A Distributed Pareto-based Path Planning Algorithm for Autonomous Unmanned Aerial Vehicles (Extended Abstract) *

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Abstract

Autonomous Unmanned Aerial Vehicles (UAVs) are in increasing demand thanks to their applicability in a wide range of domains. However, to fully exploit such potential, UAVs should be capable of intelligently planning their collision-free paths as that impacts greatly the execution quality of their applications. While being a problem well-addressed in literature, most presented solutions are either computationally complex centralised approaches or ones not suitable for the multiobjective requirements of most UAV use-cases. This extended abstract introduces ongoing research on a novel distributed Pareto path planning algorithm incorporating a dynamic multi-criteria decision matrix allowing each UAV to plan its collision-free path relying on local knowledge gained via digital stigmergy. The article presents some initial simulations results of a distributed UAV Traffic Management system (UTM) on a weighted multilayer network.

1 Introduction

With the miniaturisation of low energy consumption sensors, the recent introduction of 5G and the wide adoption of Internet of Things (IoT), the autonomous mobile robotics industry and specifically the UAV industry is set to register some of its highest Compound Annual Growth Rates (CAGR) for the coming decade. The demand for autonomous UAVs is increasing enormously, owing to their flexible operational potential in a wide array of applications that were previously deemed infeasible. Some predominant examples in literature include logistics [Fernández-Caramés et al., 2019], monitoring, surveillance and disaster management [Feng et al., 2015]. Nevertheless, to fully exploit such potential let alone safely manage UAV traffic, autonomous UAVs should be capable of intelligently and safely navigating their dynamic environments since in majority of scenarios, how well they plan their paths impacts greatly the execution quality of their application.

Mobile robot path planning is an optimisation problem that has been well-addressed in the literature over the past years. However, most of the approaches have mainly focused on 2-dimensional (2D) and 2.5-dimensional (2.5D) methods [Yang et al., 2016] which are suitable for ground or water surface mobile robots, while approaches for UAVs and other highly mobile autonomous robots requiring 3-dimensional (3D) path planning, remain less explored. As mobile robot path planning is proven to be NP-hard, 3D path planning is also NP-hard with an additional dimension, altitude [Yang et al., 2016]. In the recent years, several methods were proposed in the literature to address this challenging problem. Yang et al. in [Yang et al., 2014] analyse and categorise some of the main 3D path planning algorithms. Some predominant examples building on classical approaches include the anytime heuristic search algorithm [Likhachev et al., 2004], an Anytime Dynamic A* [Likhachev et al., 2005] and Lazy Theta* [Nash et al., 2010]. While the aforementioned algorithms can find optimal paths through decomposing networks, they typically optimise the path efficiency for one objective which makes them less suitable for applications in complex environments [Jun and Qingbao, 2010].

To address this, research turns to multiobjective optimisation approaches which call for solutions that account for multiple cost criteria, where optimising one criterion may be at the cost of another. The complexity of such problems significantly increases with the number of objectives to be optimised, hence researchers’ often shift to approximate methods to obtain good quality solutions in reasonable time. Broadly, approximate methods can be classified under four main categories namely, scalar approaches, criterion-based approaches, indicator-based approaches and dominance-based approaches [Talbi, 2009].

Such methods have been investigated in the literature for decades with predominant examples of bio-inspired search paradigms like the non-dominated sorting genetic algorithm (NSGA)[Srinivas and Deb, 1994] and variations of NSGA-II [Deb et al., 2000] and NSGA-III [Deb and Jain, 2014] for different environmental models, robot types and applications. The main drawback, however, of using evolutionary algorithms for path planning is computational complexity making them more fit for offline centralised approaches than distributed online path planning in autonomous mobile robots.

In the context of UAV dynamic online path planning, the

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majority of presented solutions either address a single optimisation objective or the multiobjective optimisation problem with centralised approaches. Such approaches will eventually face the inherent limitations of centralised systems when it comes to scalability and resilience of UAV applications and UAV Traffic Management. To this end, this article presents our work in progress and outlines a novel distributed Pareto-based path planning algorithm for autonomous UAVs. The proposed algorithm incorporates an initial path planner complemented by a dynamic online multiobjective path planner extending the Local Pheromone Guided (LPG) A* heuristic presented in [S. Labib et al., 2019] allowing individual UAVs to compute a non-dominated set of paths at every individual search step, i.e. when facing traffic congestion, and rely on dynamically updated multi-criteria decision matrix to select a solution autonomously.

