A Glimpse into the Adaptive Path Planner for a UAV

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Abstract. Path planning is a crucial problem in Unmanned Aerial Systems. It becomes even more complicated if more complex mission scenarios are involved, thus requiring sophisticated multi-criteria optimization algorithms. Finding a valid path in a 3D environment usable for real-time control application is a compromise between optimality and computation time. This article responds to this issue by proposing a two-level approach. First, the optimized guidance points are computed offline. Second, they are connected sequentially with fast tree-based algorithms during the flight to provide the final path for the Unmanned Aerial Vehicle. This way soft real-time capability is maintained while keeping more intricate multi-criteria optimization required to comply with the mission scenario. The article describes the general concept of Adaptive Path Planner and presents it in the context of a measurement mission employing a High-Altitude Long Endurance UAV. The idea is then supported with preliminary simulation results. Conclusions and future remarks finalize the paper.

Keywords: path planning, obstacle avoidance, unmanned aerial vehicles, UAVs.

1 Introduction

Although their development began in the 19th century, Unmanned Aerial Vehicles (UAVs) have become increasingly popular in recent years [1]. Nowadays, UAVs are considered one of the most challenging and high-potential technologies in aeronautics [2]. The number of papers related to UAVs published yearly is growing since 2008 with a more dramatic increase since 2017 [2].

One of the major problems in Unmanned Aerial Systems (UASs) is path planning [1]. It means generating an admissible flight path between points in space (waypoints) with minimal comprehensive cost [2]. And to be admissible, the path must be subject to kinodynamic constraints of the UAV. Yang et al. argues that simple 2D planning algorithms are unable to handle complex 3D environments, thus dedicated 3D algorithms are needed [1]. Nevertheless, finding a 3D complete path is classified as an NP-hard problem [1], so it is always a struggle between optimality and performance.

This paper addresses the path planning of a meteorological High-Altitude Long Endurance (HALE) UAV by proposing Adaptive Path Planner (APP). APP mixes existing general optimization algorithms with soft real-time capable algorithms used for obstacle avoidance and adaptive control.

2 Adaptive Path Planner

APP consists of two complementary modules: (1) Global Path Planner (GPP) and (2) Local Path Planner (LPP). Fig. 1 shows the methodology involving APP on an example of a general measurement mission scenario with a HALE UAV.

GPP optimizes the global path of the UAV using scenario-dependent criteria and an environment map. The map includes weather forecast, static terrain obstacles, airspace structure enforced by law and a measurement map. GPP produces global waypoints, which are scenario-optimized guiding points used as inputs to lower-level LPP. The order of following the global waypoints is strict. However, as the actual conditions may differ from predicted, the exact way of reaching global waypoints is resolved dynamically by LPP. The result is then verified in Model-In-the-Loop simulation of the flight. GPP employs biologically inspired optimization algorithms such as I-GWO, ACO, GA and PSO [1] and is used offline in Ground Control Station (GCS) for static planning.

