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Review:

A review of cooperative path planning of an unmanned aerial vehicle group*

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Abstract: As a cutting-edge branch of unmanned aerial vehicle (UAV) technology, the cooperation of a group of UAVs has attracted increasing attention from both civil and military sectors, due to its remarkable merits in functionality and flexibility for accomplishing complex extensive tasks, e.g., search and rescue, fire-fighting, reconnaissance, and surveillance. Cooperative path planning (CPP) is a key problem for a UAV group in executing tasks collectively. In this paper, an attempt is made to perform a comprehensive review of the research on CPP for UAV groups. First, a generalized optimization framework of CPP problems is proposed from the viewpoint of three key elements, i.e., task, UAV group, and environment, as a basis for a comprehensive classification of different types of CPP problems. By following the proposed framework, a taxonomy for the classification of existing CPP problems is proposed to describe different kinds of CPPs in a unified way. Then, a review and a statistical analysis are presented based on the taxonomy, emphasizing the coordinative elements in the existing CPP research. In addition, a collection of challenging CPP problems are provided to highlight future research directions.

Key words: Unmanned aerial vehicle group; Cooperation; Path planning; Optimization problem
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1 Introduction

The advent of the single-wing unmanned aerial vehicle (UAV) in 1927 caused a great sensation in the world, marking another milestone in aviation technology development since human beings first flew. In the ensuing decades, aided by the rapid development of automation and artificial intelligence technologies, research on UAVs has blossomed and made substantial progress (Zhong et al., 2019; Khoshnoud et al., 2020). Because tasks faced by UAVs are increasingly complex, a single UAV is usually not capable of performing extensive tasks, such as express transportation, disaster relief, surveying and mapping, and power-line inspection. With in-depth research on artificial intelligence technology, UAVs have tended to gradually become more autonomous and intelligent, and a significant shift of focus occurred as researchers began to investigate problems involving UAV groups rather than a single UAV (Mohiuddin et al., 2020; Skorobogatov et al., 2020). Coordinating the performance of UAV tasks can dramatically improve the effectiveness of entire systems from the viewpoint of robustness, reliability, and performance. Nowadays, the cooperation of UAVs has become a highly active

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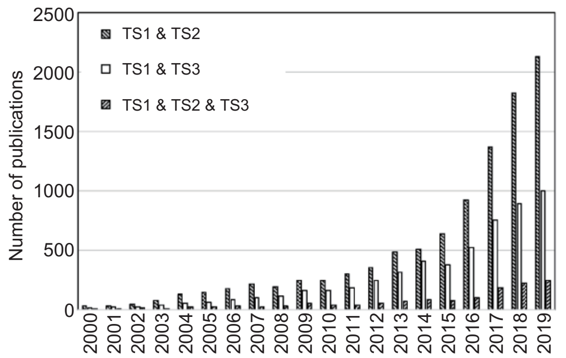
research area and has been extensively employed in various applications, such as border patrol (Girard et al., 2004), fire detection (Merino et al., 2005; Casbeer et al., 2006), cooperative target reconnaissance (Zengin and Dogan, 2007; Zhu and Wang, 2012), and mobile sensor networks (Li XY et al., 2012).

As one of the key technologies of coordinating UAVs, cooperative path planning (CPP) has attracted significant attention from global scholars (Cheng et al., 2014). Fig. 1 shows the data from Web of Science based on a topic search on three terms marked by TS1, TS2, and TS3. Each year's results indicate the number of publications appearing that year. It is quite clear that there is a significantly increased interest in research on UAV cooperation. In addition, considering that path planning is one of the core UAV technologies, most of the studies focus on the path planning of a single UAV (Li CH et al., 2019). However, the relevant research on CPP of multiple UAVs, as opposed to that of UAV cooperation, is still fairly limited.

Generally speaking, the focus of CPP of a UAV group is concentrated on finding a feasible path for each UAV in the same field to achieve a common goal. The largest difference with single-UAV path planning is the cooperation constraint of the UAV group, which makes CPP more complex. It should be noted that trajectory planning and motion planning are similar but different from path planning. They can generate paths, but also generate information on time and state of motion. However, in view of the similarity among trajectory planning, motion planning, and path planning, all of them can generate paths. Also summarized in this paper is the research on cooperative trajectory planning and cooperative motion planning.



TS1 = UAV OR UAVS OR VTUAV OR SUAV OR drone* OR (unmanned OR pilotless) AND (aerial vehicle* OR air vehicle* OR aircraft* OR air-craft* OR aerocraft* aero-craft* OR plane* OR airplane* OR aeroplane*)
TS2 = cooperat* OR coordinat* OR collabor* OR synergy* OR team
TS3 = (rout* OR path* OR trajectory* OR motion*) AND planning*

Fig. 1 Topic search results in Web of Science

In recent years, several surveys on UAV path planning (Souissi et al., 2013; Radmanesh et al., 2018b; Zhao YJ et al., 2018; Aggarwal and Kumar, 2020) and CPP of UAV groups (Cheng et al., 2014; Aggarwal and Kumar, 2020) have been conducted. Souissi et al. (2013) presented a literature review on path planning methods, described several methods, and exposed their advantages and drawbacks. Cheng et al. (2014) gave several related descriptions of the CPP problem and constraints, and summarized the solution frameworks, path coordination approaches, and several cooperative control methods. Radmanesh et al. (2018b) presented a comparative study of the algorithms for path planning for different scenarios and obstacle layouts in terms of computation time and solution optimality. Zhao YJ et al. (2018) provided a comprehensive analysis of computational intelligence (CI) methods as applied to UAV path planning that includes three dimensions: CI algorithms used in UAV path planning, types of time domains in UAV path planning, and types of environmental models. Aggarwal and Kumar (2020) presented a taxonomy of cooperative techniques in UAV path planning to recognize many learning methods.

According to the literature survey, a variety of specific research and applications of UAV path planning have been proposed and validated, but there are still few studies related to CPP. Cheng et al. (2014) presented a preliminary survey of recent research on this topic, in which the constraints, solution framework, approaches, and several future directions of CPP are discussed. Aggarwal and Kumar (2020) reviewed the research of CPP from the perspective of cooperation techniques.