The remainder of this article is as follows. Section 2 outlines an operational example of a distributed UAV Traffic Management system relying on the proposed multilayer model of the Class G airspace initially presented in [S. Labib et al., 2019] followed by an initial optimisation problem formulation. Section 3 outlines the proposed technical approach followed by initial validation results in Section 4. Finally Section 5 concludes and presents the next steps and future work.

2 Use Case: UAV Traffic Management

To validate the path planning algorithm, this section narrates an operational example of a distributed UAV Traffic Management (UTM) system relying on the proposed multilayer model of the Class G airspace initially presented in [S. Labib et al., 2019] (see Figure 1).

The use case illustrates an operational scenario where a group of multi-rotor autonomous UAVs are deployed on a collective monitoring mission similar to that presented in [Feng et al., 2015]. UAVs are considered to have different individual roles in the mission, hence having priorities and incentives to get to their destination. The UAVs enter the airspace through different nodes and traverse from origin to destination along paths at different layers. Each altitude segment, referred to as layer, allows different velocity ranges that increase at higher altitude layers. We assume that higher altitudes offer shorter travel times at the cost of higher energy consumption. This assumption is supported by the work presented in [Cho and Yoon, 2018] where higher altitude layers are less cluttered with static obstacles in comparison to lower ones. This will in turn allow UAVs to fly at higher lateral velocities and consume more energy as explained in [Hwang et al., 2018]. As each UAV traverses the network, and precisely at network nodes, it communicates and exchanges information (awareness messages) with other UAVs within its communication range as explained in our previous work [Labib et al., 2019]. Based on the exchanged rules and traffic information such as traffic density and flight velocities, UAVs make local path planning decisions. In turn, switch between airways, airspace layers and flight modes, namely, lateral, vertical and hover, according to their current battery status and percentage of mission completion (see Figure 2) while trying to minimise both their time of flight and energy consumption.

2.1 UAV Traffic Optimisation and Deconfliction

In alignment with the aforementioned use case, this sub-section presents the corresponding formulation of the bi-objective optimisation problem of minimising the total travel time and energy consumption of UAV traffic in the network. Based on our weighted multilayer network description [Labib et al., 2019], the bi-objective function $F$ we aim to optimise
can be expressed as:

\[
\begin{align*}
\min F &= (f_1, f_2) \\
\min f_1 &= T = \sum_{i=1}^{I} \sum_{l=1}^{L} a_{il} \times t_l \\
\min f_2 &= E = \sum_{i=1}^{I} \sum_{l=1}^{L} a_{il} \times e_l \\
\text{s.t.} \quad \sum_{i=1}^{I} a_{il} &= c_l, \quad l = 1, \ldots, L, \\
&\quad c_l \leq c_{l}^{\text{max}}, \quad l = 1, \ldots, L, \\
&\quad a_{il} \in \{0, 1\}, \quad i = 1, \ldots, I, \quad l = 1, \ldots, L, \\
&\quad E, T \in \mathbb{N}, \\
&\quad e_l, t_l, c_l \in \mathbb{N}, \quad l = 1, \ldots, L,
\end{align*}
\]

where:
\[ \begin{align*}
F &- \text{bi-objective function } (f_1, f_2), \\
T &- \text{objective function (time elapsed)}, \\
E &- \text{objective function (energy consumed)}, \\
I &- \text{number of UAVs}, \\
i &- \text{index for UAVs}, \\
L &- \text{number of airways}, \\
l &- \text{index for airways}, \\
a &- \text{selection indicator for airways / UAVs } (\in \{0,1\}), \\
e &- \text{energy consumption component for airways}, \\
t &- \text{time elapse component for airways}, \\
c &- \text{traffic capacity for airways}, \\
c_{l}^{\text{max}} &- \text{maximum traffic capacity for airways}.
\end{align*} \]

In the proposed model, each airway in a path has a critical traffic capacity of UAVs that it can traverse; in addition to an allowable maximum velocity which is expressed in terms of time \(t\) and energy \(e\). Therefore, for a number of UAVs \(I\) over a complete path our first utility function (1) addresses our first objective, minimising the total energy consumption while (2) addresses our second objective which is minimising the total travel time. Complementing this approach, is the deconfliction process. Conflict management is the process of ensuring that UAVs do not collide, we achieve this by following a strategic then tactical approach (c.f. Table 1). The process is divided into three levels where the aim of each is to reduce the need to apply the proceeding level. Starting with strategic traffic density management in the mission planning phase, signified in equation 5, following through with the dynamic tactical level of maintaining separation and finally evasive manoeuvres.