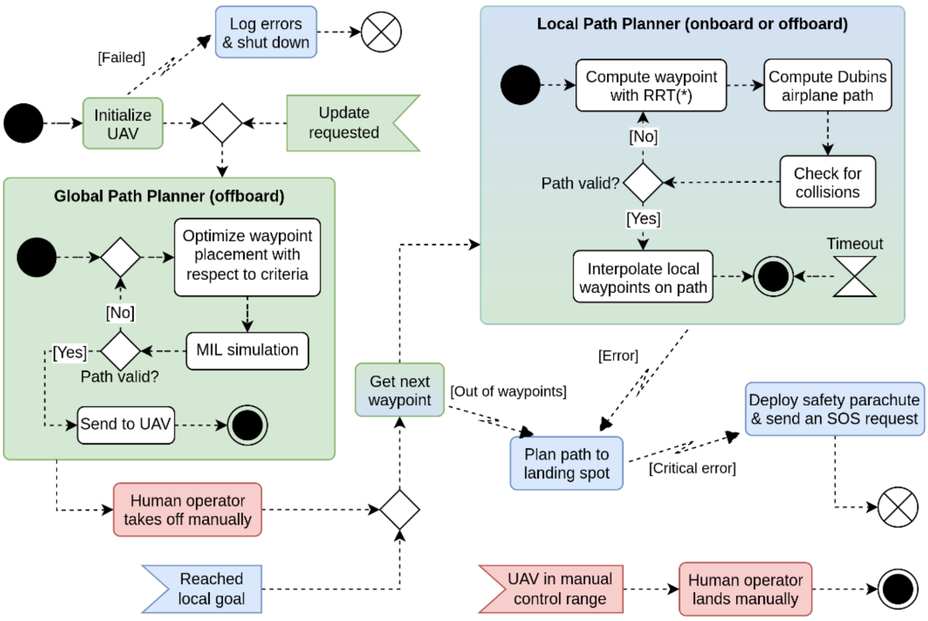

Fig. 1. A typical HALE UAV measurement mission using APP

LPP dynamically generates local paths between the global waypoints supplied by GPP. Thus, it allows the UAV to dynamically adapt to any unpredictable position errors caused by wind gusts etc. LPP connects two global waypoints with an admissible path, that is subject to kinematic constraints of the aircraft. First, it employs Rapidly exploring Random Tree (RRT) or RRT* algorithms [3] to generate a local goal waypoint. RRT and RRT* achieve soft real-time performance [1], but only grant probabilistic optimality [4]. Then, a Dubins airplane model [5] is used to validate the path by checking for collisions between the start and goal. Finally, the path is interpolated into local waypoints used by the controller of the UAV. LPP runs online in GCS (if the UAV is in communication range) or onboard using the UAV's embedded computer (if out of range or attempting an emergency maneuver). LPP considers only static obstacles.

The mission starts in GCS by initializing the UAV and manually planning the mission scenario. Then, GPP computes the optimal global waypoints, which are then sent to the UAV. GPP can dynamically recalculate the path on demand during the mission.

Now, a human operator takes off using remote control (RC) and flies the UAV to the first global waypoint. Then, the autonomous UAS takes over the aircraft and uses LPP to plan the local path to the next global waypoint, pair-by-pair. The path is recomputed dynamically if the UAV deviates too much from the previous one. This behavior loops until all the global waypoints are reached or an error occurs. In any case, the UAS plans the path to a predefined landing spot. When the UAV is back in RC range, the human operator manually lands the aircraft. The mission is completed. If a critical error occurs during the flight to the landing spot, the UAV enters emergency mode, deploys a parachute and sends an SOS request, aborting the mission.

3 Preliminary Results

APP was implemented in MATLAB R2021b. GPP featured I-GWO, while LPP used RRT. For preliminary tests a built-in probabilistic 3D occupancy map based on OctoMap [6] was employed instead of a dedicated environment map mentioned in section 2. A sample output produced by APP for a fixed-wing UAV is shown in Fig. 2.

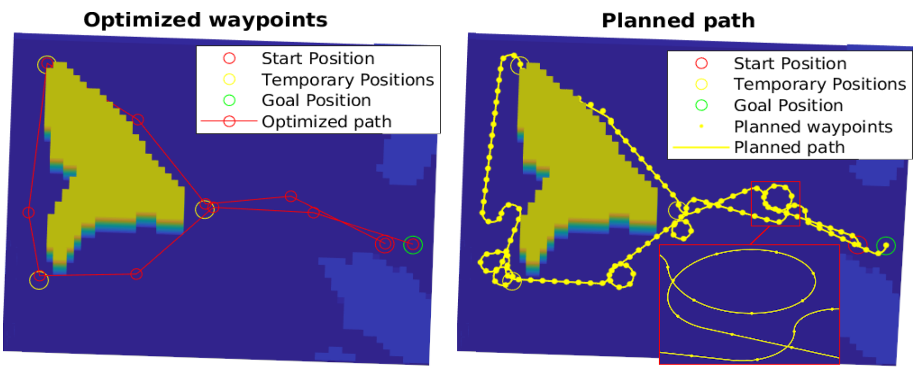

Fig. 2. Sample output of APP: global waypoints (left) and concatenated local path (right)

Fig. 2 illustrates an obstacle map of the city of Żywiec (Poland) and Żar Airport (ICAO: EPZR). The city is considered a no-fly zone and modeled as an obstacle. Red and green circles denote the points, where the control over the UAV is passed to/from the autonomous system, respectively. They should not be confused with exact takeoff/landing spots. Yellow circles denote the predefined waypoints specified by a human operator according to the mission requirements. In this example they restrict only the horizontal positions, i.e., the planner optimizes the final altitude at these points.

The left figure displays an optimized path generated by GPP. Global waypoints are represented by small red circles connected by line for clarity. Here, GPP optimizes the positions of global waypoints located between the predefined waypoints. This approach shapes the path accordingly to a set of test criteria using I-GWO.

The right figure shows the local path computed by LPP. The path concatenates several local path segments computed between the pairs of global waypoints using RRT. This example assumes the UAV has not deviated from its original path. Hence, the goal of the previous segment is the input for the next one. The "loops" seen on the figure are helices used to descend or ascend the UAV. LPP returns a set of local waypoints.

4 Conclusions

APP merges a higher-level optimization with a faster and adaptive lower-level obstacle avoidance. This keeps the optimality of the global path, which can be computed offline, while achieving soft real-time performance required for adaptive flight control.

The concept was positively verified in preliminary simulation tests in MATLAB. However, to be considered feasible, more extensive tests must be conducted to provide quantitative results. Further research will focus on the verification of GPP and LPP using model-based verification. This will involve kinematic and dynamic models of the aircraft, as well as the real HALE UAV platform.

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