Aerospace Science and Technology 77 (2018) 168–179

Contents lists available at ScienceDirect

Aerospace Science and Technology

www.elsevier.com/locate/aescte

# Grey wolf optimization based sense and avoid algorithm in a Bayesian framework for multiple UAV path planning in an uncertain environment ☆

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ARTICLE INFO

*Article history:*
Received 16 May 2017
Received in revised form 22 January 2018
Accepted 20 February 2018
Available online xxxx

*Keywords:*
Grey wolf optimization
Trajectory planning
Cooperative flight
Bayesian framework

ABSTRACT

Unmanned Air Vehicles (UAVs), which have been popular in the military context, have recently attracted attention of many researchers because of their potential civilian applications. However, before UAVs can fly in civilian airspace, they need to be able to navigate safely to their goal while maintaining separation with other manned and unmanned aircraft during the transit. Algorithms for autonomous navigation of UAVs require access to accurate information about the state of the environment in order to perform well. However, this information is often uncertain and dynamically changing. In this paper, a Grey Wolf Optimization (GWO) based algorithm is proposed to find the optimal UAV trajectory in presence of moving obstacles, referred to as Intruder Aircraft (IAs), with unknown trajectories. The solution uses an efficient Bayesian formalism with a notion of cell weighting based on Distance Based Value Function (DBVF). The assumption is that the UAV is equipped with the Automatic Dependent Surveillance-Broadcast (ADS-B) and is provided with the position of IAs either via the ADS-B or ground-based radar. However, future trajectories of the IAs are unknown to the UAV. The proposed method is verified using simulations performed on multiple scenarios. The results demonstrate the effectiveness of the proposed method in solving the trajectory planning problem of the UAVs.



## 1. Introduction

Unmanned Air Vehicles (UAVs) have traditionally been used in military operations for a number of years. Recently, UAVs have generated a lot of interest due to their potential application in civilian domains such as emergency management, law enforcement, precision agriculture, package delivery, and imaging/surveillance [1]. However, before the usage of UAVs becomes a reality in civilian domains, a number of technological challenges need to be overcome. Particularly, the challenges emanating from integration of UAVs in the National Airspace System (NAS) are extremely critical to be solved before they can start flying in civilian airspace. An important challenge among these is the ability for the UAVs to not only plan their path for fulfilling a mission but also to re-plan or adjust the trajectory (called Sense and Avoid capability) in order to avoid collision with other aircraft. Furthermore, the increase in the number of aircraft has been dramatic over the last 50 years. This increase in manned aircraft along with incorporation of unmanned fleet in future will pose severe challenges to the current Air Traffic Control (ATC). Hence, the Radio Technical Commission for Aviation (RTCA) and Federal Aviation Administration (FAA) have been charged with a responsibility to implement a seamless change from ATC to Air Traffic Management (ATM) by 2020 [2,3] and [4]. For the manned aircraft, the notion of pilot preferred trajectories (PPT) has been implemented to allow pilots and airlines to plan and manage the flight trajectories to their unique operational requirements. This system has been shown to be unreliable and will become less useful in a futuristic scenario that will include UAVs in the airspace. As a solution to this problem, the automatic dependent surveillance broadcast (ADS-B) system for transfer of in-flight data is proposed to be used during the flight by the year 2020. One of the predicted advantages of implementing ADS-B is that by enhancing the autonomy of flights in NAS, an

☆ A preliminary version of this paper was presented in International Conference on Unmanned Aircraft Systems 2016 (ICUAS 2016).

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https://doi.org/10.1016/j.ast.2018.02.031
1270-9638/

**Nomenclature**

| | |
|---|---|
| $\rho$ | Flight path |
| $d$ | Rows in tessellated area |
| $DBVF$ | Distance Based Value Function |
| $E_{m,t}^{i\in\phi}$ | Event of receiving the accurate data in next step $t+1$ |
| $F_{m,t}$ | Set of cells in $\phi$ that provides the danger of collision by IA in time step $t+1$ |
| $F_{m,t}^{i\in\phi}$ | Event of all cell $i \in \phi$ in the neighborhood of UAV $m$ which has the possibility of collision in the next step $t+1$. |
| $H_{m,t}$ | Set of all decisions that IA could make for the next time step $t+1$. |
| $H_{m,t}^{i\in\phi}$ | Event of choosing cell $i \in H_{m,t}$ by the IA as the next position at time step $t+1$. |
| $J$ | Cost function |
| $m$ | Index of the UAV |
| $R_{m,t}$ | Set of all cells in $\phi$ which the UAV $m$ can occupy in the next time step $t+1$ |
| $R_{m,t}^{i\in\phi}$ | Event of choosing the $i$th cell from the $R_{m,t}$ which can be occupied by the UAV $m$ in next step $t+1$ |
| $t$ | Time step |
| $T_{m,t}$ | Set of all cells around UAV $m$ which can be intruded by IA at time $t+1$. |
| $T_{m,t}^{i\in\phi}$ | Event of intruding the $i$th cell in collision area around UAV $m$ being intruded by the IA in the next step $t+1$ |
| $v$ | Columns in tessellated area |
| $x_{0,m}$ | Initial location of UAV $m$ |
| $x_{f,m}$ | Final location of UAV $m$ |

aircraft could navigate with minimum pilot interference and ultimately fly fully independent of pilots [5–7].

