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Fast and coupled solution for cooperative mission planning of multiple heterogeneous unmanned aerial vehicles

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ABSTRACT

This paper studies a problem in which a fleet of heterogeneous fixed-wing unmanned aerial vehicles (UAVs) must identify the optimal flyable trajectory to traverse over multiple targets and perform consecutive tasks. To obtain a fast and feasible solution, a coupled and distributed planning method is developed that integrates the task assignment and trajectory generation aspects of the problem. With specific constraints and a relaxed Dubins path, the cooperative mission-planning problem is reformulated. A distributed genetic algorithm is then proposed to search for the optimal solution, and chromosomal genes are modified to adapt to the heterogeneous characteristic of UAVs. Then, a fixed-wing UAV model with 6 degrees of freedom (DOF) and a path-following method is used to verify this proposed mission-planning method. The simulation results show that the proposed approach obtains feasible solutions and significantly improves the operating rate, with the potential for use in a real mission.

1. Introduction

The increased use of unmanned aerial vehicles (UAVs) for complex missions has motivated the development of autonomous mission-planning methods that ensure the spatial and temporal coordination among teams of cooperating UAVs. These planning methods can be applied for teams of heterogeneous networked agents tasked with completing autonomous missions [1], such as reconnaissance, strike, and verification operations for terrorist plots. In such missions, the task coordination, task precedence, and flyable trajectories generation are three basic requirements for the mission-planning solution [2]. The complexity of this class of problem arises when the number of UAVs and mission tasks increases [3]; furthermore, the inherent coupling between the task assignment and the trajectory generation prohibits a convergence to the global optimum.

Previous works have treated the two sub-problems separately and applied approaches that include mixed integer linear programming [4,5], capacitated transhipment network solvers [3], tree searches [6], genetic algorithms [7–10], alternating algorithms [11], and two-point algorithms [12]. The main characteristic of this class of planning techniques is as follows: Given a feasible task allocation, the problem is simplified to trajectory generation, which significantly reduces the complexity but may lead to poor solutions if the trajectories significantly vary from those assumed in the task assignment process.

Thus, Richards et al. [3] proposed a coupled solution; however, it uses Euclidean distances without obtaining the flyable trajectories. Another coupled method that merges Dubins trajectories with cooperative multiple task assignment problems (CMTAPs) to obtain the flyable trajectories has been presented [13–15], and this method transforms the CMTAP into a directed graph by discretizing the possible heading angle of the vehicle over each target; however, an infinitesimal change in value of a heading can cause the overall length of the tour to jump to a higher value, and the adopted centralized genetic algorithm (CGA) cannot guarantee convergence within an acceptable operation time. An updated method that integrates Dubins path costs into the task assignment process has been shown to obtain a better solution in a single-UAV case [16,17], although it is not used in multiple UAV cases.

The GA can provide good approximated solutions for the CMTAP [7,18]. The process of a genetic algorithm can be significantly accelerated by using a distribution technique, and a newly developed distributed genetic algorithm (DGA) has been shown to obtain the global optimal solution [19], which makes it practical for planning in a dynamic environment.

In this paper, the CMTAP is modified to cover the features of UAVs, targets, and tasks in the mission, such as the heterogeneity of the UAVs, limitations of onboard resources, threat circle of targets, task precedence, and task execution time. Without decoupling this pair of sub-problems, Dubins path cost is added to

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Nomenclature

$\mathbf{U}$	set of all UAVs
$\mathbf{U}^r$	set of reconnaissance UAVs
$\mathbf{U}^s$	set of strike UAVs
$\mathbf{U}^c$	set of combat UAVs
N^r	total number of reconnaissance UAVs
N^s	total number of strike UAVs
N^c	total number of combat UAVs
N_u	total number of UAVs
$r^r_{\det ect}$	detection range of the reconnaissance UAV
$r^c_{\det ect}$	detection range of the combat UAV
t^r_r	required execution time for the reconnaissance task
t^c_r	required execution time for the reconnaissance task
t^r_v	required execution time for the verification task
$r^r_{\lim it}$	minimum turning radius of the reconnaissance UAV
$r^s_{\lim it}$	minimum turning radius of the strike UAV
$r^c_{\lim it}$	minimum turning radius of the combat UAV
L_i	maximum number of weapons on-board
$\mathbf{T}$	set of all targets
N_T	total number of targets
$\mathbf{T}_d$	set of all targets that require double attacks
$\mathbf{T}_s$	set of all targets that require single attacks
N_{Task}	total number of tasks
m_i	quantity of tasks for target i
$\kappa_i(t)$	curvature of UAV i at moment t
φ_{ter}	heading angle on the target
$\varphi_{\min}, \varphi_{\max}$	minimum and maximum values of φ_{ter}
r_{threat}	radius of the threatening circle
$(x_i(t), y_i(t), h_i(t))$	location of UAV i at the moment t on the North, East, Height inertial frame
(x^i_t, y^i_t)	location of target i
$t_{duration}$	actual consumed time to execute the task
t_{req}	required task execution time
J	cost function in Eq. (10)
$x_{l,i,j}$	binary decision variable
$c_{l,i,j}$	distance traveled by UAV i to execute task l on target j
$\mathbf{U}^{sur}$	set of UAVs with the reconnaissance ability
$\mathbf{U}^{att}$	set of UAVs with the attack ability
$\mathbf{U}^{att}_{ca}$	set of available weapons
N_{att}	total number of weapons
N_p	population quantity of chromosomes
N_e	total number of chromosomes selected by the elitism process
N_{cro}	total number of chromosomes generated by the crossover operator
$P_{mutation}$	mutation probability
N_{cp}	coordination period
$Index_i$	quality index of the adoptive algorithm when the ith run is executed
J_{best}, t_{best}	minimum cost and minimum operation time for a single trial
α, β	weight coefficient of the cost and operation time
$J_{initial_g}$	average cost in the initial generation
$J_{generation(i)}$	average cost of the ith generation