Compared with the existing research, in this paper, more attention is paid to the review of CPP problems from the perspective of optimization, and more focus is on the analysis and classification of CPP problems. The existing surveys are extended herein. A generalized framework of CPP problems is developed to allow different problems to be described in a unified way, and an optimization perspective is provided to analyze and classify the existing research.

2 Key elements of cooperative path planning

In this section, the essential elements of CPP are introduced, including tasks, UAV group, and environment. Based on these elements, the framework of CPP is discussed, including path generation, constraints, and optimization objectives. All these help to form a taxonomy and in analysis in the subsequent review.

2.1 Tasks

Due to the diversity of tasks, CPP problems take many forms. The tasks can be generally divided into three categories: rendezvous, allocation, and coverage tasks.

1. Rendezvous tasks

CPP for a UAV group in this task category aims at finding an optimal or feasible flight path for each UAV from the initial location to the same target location in the planning space (Fig. 2). Generally, multiple UAVs must reach a target location at the same time to perform a cooperative task (Liu Y et al., 2019).

2. Allocation tasks

Similar to rendezvous tasks, CPP for a UAV group in this task category aims at finding an optimal or feasible flight path for UAVs from their initial locations to different target locations in the planning space (Fig. 3). Generally, UAVs must approach the different target locations with a target assignment to minimize total task completion time (Zhao M et al., 2017).

3. Coverage tasks

Coverage CPP tasks aim at finding paths for the members of a UAV group that are equipped with sensors. The path represents a limited footprint and covers all points in an area at the lowest possible cost. In this type of task, the starting locations of UAVs can be different, and the target locations are not pre-determined (Fig. 4) (Azpùrua et al., 2018). It is noteworthy that UAVs need to cover part of the whole task space to search for several targets (Yao P et al., 2017), so a search task can be considered as a variant of the coverage task.

In the above tasks, the initial location and sensors of each UAV can be different depending on the detailed task requirements.

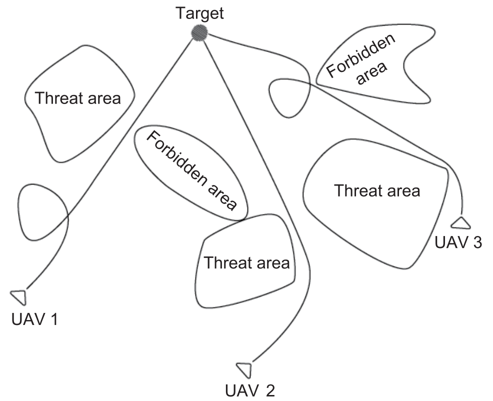


Fig. 2 Cooperative path planning in rendezvous tasks

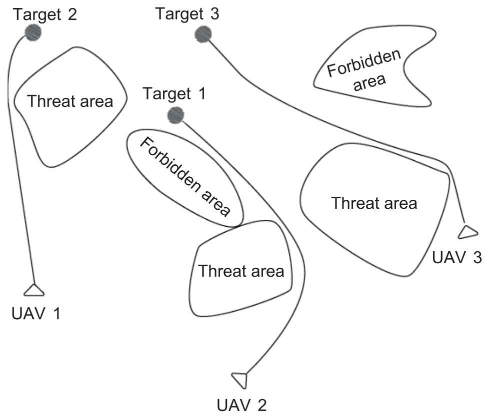


Fig. 3 Cooperative path planning in allocation tasks

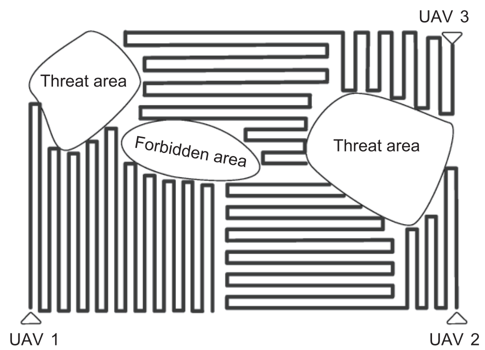


Fig. 4 Cooperative path planning in coverage tasks

2.2 UAV group

The following attributes of the CPP executor, i.e., UAV group, must be considered.

1. Organizational framework

This aspect determines the decision-making mode among UAVs, which includes mainly the centralized, decentralized, and hybrid frameworks. In a centralized framework, a central UAV collects task-related information from other UAVs and makes decisions for all members of the UAV group.

Although a higher communication and computation loading on the central vehicle occurs, the solution obtained by global programming in the centralized framework is often close to the global optima. In contrast, if a decentralized framework is adopted, each UAV has autonomy and makes its own decisions using only the information of its neighbors. Hence, the decentralized framework has better robustness and scalability than the centralized framework, but may not represent an optimal solution.

Both frameworks have their advantages and are suitable for certain situations. For small-scale systems, centralized frameworks are likely a better choice, whereas decentralized frameworks are fit for large-scale systems. The hybrid framework combines the advantages of both centralized and decentralized frameworks, which can achieve a better tradeoff between solution quality and time cost for decision making (Chen J et al., 2016). One of the simplest implementations is to use centralized frameworks within each subgroup and decentralized frameworks among subgroups.

2. Spatial relationship

This aspect determines the locations of UAVs at the beginning of the task, and includes mainly two cases: aggregated and dispersed cases. In the aggregated case, UAVs are considered to have the same initial locations; for example, UAVs take off from the same base. In contrast, in the dispersed case, UAVs have different initial locations; for example, UAVs take off from different bases.

3. UAV type

In terms of different types of UAVs, UAVs can be further categorized as fixed- and rotary-wing, which are similar but still very different. As shown in Table 1, fixed-wing UAVs are generally faster and have a more massive payload capacity than rotary-wing UAVs, whereas rotary-wing UAVs can hover and vertically take off and land. Therefore, their flight paths usually have different features.

2.3 Environment

Environmental diversity creates challenges in the CPP problems, mainly in the areas of dimension, uncertainty, and complexity.