### 3 Multilayer Multiobjective Path Planning

This section outlines the two stages of the approach followed through the work. The first stage, completed and detailed in [Labib et al., 2019], presented three devised heuristics, namely Global Offline Static heuristic (GOS), Global Probabilistic Dynamic heuristic (GPD) and the Local Pheromone Guided heuristic (LPG). The aim of the first stage was to assess the performance of a completely distributed traffic management system in comparison to a centralised one. The ongoing second stage builds on the first stage’s LPG with the main goal of extending the proposed approach to consider multiple optimisation objectives and rely a dynamic multi-criteria decision making approach to allow UAVs to autonomously select a solution based on their current status and local knowledge.

<table>
<thead>
<tr>
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<tbody>
<tr>
<td>Strategic</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Tactical</td>
<td></td>
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stead of summing them, hence the name *Pareto* A*.

Figure 3 illustrates a simplified flowchart of the proposed algorithm divided into a higher proactive layer, a responsive dynamic intermediate layer and a reactive lower layer.

**Heuristic 1**: Distributed Pareto-based Path Planning (D3P)

**Data**: network, weights *(t, e, c)*, start, destination *(dest)*, traffic_threshold *(T_{lim})*, criteria_matrix

```plaintext
while UAV not at dest do
  compute set of solution_paths
    ▷ using Pareto_A*
  select best_path
    ▷ using criteria_matrix
  take next_move from best_path
  if \( c_l \leq T_{lim} \) then
    set current to next_move
    ▷ UAV move
    update \( t_l, e_l, c_l \)
  else
    compute solution_paths to dest
      ▷ using Pareto_A*
    update criteria_matrix
      ▷ dAHP
    select best_path
      ▷ using criteria_matrix
    set current to next_move
      ▷ UAV move
    update \( t_l, e_l, c_l \)
    update pheromone \( \tau \)
  end
end
```

Knowing their destination, UAVs generate a set of solutions/paths using *Pareto* A* then relying on their multi-criteria decision matrix, each UAV selects one of the generated paths to follow. UAVs start following the selected shortest path until the traffic on the next airway is superior to a predefined threshold defined by \( T_{lim} \), that is, when \( c_l = T_{lim} \) where \( T_{lim} \) is \( c_l^{max} \) (cf. lines 1–4 in Heuristic 1). In reality, \( T_{lim} \) would correspond to the critical traffic density explained in traffic theory as the capacity after which traffic flow becomes congested. At that stage each UAV lays down a pheromone trail \( \tau \), where \( \tau_l = 1/c_l^{max} \) of airway \( l \). The deposited trail of pheromone acts as a repeller to other UAVs, hence making the airway less desirable to take. In the devised model, intersecting nodes act as decision points at which the following UAVs receive the updated pheromone level and use it to estimate an update of corresponding airways’ weights in order to locally compute new alternative paths to their destination (cf. lines 4–6 in Heuristic 1). At this stage, in place of the probabilistic state transition rule used in [Labib et al., 2019], here UAVs rely on a dynamic analytical hierarchy process (dAHP) to make their selection between the generated set of solution from the Pareto-based approach. While dAHP applies the same methodology of the classical Analytical Hierarchy Process (AHP) [Saaty, 1988], it considers the AHP criteria and alternatives as temporary variables instead of and therefore provides autonomous UAVs a logical framework to determine the cost of each alternative at a given step. In other words, as UAVs traverse the network, alternatives present the different solutions/paths at every decision step where the criteria at that step vary with the state of each UAV. As an initial stage, we consider the energy criterion weight to vary with the level of consumption as guided by \( c_i = c_i^p \cdot e^{k \cdot p_i} \) where \( c_i^p \) is the energy criterion weight at step \( i \), \( c_i^p \) is the initial weight of the criterion, \( k \) a growth constant and \( p_i \) represents the battery consumption level. Hence, the more energy UAVs consume the greater the impact of energy conservation would be on their decision between alternatives.

### 4 Simulations and Initial Results

This section outlines our experimental setup and presents a snapshot of the first stage of simulation results, detailed in [Labib et al., 2019], corresponding to the first stage in the optimisation approach presented in section 3.