Definitions, Acronyms and Abbreviations

UAV	unmanned aerial vehicle
DOF	degrees of freedom
DGA	distributed genetic algorithm
CMTAP	cooperative multiple task assignment problem
CGA	centralized genetic algorithm
RSV	reconnaissance, strike, verification
GTSP-GA	general traveling salesperson problem with discretized heading angle by genetic algorithm

the CMTAP, and the DGA is then used to obtain the feasible solution within an acceptable operation time length, and the genes of the DGA are modified to adapt to the heterogeneous characteristic of UAVs. From the perspective of an autonomous UAV guidance and control system, this method is tested on a fixed-wing UAV model with 6 degrees of freedom (DOF) using a path-following method.

2. Modified CMTAP with constraints

In this section, the coupled task assignment and trajectory generation problem for a fleet of heterogeneous UAVs is presented in the form of a modified CMTAP with constraints. The problem is considered for scenarios where a fleet of heterogeneous UAVs execute sequential operations including reconnaissance, strike, and verification on several known targets. The modified CMTAP with constraints is an extensional work of Edison et al. [13] and Deng et al. [14].

2.1. Parameter definitions

2.1.1. UAVs

The inherent heterogeneity mainly arises from different types of UAVs. Three vehicle specialties are presented in this scenario: reconnaissance UAVs, strike UAVs, and combat UAVs. Reconnaissance UAVs can perform all types of tasks except the strike task, strike UAVs can only perform the strike task, and combat UAVs can perform all types of tasks. Here, $\mathbf{U} = \{\mathbf{U}^r, \mathbf{U}^s, \mathbf{U}^c\}$ represents the set of all UAVs.

Reconnaissance UAV:

Let $\mathbf{U}^r = \{u^r_1, u^r_2, \ldots, u^r_{N^r}\}$ be the set of N^r reconnaissance UAVs, where r denotes the type of UAV.

To reveal the actual scenario, certain features of this type of UAV should be considered, such as the detection range of the onboard sensor (represented by $r_{\det ect}$), the necessary execution time for the reconnaissance task and verification task (represented by t_r and t_v, respectively), and the minimum turning radius (represented by $r^r_{\lim it}$).

Strike UAV:

Let $\mathbf{U}^s = \{u^s_1, u^s_2, \ldots, u^s_{N^s}\}$ be the set of N^s strike UAVs, where s denotes the type of UAV. In this scenario, L_i denotes the limitation on the number of onboard weapons, with $i \in \{1, \ldots, N^s\}$; and $r^s_{\lim it}$ denotes the minimum turning radius of this UAV.

Combat UAV:

Let $\mathbf{U}^c = \{u^c_1, u^c_2, \ldots, u^c_{N^c}\}$ be the set of N^c combat UAVs, where c denotes the type of UAV. Similarly, the detection range of the onboard sensor (represented by $r^c_{\det ect}$), the necessary execution time for the reconnaissance task and verification task (represented by t^c_r and t^c_v, respectively), and the minimum turning radius (represented by $r^c_{\lim it}$) are presented.

The mobility of the three types of UAVs varies because of the different onboard resources. In general, $r^r_{\lim it} = r^c_{\lim it} > r^s_{\lim it}$, which shows that the strike UAV has better mobility without onboard sensors. $N_u = \|\mathbf{U}\| = N_r + N_s + N_c$ is the total number of UAVs.

For simplicity, we assume that the UAVs can maintain flight level during the mission, and the involved UAVs have collision free

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