1. Dimension

The dimension of the environment determines the size of the planning space, and it can be generally divided into two-dimensional (2D) and three-dimensional (3D) environments. The 2D environment usually includes only information on the environment size and obstacle locations. The planning space is relatively small, but the information contained in the 2D environment is incomplete. In contrast, the 3D environment is more beneficial for accurately representing various information, such as topography, meteorology, and threat, but the planning space is very large, which makes the solution of the problem more complicated.

2. Uncertainty

There may be unpredictable dynamic factors in the environment, such as an intruder aircraft (IA) with unknown trajectories (Radmanesh et al., 2018a) and pop-up threads (Zhen et al., 2018), which makes the environmental information change with time. It is unrealistic to globally re-plan frequently in such an environment because the extensive calculation makes it impossible to follow the change.

3. Complexity

The air through which UAVs move can be regarded as a medium, and many factors cause changes in the medium, such as thunderstorms and wind, which seriously affect UAV flight (Chen YB et al., 2016). In addition, in different task scenarios, the environment may show different complexities and features. For example, the plain and ocean environment is flat and almost free of obstacles (Yang XX et al., 2016); the obstacle environment may include some infeasible areas in space caused by terrain and special weather (Ergezer and Leblebicioğlu, 2014); the urban environment has many regular obstacles and may include a lot of unpredictable factors (Sun

Table 1 Characteristics of different types of UAVs

UAV type	Advantages	Disadvantage	Flight path
Fixed-wing UAV	High speed, large scope of observation, strong communication ability	Low observation accuracy	Smooth curve
Rotary-wing UAV	Vertical takeoff and landing, hovering ability, precise inspection	Low payload capability	Polyline or smooth curve

JY et al., 2017). The battlefield environment has a large number of dangerous areas, such as the coverage areas of enemy radars, which may also include unpredictable factors (Zhang QJ et al., 2015).

2.4 CPP framework

In view of the above elements, a framework is provided herein for CPP problems, which consists of three elements: path generation, constraints, and optimization objective. Table 2 lists the key symbols used to describe the subsequent CPP problems.

2.4.1 Path generation

In this subsection, an attempt is made to give a general way of generating UAV flight paths. The flight paths of a UAV group are composed of the path of each UAV in the group. Waypoints of UAV^i consist of three parts, i.e., initial waypoint, intermediate waypoints, and end waypoint. The states of UAV^i at its waypoints can be represented as $[\boldsymbol{S}_0^i, \boldsymbol{S}_1^i, \boldsymbol{S}_2^i, \ldots, \boldsymbol{S}_{w_i}^i, \boldsymbol{S}_{\text{end}}^i]$. Then, a path can be generated by connecting with waypoints.

With the various combinations of elements aforementioned, the representation of the paths may be different.

In the rendezvous task, UAVs fly through a series of generated waypoints and finally approach the same target with cooperation constraints. They can take off from the same base or different bases. For UAV^i, $\boldsymbol{P}_0^i$ and H_0^i are the position and heading respectively when the UAV leaves the base. $\boldsymbol{P}_1^i, \boldsymbol{P}_2^i, \ldots, \boldsymbol{P}_{w_i}^i$ are positions of the generated waypoints. If the path of the UAV is constrained by curvature, taking the Dubins path (Dubins, 1957) as an example, headings of the UAV at waypoints can affect the path length, so $H_1^i, H_2^i, \ldots, H_{w_i}^i$ also need to be optimized. $\boldsymbol{P}_{\text{end}}^i$ is the pre-determined target position, and H_{end}^i is the heading when the UAV approaches the target, which needs to meet the heading coordination constraint. Different from single-UAV path planning, CPP in the rendezvous task needs to generate multiple collision-free paths that meet the constraints of time synchronization (Radmanesh et al., 2018a) and heading coordination (Yang XX et al., 2016) among UAVs.

The allocation task, with respect to the numbers of UAVs and targets, can be divided into three cases: $n = m$, $n < m$, and $n > m$ (Zhao M et al., 2017), leading to different CPP problems.

In the $n = m$ case (Wu JY et al., 2017), each UAV is assigned to a single target and each target is also assigned to a single UAV. Then, each UAV flies to its destination. UAVs start from their initial waypoints, fly through a series of generated waypoints, and finally reach their destinations. Paths of UAVs are similar to those in the rendezvous task, but with different end waypoints. For UAV^i, $\boldsymbol{P}_{\text{end}}^i$ is the position of the assigned target, and H_{end}^i is the heading when the UAV approaches the target. Although H_{end}^i is no longer constrained by heading coordination, if the path of the UAV is constrained by curvature, H_{end}^i can affect the path length, so it still needs to be optimized.

In the $n < m$ case (Zhang X et al., 2014), each UAV may be assigned to multiple targets, and each target can be visited only once. Each UAV needs to visit its targets with an optimal sequence. For UAV^i,

Table 2 Description of key symbols

Symbol	Description
n	Number of UAVs in the group
m	Number of targets
UAV^i	The i^{th} UAV in the group, $i = 1, 2, \ldots, n$
w_i	Number of intermediate waypoints of UAV^i
$\boldsymbol{P}_0^i$	Coordinates of the initial waypoint of UAV^i
H_0^i	Heading of UAV^i at the initial waypoint
$\boldsymbol{P}_{\text{end}}^i$	Coordinates of the end waypoint of UAV^i
H_{end}^i	Heading of UAV^i at the end waypoint
$\boldsymbol{P}_j^i$	Coordinates of the j^{th} intermediate waypoint of UAV^i, $j = 1, 2, \ldots, w_i$
H_j^i	Heading of UAV^i at the j^{th} intermediate waypoint, $j = 1, 2, \ldots, w_i$
$\boldsymbol{S}_0^i$	$\boldsymbol{S}_0^i = (\boldsymbol{P}_0^i, H_0^i)$ represents the state of UAV^i at the initial waypoint
$\boldsymbol{S}_{\text{end}}^i$	$\boldsymbol{S}_{\text{end}}^i = (\boldsymbol{P}_{\text{end}}^i, H_{\text{end}}^i)$ represents the state of UAV^i at the end waypoint
$\boldsymbol{S}_j^i$	$\boldsymbol{S}_j^i = (\boldsymbol{P}_j^i, H_j^i)$ represents the state of UAV^i at the j^{th} intermediate waypoint, $j = 1, 2, \ldots, w_i$