#### Table 2: Experiment parameters.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
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<tbody>
<tr>
<td>Number of UAVs (hundreds)</td>
<td>0.1, 0.5, 1, 2, 5, 10, 15</td>
</tr>
<tr>
<td>Number of nodes</td>
<td>100 per layer</td>
</tr>
<tr>
<td>Number of layers</td>
<td>3</td>
</tr>
<tr>
<td>Edge creation probability</td>
<td>20%</td>
</tr>
<tr>
<td>Interlayer capacity weight interval</td>
<td>[15,20]</td>
</tr>
<tr>
<td>Intralayer energy weight intervals</td>
<td>[5,10],[15,20],[25,30]</td>
</tr>
<tr>
<td>Interlayer time weight interval</td>
<td>[1,5]</td>
</tr>
<tr>
<td>Intralayer time weight intervals</td>
<td>[25,30],[15,20],[5,10]</td>
</tr>
<tr>
<td>Interlayer capacity weight interval</td>
<td>50</td>
</tr>
<tr>
<td>Intralayer capacity weight interval</td>
<td>1.5</td>
</tr>
<tr>
<td>GPD decision probability ( p_{reroute} )</td>
<td>100%</td>
</tr>
<tr>
<td>LPG ( T_{lim} ) percentage of ( c_i^{max} )</td>
<td>50%</td>
</tr>
</tbody>
</table>

For the first stage, experiments are conducted on a three layer network based on the Erdős – Rényi model using Python’s NetworkX library and the multiNetX package. Each layer contains the same number of nodes and each airway (intra and inter network) is assigned three weights, \( t, e \) and \( c \), uniformly at random in predefined intervals. A single network with a total of 300 nodes and 3 layers (100 nodes per layer) has been used. Between every pair of nodes, there is a 20% probability an edge is created. Table 2 describes the parameters used at this stage of experiments. As a first stage of validation, the experiment is run with the aim of studying the performance of the three heuristics GOS, GPD, LPG with a single optimisation objective in a more realistic scenario to address some of the assumptions made in the previous work in the literature [S. Labib et al., 2019]. Here each UAV has a different origin and destination pair as well as one of the two minimisation objectives.

Figures 4(a) and 4(b) as well as Table 3 present the obtained results when comparing the impact the three heuristics (GOS, GPD, LPG) have on traffic performance in a more realistic scenario.

Figures 4(a)–4(b) present the impact in traffic performance by indicating the median, 25th and 75th percentile, while Table 3 presents the mean and standard deviation in the results after 30 runs of the probabilistic heuristics for every varied parameter over all traffic samples: for every \( T_{lim} \) in LPG and for every \( p_{reroute} \) in GPD. It can be observed that, with the exception for traffic sample 10, LPG results show improvement in total UAVs’ travel time for all traffic samples.

On the other hand, it is worth to mention that due to the selected parameters and the nature of GPD, encouraging UAVs
to be more inclined to reduce layer changes, these led to a significant difference in reduction of energy consumption in comparison to LPG for traffic samples 50-200. However, what is of greater interest are the results obtained for the larger traffic samples, which are more decisive in the devised scenario. LPG outperforms GPD with significant difference across 4 of the 5 main parameters of comparison, with the exception of the total number of layer changes, which can be explained by the nature of the heuristic LPG which encourages UAVs to explore vertical airways between layers as they offer a higher $c_i^{max}$. Statistical confidence in our comparisons is assessed by performing the Wilcoxon test [Wilcoxon, 1992]. The overall best result per comparison parameter is shown in bold. Additionally, the dark grey background emphasises the best results that showed statistically significant difference with a 95% confidence.

5 Conclusion and future work

The recent developments in technologies has surged the demand for autonomous mobile robots and specifically UAVs. Nevertheless, for such autonomous UAV systems to be utilised to their fullest potential, UAVs have to be capable of safely and intelligently planning their paths.
In this extended abstract, we presented our work in progress and outlined a novel distributed Pareto-based path planning algorithm for autonomous UAVs. The proposed algorithm incorporates an online dynamic multiobjective path planner extending the LPG A* heuristic in [S. Labib et al., 2019] allowing individual UAVs to compute a non-dominated set of paths at every search step and rely on a dynamically updated multi-criteria decision matrix to select a solution autonomously.

Whilst the first stage of simulations was run to validate the model by only considering a single optimisation objective, the second stage of simulations to evaluate the Pareto-based approach are currently ongoing. Additionally, a more realistic instance of the airspace is being used for traffic management testing. Moreover, our future work will build on the second stage by incorporating a more realistic communication scenario and investigate the impact of coverage and different protocols on traffic behaviour as well as explore more realistic communication metrics, given the challenging nature of UAV networks.

Acknowledgments

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