The variable cost c_{ij} is charged to UAVs moved between i and j. Furthermore, δ_k is a binary decision variable for the kth UAV and works as a service-indicator. If δ_k is 1, then the kth UAV is put into use, and, if δ_k is 0, the kth UAV is not used. γ is the fixed cost of using a UAV, and s is the total number of UAVs registered in depots.

Research outcomes

UAV routing and trajectory optimization difficulties focused in the study. Because it combines routing, a combinatorial optimization problem, and optimum control, which is frequently nonlinear and nonconvex, this type of problem is more difficult than the standard VRP. For the challenge of simultaneously optimizing the paths and trajectories of a fleet of aerial gliders, we also concentrated on precise and heuristic methods.

A formal formulation of the UAV Routing and Trajectory Optimization Problem (ORPPUAV) hadn't yet been put forth, according to examination of the literature. The majority of research studies that addressed UAV routing and trajectory optimization issues depended on oversimplifying presumptions that did not accurately reflect how complicated these issues were in practical applications. To ensure that routes are feasible in a variety of conditions, we think it is essential to integrate routing with UAV flight dynamics. When working with ORPPUAVs. Typically, there are three key concerns to solve: I managing the set of ODEs that describe flight dynamics; (ii) integrating routing and trajectory optimization in the same framework; and (iii) is creating a scalable strategy that can solve problems in a reasonable amount of time.

This study primary contribution can be summed up as follows:

We devised a variant of the ORPPUAV known as the Glider Routing and Trajectory Optimization Problem in response to a catastrophe assessment application (GRTOP). Gliders with cameras are scheduled to survey a number of hazardous areas in the GRTOP in the aftermath of a tragedy. To model the motion and flight dynamics of gliders, we employed a set of ODEs known as the gliders' EOMs. We introduced a single-phase MINLP to address the GRTOP. We linearized the EOMs around a few steady-state criteria to prevent the formulation from being nonconvex and nonlinear. To discretize the resulting linear EOMs, a number of integration techniques were described, including two Runge-Kutta methods, two Adams-Bashforth methods, an Euler's approach, and a trapezoidal method. A penalty term was also introduced to the goal function, loosening restrictions on the gliders' EOMs, which led to a more manageable MISOCP formulation.

We evaluated the suggested formulation using both real-world and a large number of randomly created situations. We compared the model's performance in various circumstances while taking alternate solvers, discretization’s, and an alternative EOM relaxation into consideration. To the best of our knowledge, this is among the first approaches in the literature to incorporate UAV routing and trajectory optimization into a unified framework.

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