$\boldsymbol{P}_0^i$ and H_0^i are the position and heading respectively when the UAV leaves the base. $\boldsymbol{P}_1^i, \boldsymbol{P}_2^i, \ldots, \boldsymbol{P}_{w_i}^i$ are the visiting positions when the UAV approaches its targets. If each target has a requirement for the visiting heading of the UAV, or if the path of the UAV is constrained by curvature, $H_1^i, H_2^i, \ldots, H_{w_i}^i$ need to be optimized. In addition, the visiting sequence of targets needs to be optimized. If the UAV returns to the base after visiting all targets, $(\boldsymbol{P}_{\text{end}}^i, H_{\text{end}}^i)$ is equal to $(\boldsymbol{P}_0^i, \pi - H_0^i)$; otherwise, $(\boldsymbol{P}_{\text{end}}^i, H_{\text{end}}^i)$ is equal to $(\boldsymbol{P}_{w_i}^i, H_{w_i}^i)$, or is the state when the UAV reaches a pre-determined end waypoint. It is noted that when the UAV lands on the base, the heading is opposite to the initial.

In the $n > m$ case (Zeng et al., 2018b; Yan et al., 2019b), each target may be assigned to multiple UAVs, and each UAV can be assigned only once. This case can be regarded as the UAV group performing several rendezvous tasks simultaneously.

In the allocation task, CPP should not only generate collision-free paths, but also consider the assignment between targets and UAVs, which is the most significant difference from single-UAV path planning.

In the coverage task, the whole task area is usually divided into several sub-areas. With respect to the numbers of UAVs and sub-areas, the assignment of sub-areas is similar to that of targets. Then, UAVs fly to their sub-areas and complete the coverage task. UAV paths are similar to those in the rendezvous task, but with different end waypoints. If UAV^i returns to the base after the coverage task, $(\boldsymbol{P}_{\text{end}}^i, H_{\text{end}}^i)$ is equal to $(\boldsymbol{P}_0^i, \pi - H_0^i)$; otherwise, $(\boldsymbol{P}_{\text{end}}^i, H_{\text{end}}^i)$ is equal to $(\boldsymbol{P}_{w_i}^i, H_{w_i}^i)$, or is the state when the UAV reaches a pre-determined end waypoint. In the coverage task, to achieve full coverage of the task area, CPP should not only generate collision-free paths, but also consider the area division and the assignment of sub-areas.

The above describes the path representation in different tasks. Then, according to the type of UAV, complete flight paths can be generated by connecting a series of waypoints by lines or curves with curvature constraints. In addition, according to the dimension of the environment, the waypoint can take 2D or 3D coordinates.

2.4.2 Constraints

In this subsection, we summarize several typical constraints that are used widely in CPP problems. In general, the constraints can be divided into four categories, autocorrelation, environmental, task, and cooperation (Cheng et al., 2014), as summarized in Table 3. It should be noted that the formulas presented in the table are just examples to aid reader understanding. According to different studies, formulas may be different.

1. Autocorrelation constraints

This kind of constraints includes mainly dynamics and pose limitations (Cheng et al., 2014; Chen QY et al., 2018; Liu Y et al., 2019). Considering dynamics limitations, such as the maximum turn angle and maximum climb angle constraints, will make the planned path closer to reality and reduce the difficulty of UAV trajectory tracking. For some particular task requirements, pose limitations are used to ensure that UAV approaches the target point on a pre-determined heading.

2. Environmental constraints

There may be no-fly areas and dangerous areas in the environment, such as bad meteorological areas and electromagnetic interference areas (Liu W et al., 2013; Bouzid et al., 2019), which require the UAV's path should avoid those areas or pass through those areas in the shortest possible time.

3. Task constraints

Owing to the diversity and complexity of problems, task constraints need to be considered (Zhao M et al., 2017; Guo et al., 2020). If a UAV needs to visit several targets during the flight, or if a target needs to be visited by multiple UAVs, the assignment and capability restrictions must be considered (Table 3).

4. Cooperation constraints

Constraints among UAVs include mainly collision avoidance (Liu Y et al., 2019), connectivity maintenance (Zhang DF and Duan, 2018), synchronicity requirements (Cheng et al., 2014), heading coordination (Yang XX et al., 2016), and formation constraints (Wang et al., 2017). Collision avoidance and connectivity maintenance are spatial cooperation constraints, and require the distances between UAVs be larger than the safe flying distance and smaller than the effective communication range. The synchronicity requirement, heading coordination, and formation requirement involve both spatial and temporal constraints. For example, in the rendezvous task, UAVs are required to approach the target at the same time from different directions or in a required formation (Zeng et al., 2018a; Ding et al., 2019a).

If the UAVs' flight paths do not violate any constraints, they are called feasible paths. To obtain optimal feasible paths, it is necessary to determine an objective function. Typical objectives are summarized below.