There are various methods for calculating escape trajectories that have been proposed in literature for collision avoidance including classical control [8], Fuzzy Logic [9], E-Field maneuver planning [10,11], game theory [12], Mixed Integer Linear Programming (MILP) [13,14], and its application in NC Machines path planning [15,16], automotive trajectory planning [17], and air traffic management [18]. Path planning for UAVs have been studied as a part of task assignment problem [19–23] and [24].

Applications of multiple UAVs for different applications have attracted many researchers. Apart from the fact that multiple UAVs provide the ability to perform complex and heterogeneous tasks, one of the advantages of cooperative flight performances is also fuel saving [25,26]. Path planning of such systems offers many challenging problems from both theoretical and practical points of view [27]. Flight formation refers to a particular problem of management of a group of UAVs flying in tight cooperation within a defined volume [28], and often with a pre-defined shape. Although studies on active path planning of a UAV have been considered many times (e.g., see [29–31]), cooperative path planning approaches for UAVs have only recently begun to appear. The problem of formation flight is widely studied in literature. Considering only the flight control, classical leader-wingman configuration is investigated via proportional-integral control [32] or non-linear control [33]. A reactive behavior-based controller is discussed in [34]. Proposed solution for trajectory optimization of large formations using centralized or distributed algorithms is discussed respectively in [35,36], taking into account some constraints on the shape of the formation. Reconfiguration in the formations is introduced in [37] by proposing a scheme where trajectories are computed off-line for switching between a limited number of formation configurations. In [38,20,39,40], by implementation of mixed-integer linear programming (MILP), tightly-coupled task assignment problems with timing constraints are solved for a group of UAVs.

The problem of collision avoidance becomes more complicated in real-world scenarios which present several challenges, the most significant among them being uncertainty. This is relevant in NAS since IAs could be added at any time, their flight plans may not be shared (non-cooperating IAs) or erroneous due to sensing errors or communication delays. Keeping these issues in view, this paper focuses on scenarios where the information about IAs has uncertainties associated with it. There has been a mass of work for UAV trajectory planning under uncertainties [41–44] and [45]. Furthermore, methods based on Bayesian mathematics have been vastly used to overcome different challenges during the path planning of the UAVs and proved to be very helpful in this area [46–48] and [49].

This paper extends the previous works via the use of Distance Based Value Function (DBVF) and utilization of Bayesian update method for building the risk map based on uncertain information provided by ADS-B and radar. This then allows the information to be incorporated into an optimization scheme based on Grey Wolf Optimization (GWO) that plans the paths for the vehicles during the flight mission. GWO is a novel intelligent algorithm developed in [50]. Implementation of this method on a number different applications has shown its stability and promising convergence speed [51,52] and [53]. This method is developed based on social hierarchy of predatory grey wolves. The approach exploits the information that is used to model the intruder aircraft with uncertain motion and appropriately takes that into account while planning the paths in a dynamic fashion. In [54], a GWO algorithm was employed to find an optimal path for UAVs two-dimensional path planning problem in difficult combating environments. The cooperative target tracking by multi-UAVs in urban environment was studied in [55]. In [55], by formulating the problem as an optimization problem, and solving that by integrating the real-time performance of Model Predictive Control (MPC) and the strong searching ability of GWO, trajectory planning is achieved in an optimal manner. Finally, multiple flight scenarios relevant to NAS are utilized to demonstrate the effectiveness of the proposed method.

The paper is organized as follows: in the next section, a cost function is formulated for this problem. Then, in section 3, the DBVF method is introduced. In section 4, a general formulation of the problem is presented. Then in section 5, we describe our efficient Bayesian method. Subsequently, the GWO algorithm is presented in section 6. Dynamics of the quadcopter considered for this problem is defined in section 7. Finally, several flight scenarios and flight simulation results and analysis are provided in sections 8 and 9 respectively.

## 2. Trajectory planning model and formulation

We assume that the UAV can fly only within a defined speed range and has limited maneuverability. The UAV $m$ travels in the region $R$. In this paper, $\rho$ is the flight path of the UAV denoted as the set of all unit areas or cells in $R$ from the initial location $x_{0,m}$ to the goal position of $x_{f,m}$. The problem under consideration can be formulated as weighted anisotropic shortest path problem. The objective is to look for optimal path $\rho^*$ such that:

$$J[\rho^*] = min(J[\rho]_{\rho\in R}) \quad (1)$$