Table 3 Typical constraints in cooperative path planning problems

Type	Subtype	Description
Autocorrelation constraints	Minimum segment length	$l_j \geq l_{\min}$ $(j=1,2,\ldots,q)$, where q is the number of flight segments of a path, l_j is the length of the j^{th} flight segment, and $l_{\min}$ is the shortest distance that a UAV must maintain before changing its attitude in flight (Cheng et al., 2014)
	Maximum voyage	$\sum_{j=1}^{q} l_i \leq l_{\max}$, where $l_{\max}$ is the maximum voyage, which depends on the fuel carried by a UAV (Liu Y et al., 2019)
	Maximum turn angle	$\cos\theta \leq \boldsymbol{a}_j^{\mathrm{T}} \cdot \boldsymbol{a}_{j+1} / (\lvert\boldsymbol{a}_i\rvert \cdot \lvert\boldsymbol{a}_{j+1}\rvert)$ $(j=1,2,\ldots,q-1)$, where θ is the maximum turn angle and $\boldsymbol{a}_j$ is the projection of the j^{th} flight segment on the horizontal plane (Liu Y et al., 2019)
	Minimum flight altitude	$H_{j,\min} \geq H_{\min}$ $(j=1,2,\ldots,q)$, where $H_{j,\min}$ is the minimum altitude of the j^{th} flight segment and $H_{\min}$ is the minimum flight altitude (Liu Y et al., 2019)
	Maximum climb angle	$\tan\beta \geq \lvert z_{j+1} - z_j\rvert / \lvert\boldsymbol{a}_j\rvert$ $(j=1,2,\ldots,q)$, given that (x_j, y_j, z_j) are the coordinates of a waypoint and β is the maximum climb angle (Liu Y et al., 2019)
	Curvature	A fixed-wing UAV cannot suddenly change its attitude during flight, and its flight path must be a smooth curve (Chen QY et al., 2018)
Environmental constraints	Obstacle avoidance	$(x_j, y_j, z_j) \notin Z$ $(j=1,2,\ldots,h)$, where Z is the set of no-fly areas and the size of h depends on the discretization degree of the path (Bouzid et al., 2019)
	Dangerous avoidance	$\text{Threat}_i \leq \text{Threat}_{\max}$ $(i=1,2,\ldots,n)$, where Threat_i is the threat faced by UAV^i and $\text{Threat}_{\max}$ is the maximum threat that the UAV can tolerate (Liu W et al., 2013)
Task constraints	Assignment and visiting restriction	$\sum_{j=1}^{k} y_{ji} \leq 1$ means that each UAV is assigned at most once, where k is the number of targets and y_{ji} is the binary variable of the j^{th} target assigned to UAV^i. $\sum_{i=1}^{n} x_{ij} \leq 1$ means that each target is visited at most once, where x_{ij} is the binary variable of UAV^i visiting the j^{th} target (Zhao M et al., 2017)
	Capability requirement	UAVs may carry different payloads and have different capabilities. At the same time, different targets may have different requirements for payloads. Therefore, the overall capability of the UAV team should meet the diverse requirements of assigned tasks (Guo et al., 2020)
Cooperation constraints	Collision avoidance	$d\left((x_{U_i}^t, y_{U_i}^t, z_{U_i}^t), (x_{U_j}^t, y_{U_j}^t, z_{U_j}^t)\right) \geq d_{\text{safe}}, \forall i, j = 1,2,\ldots,n, i \neq j$, where t is a timestamp. The distance between any two UAVs, such as U_i and U_j, at the same time should be greater than the safe distance d_{safe} (Liu Y et al., 2019)
	Connectivity maintenance	$d\left((x_{U_i}^t, y_{U_i}^t, z_{U_i}^t), (x_{U_j}^t, y_{U_j}^t, z_{U_j}^t)\right) \leq d_{\max}, \forall i, j = 1,2,\ldots,n, i \neq j$. The distance between any two UAVs at the same time should be smaller than the effective communication range $d_{\max}$ (Zhang DF and Duan, 2018)
	Synchronicity requirement	All UAVs can reach the target point simultaneously or sequentially in accordance with a certain time interval (Cheng et al., 2014)
	Heading coordination	UAVs approach the target point with pre-determined angles or specific combination angles, so that UAVs can attack the most vulnerable place of the target or carry out a multi-faceted investigation on the target (Yang XX et al., 2016)
	Formation requirement	The UAV group must maintain the shape of a particular formation during the flight (Hoang et al., 2018) or form a formation when reaching the target (Wang et al., 2017)

2.4.3 Optimization objective

For optimal CPP, the construction of the objective function is the primary way of achieving paths with desirable properties. Under different organizational frameworks, the construction of objective functions is different. In a centralized framework, the decision-making UAV has global information, and multiple paths can be obtained by constructing a global objective function for planning. In a decentralized framework, each UAV has limited information, and its path is obtained by constructing a local objective function for planning. According to the different roles, different UAVs can have different objective functions when planning (Liu W et al., 2013), and how to design a series of reasonable objective functions is extremely worthy of research.

Regardless which framework is adopted, the issues listed in Table 4 should be considered in the design of the objective function. Similar to Table 3, issues listed in this table may have different formulations in different scenarios.

1. Cost minimization

This kind of objective is intended to minimize the overall consumption when a UAV group completes its mission, usually including the time and resource costs (Zhang X et al., 2014; Chen YB et al., 2016). Different from single-UAV path planning, CPP pays more attention to the integration cost of all UAVs in the group.

2. Payoff optimization

The goal of this kind of objective is to guide the UAV group to complete a mission within a limited time and achieve the maximum payoff, such as achieving the maximum environment exploration or coverage rate in a coverage search task (Wu QP et al., 2014; Zhen et al., 2018).

3. Performance optimization

This kind of objective aims to make the generated paths more realizable, such as coordination performance and smoothness (Liu Y et al., 2019), which can reduce the difficulty of UAV trajectory tracking or cooperative control. How to provide cooperative

Table 4 Typical optimization objective in cooperative path planning problems

Type	Subtype	Description
Cost minimization	Fuel consumption	$\sum_{i=1}^{n}\sum_{j=1}^{w_i}\|\boldsymbol{o}_{j+1,i}-\boldsymbol{o}_{j,i}\|$ represents the total range of all UAVs, which reflects the fuel consumption. $\|\boldsymbol{o}_{j+1,i}-\boldsymbol{o}_{j,i}\|$ represents the distance between adjacent waypoints of UAV^i (Chen YB et al., 2016)
	Makespan	$\max_{i=1}^{n}\sum_{j=1}^{w_i}\|\boldsymbol{o}_{j+1,i}-\boldsymbol{o}_{j,i}\|$ represents the maximum range of all UAVs, which reflects the time cost of completing the task (Zhang X et al., 2014)
Payoff optimization	Environment exploration	$\sum\limits_{(x,y)\in B_{\mathrm{R}}}(z(x,y,t+1)-z(x,y,t))$ represents the uncertainty reduction at time $t+1$. $z(\cdot)$ represents the UAVs' uncertainty concerning the target distribution in that cell (Wu QP et al., 2014). (x,y,t) is a state that includes a coordinate and a timestamp, and B_{R} represents the reachable set
	Coverage rate	$\sum_{i=1}^{n}\mu_i\cdot J_i$ represents the total coverage of UAVs of an area. μ_i and J_i are the weight coefficient and coverage rate of UAV^i, respectively (Zhen et al., 2018)
Performance optimization	Coordination performance	$T=T_1\cap T_2\cap\ldots\cap T_n$ (Liu Y et al., 2019), where the coordinated time of arrival of UAVs can be guaranteed to be contained in the time intersection T of T_i, $i=1,2,\ldots,n$
	Smoothness	$\theta_{ij}=\left\|\arctan\big((y_{i,j+1}-y_{ij})/(x_{i,j+1}-x_{ij})\big)\right\|$, where $j=1,2,\ldots,w_i$, and θ_{ij} is the turning angle of the j^{th} waypoint of UAV^i. Theoretically, the smaller the turning angle is, the smoother the path will be (Liu Y et al., 2019)
Risk minimization	Flight altitude	$\frac{1}{w_i}\sum_{j=1}^{w_i}(z_{ij}-f(x_{ij},y_{ij})-H_{\min})$ is the average flight altitude of UAV^i's path, where $j=1,2,\ldots,w_i$, (x_{ij},y_{ij},z_{ij}) are the 3D coordinates of the j^{th} waypoint, $f(x_{ij},y_{ij})$ is the terrain height at position (x_{ij},y_{ij}), and $H_{\min}$ is the minimum flying height of the UAV (Liu Y et al., 2019). Theoretically, it is safer to fly at low altitude in the shelter of a valley
	Threat	$J_{\mathrm{in}}(i)+J_{\mathrm{path}}(i)$ denotes the total threat of UAV^i. $J_{\mathrm{in}}(i)$ is the threat when the UAV flies into danger zones and $J_{\mathrm{path}}(i)$ is the total effect of danger zones on UAV^i's path (Liu Y et al., 2019)

paths makes CPP more challenging than single-UAV path planning.

4. Risk minimization

This kind of objective aims at making the generated paths safe and ensuring that UAVs can complete their tasks successfully. Usually, it is favorable for UAVs to fly under the cover of terrains to approach a threatening target (Liu Y et al., 2019).

3 Taxonomy and analysis of CPP

To date, a variety of CPP problems have been studied, and to study these problems in a more organized way, a taxonomy of CPP problems along three different axes is proposed, as shown in Fig. 5.

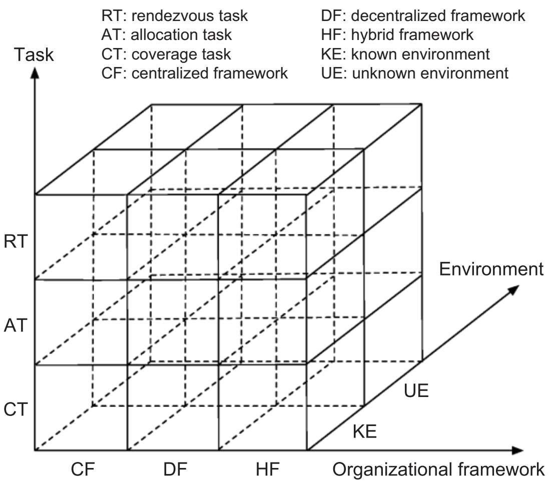


Fig. 5 Visual representation of cooperative path planning problems used in the taxonomy

In this taxonomy, the three elements, including the task, organizational framework, and environment mentioned in Section 2, are considered. First, the optimization objectives and constraints are diverse in different tasks. Second, the organizational framework is related to the scale of the problem. A large-scale optimization problem is very hard to solve in real time in a centralized framework. However, the problem can be decomposed into multiple small sub-problems, which are easier to solve in a decentralized or hybrid framework. Third, the uncertain environment includes many unpredictable dynamic factors that will change with time. It is impossible to make a full-course global plan for a UAV group in such an environment. In contrast, local planning is more adaptable to the uncertain environment.

Once the elements of a problem along the three axes are identified, the corresponding properties for the CPP problem can be determined. Therefore, the taxonomy, along with specifically designed axes, provides a useful tool to describe different kinds of CPP problems under a generalized optimization framework, which benefits a comprehensive understanding and general analysis of such problems. In the following, the various cases that appear along each axis are discussed, and the key symbols used for describing a CPP problem are shown in Table 5.

Table 5 Key symbols used for describing a cooperative path planning problem

Symbol	Description
h	Number of optimization objectives
h_i	Number of optimization objectives for UAV^i
J_k	k^{th} optimization objective, $k=1,2,\ldots,h$
J_k^i	k^{th} optimization objective of UAV^i, $k=1,2,\ldots,h_i$
$\boldsymbol{L}_i$	Path of UAV^i that needs to be optimized
A_i	A target needed to be assigned, $i=1,2,\ldots,m$
f	Relevant equality constraint functions
g	Relevant inequality constraint functions
E	Environmental factors including obstacles and threats
$\boldsymbol{L}_i(t)$	Predicted path of UAV^i at time t (Fig. 6)

1. Rendezvous task versus allocation task versus coverage task

As discussed in Section 2.4, the representation of paths is different in different tasks. In the rendezvous task, a series of waypoints must be generated to guide the UAVs to approach their end waypoints from their initial waypoints. The CPP problem of a rendezvous task can be formulated as

$$\begin{aligned} &\min \sum_{k=1}^{h} J_k(\boldsymbol{L}_1,\boldsymbol{L}_2,\ldots,\boldsymbol{L}_n/E) \\ &\text{s.t. } f(\boldsymbol{L}_1,\boldsymbol{L}_2,\ldots,\boldsymbol{L}_n/E)=0, \\ &\qquad g(\boldsymbol{L}_1,\boldsymbol{L}_2,\ldots,\boldsymbol{L}_n/E)\geq 0, \end{aligned} \tag{1}$$

where $\boldsymbol{L}_i=\left[\boldsymbol{S}_0^i,\boldsymbol{S}_1^i,\boldsymbol{S}_2^i,\ldots,\boldsymbol{S}_{w_i}^i,\boldsymbol{S}_{\text{end}}^i\right]$ and $i=1,2,\ldots,n$. The end waypoints of all UAVs have the same or adjacent positions, but the UAV headings at these end waypoints may need to be optimized.

In the allocation task, the UAV targets are not pre-determined, and the assignment of targets must be considered. In the $n=m$ and $n>m$ cases, similar to the rendezvous task, waypoints must be generated for each UAV to guide the UAV as it approaches its target, and the heading may need to be optimized when the UAV approaches its target. In the $n < m$ case, each UAV needs to visit its targets with an optimal sequence, and each visiting position can be regarded as a waypoint that depends on the position of the target. Thus, the visiting sequence must be optimized, and visiting positions and headings may need to be optimized.

The CPP problem of an allocation task can be formulated as

$$\begin{aligned} &\min \sum_{k=1}^{h} J_k(\boldsymbol{L}_1, \boldsymbol{L}_2, \ldots, \boldsymbol{L}_n, A_1, A_2, \ldots, A_m/E) \\ &\text{s.t. } f(\boldsymbol{L}_1, \boldsymbol{L}_2, \ldots, \boldsymbol{L}_n/E) = 0, \\ &\quad\;\; g(\boldsymbol{L}_1, \boldsymbol{L}_2, \ldots, \boldsymbol{L}_n/E) \geq 0. \end{aligned} \tag{2}$$

In the coverage task, the whole area is divided into several sub-areas, and the assignment of sub-areas must be considered. Similar to the allocation task, a sub-area can be regarded as a target, and the CPP problem of the coverage task is similar to that of the allocation task. However, the number of sub-areas depends on the result of the area division. Thus, in addition to generating waypoints for UAVs, how to divide the area into m sub-areas and how to assign the sub-areas must be considered.

2. Centralized framework versus decentralized framework versus hybrid framework

The above discussion is based on a centralized framework, and the optimization problems can be solved by global planning. All UAV paths are evaluated together using an evaluation function. However, in a decentralized framework, each UAV makes its own decision, and the CPP problem can be solved by UAVs in a distributed manner. Taking the rendezvous task as an example, the sub-problem solved by UAV^i can be formulated as

$$\begin{aligned} &\min \sum_{k=1}^{h_i} J_k^i(\boldsymbol{L}_i/E) \\ &\text{s.t. } f(\boldsymbol{L}_i/E) = 0,\ g(\boldsymbol{L}_i/E) \geq 0. \end{aligned} \tag{3}$$

Note that the objective function of a UAV may vary with the roles of the UAV. In a hybrid framework, leaders may adopt global planning for their sub-group, while followers will make their own local planning.

3. Known environment versus unknown environment

It is possible to make a full-course global plan for a UAV group in a completely known environment. However, in an unknown environment, local planning is usually done by defining a time window (Sun XL et al., 2015). A complete path is generated gradually using receding horizon optimization, as shown in Fig. 6. Assuming that the current time is t, UAV^i flies following the last planned path; i.e., the flight plan is executed in the period of $t_{p-1} < t < t_p$. At this time, with the update of environmental information, UAV^i needs to determine its future flight plan. Assuming that the flight plan update time point is t_p, UAV^i needs to plan a new flight plan from t_p to a future time point t_N. In the planning process, UAV^i follows the last planned path. Then the flight plan is updated at the time point t_p, and UAV^i begins to follow a new path $\boldsymbol{L}_i(t)$ until the next planning time point.

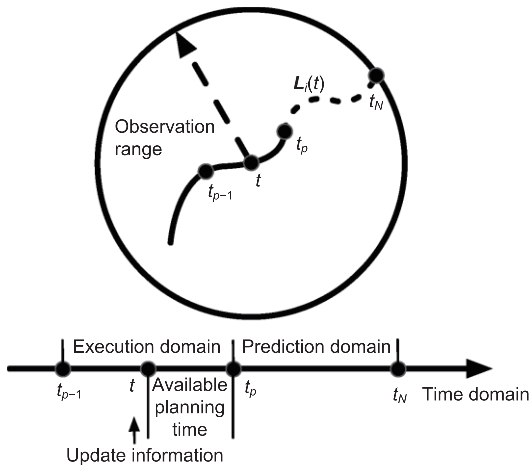


Fig. 6 Predicted path of UAV^i generated by the receding horizon optimization

Taking the rendezvous task in a centralized framework as an example, the CPP problem with an unknown environment can be formulated as

$$\begin{aligned} &\min \sum_{k=1}^{h} J_k(\boldsymbol{L}_1(t), \boldsymbol{L}_2(t), \ldots, \boldsymbol{L}_n(t)/E) \\ &\text{s.t. } f(\boldsymbol{L}_1(t), \boldsymbol{L}_2(t), \ldots, \boldsymbol{L}_n(t)/E) = 0, \\ &\quad\;\; g(\boldsymbol{L}_1(t), \boldsymbol{L}_2(t), \ldots, \boldsymbol{L}_n(t)/E) \geq 0. \end{aligned} \tag{4}$$

4 Review of CPP based on taxonomy

4.1 Classification of existing research

Based on the taxonomy proposed in Section 3, a review of CPP problems is presented below. Moreover, the representative issues are refined for different kinds of problems.

1. Rendezvous task, centralized framework, and known environment

Chen YB et al. (2016) studied cooperative trajectory optimization for a quad-rotor UAV group executing a collaborative assembling task in a complex 3D battlefield environment. As a novel parallel intelligent optimization algorithm, the central force optimization-genetic algorithm was proposed to solve offline path planning with the optimization of the total range of the UAV group. In addition, the mature sequential quadratic programming (SQP) algorithm and cubic B-spline were used to generate optimal trajectories in the sense of distance or time difference. Huang et al. (2016) applied an improved ant colony optimization algorithm and the k-degree smoothing method to generate the curve paths for a UAV group in the Voronoi environment. The goal was to minimize the risk and the total path lengths of the UAV group, and achieve synchronicity among UAVs when reaching a target. Yang XX et al. (2016) studied CPP for a UAV group reaching a target in a 2D obstacle-free environment, with the objective of generating curve paths of approximately equal length. The Pythagorean hodograph (PH) curve under the coordination of time and heading was used to solve the problem.

Sun JY et al. (2017) presented an optimized artificial potential field (APF) algorithm for cooperative UAVs in a 3D urban environment to generate collision-free and smooth trajectories that can lead UAVs to reach a target. Shao et al. (2019) proposed a distributed cooperative particle swarm optimization (DCPSO) algorithm with an elite keeping strategy to generate PH paths for UAV group formation rendezvous in a 3D obstacle environment. The optimization objectives are the total range and smoothness of the paths, while considering UAV synchronicity and collision avoidance. Collision-free 4D path planning for a UAV group in a battlefield environment was implemented in Liu Y et al. (2019), in which time variables were taken into account for UAVs. Standard PSO with a spatial refined voting mechanism (SRVM) was designed to generate several spline curves to lead UAVs to reach a target. Moreover, the authors introduced the constraints as punishment items when constructing the multi-objective optimization function, and optimized eight objectives, including several penalty items, flying height, fuel consumption, smoothness, and coordinated time of arrival.

Chen QY et al. (2018) generated Dubins paths based on the PSO algorithm for UAV rendezvous formation and reconfiguration in a 2D obstacle-free environment. The forming time of UAVs was minimized and the collision and synchronicity among UAVs were considered. Wang et al. (2017) solved the UAV minimum-time rendezvous formation planning in a 2D obstacle environment using sequential convex programming, in which collision avoidance and UAV group time consensus were considered. Zhang DF and Duan (2018) gave a 3D battlefield environment in which UAVs cooperatively execute an attack task against a specific target, and the risk and coordination performance were optimized. During the flight, the maximum communication range and safety distance were considered to ensure communication connectivity and avoid collision among UAVs. The authors proposed a social-class pigeon-inspired optimization algorithm with a novel timestamp segmentation model for the evaluation of multi-UAV path planning. This method can additionally provide the desired velocity and motion time bases as the references for UAV group coordination that the traditional waypoint models cannot provide.

2. Rendezvous task, centralized framework, and unknown environment

Radmanesh et al. (2018a) studied CPP for UAV rendezvous planning in civilian airspace, in which the environment was uncertain and changed dynamically. The authors proposed a gray wolf optimization based algorithm and an avoidance algorithm in a Bayesian framework to generate trajectories for leading UAVs to reach a goal position at the same time without collision. The optimization objective has two components: total range and a safety metric modeled as the weights of cells that represent the risk of collision.

3. Rendezvous task, decentralized framework, and known environment

In a decentralized framework, the optimization objectives for leaders and followers can be the same or different. Falomir et al. (2018) proposed an improved APF algorithm to generate smooth trajectories to lead UAVs to reach a target in a 2D urban environment, and cooperation and collision avoidance were realized by sharing data among UAVs in the group. Chen YB et al. (2015) studied formation rendezvous planning for a UAV group with a loose formation in a 3D battlefield environment. The updated APF algorithm based on the additional control force was used to generate the shortest collision-free path for each UAV with the least energy.

In addition, different optimization objectives can be designed according to the computing performance and role of UAVs. In Liu W et al. (2013), a distributed online CPP algorithm based on bi-level programming was proposed, and collision-free paths were generated to lead UAVs to a target in a 2D battlefield environment. For leader UAVs, the goal was to minimize the total flight distance of all the UAVs; for follower UAVs, the goal was to minimize the combination of the trajectory's probabilistic risk and smoothness.

4. Rendezvous task, decentralized framework, and unknown environment

Zhang QJ et al. (2015) regarded the rendezvous problem as a typical cooperative control problem, and a cooperative game-based optimal consensus (CGOC) algorithm was proposed to solve the problem. The coordination function is the performance of the system achieving effective coordination, and each UAV plans its trajectory in a 2D battlefield environment with the goal of minimizing fuel consumption and risk. Ma PB et al. (2014) proposed an expanded Voronoi diagram to represent a 2D battlefield environment, and an improved Dijkstra algorithm was used to generate initial paths for UAVs. The leader and follower had the same optimization objectives, including fuel consumption and risk. Then, the line-of-sight-based path-shortening and smoothing algorithms were proposed to make UAVs attack the target simultaneously from different terminal impact angles without collision.

The features of the studied CPP problems in rendezvous tasks are shown in Table 6.

5. Allocation task, centralized framework, and known environment

In Wang et al. (2019), rendezvous formation trajectory planning in a 2D obstacle environment was studied, including the assignment of rendezvous points and the generation of cooperative trajectories. The assignment of rendezvous points to UAVs was ensured using the enumeration method to minimize the total range, and the Dubins path was used to compute the length of an approximate trajectory. The trajectory generation of the UAV group was executed by applying sequential convex programming to ensure that the UAVs in the group simultaneously arrived at the goals without collision. Shi et al. (2017) studied CPP for an attack mission using a UAV group in a 2D battlefield environment. UAV paths were optimized using an improved ant colony algorithm and by combining it with the Hungarian algorithm; task assignment was carried out with the goal of optimizing the total length of flight paths and the degree of target destruction.

Dewangan et al. (2019) studied the path planning problem of a UAV group in a 3D obstacle environment to find the feasible trajectories between

Table 6 Features of the studied cooperative path planning problems in rendezvous tasks

Reference	Classification	Environment	UAVs	1	2	3	4	5	6
Chen YB et al. (2016)	RT-CF-KE	3D, battlefield	=	–	–	–	–	√	–
Huang et al. (2016)	RT-CF-KE	2D, battlefield	=	–	–	–	–	√	–
Yang XX et al. (2016)	RT-CF-KE	2D, obstacle-free	=	–	–	–	–	√	√
Sun JY et al. (2017)	RT-CF-KE	3D, urban	=	–	√	–	–	–	–
Shao et al. (2019)	RT-CF-KE	3D, obstacle	=	–	√	–	–	√	–
Liu Y et al. (2019)	RT-CF-KE	3D, battlefield	=	–	√	–	–	√	–
Chen QY et al. (2018)	RT-CF-KE	2D, obstacle-free	=	–	√	–	√	√	–
Wang et al. (2017)	RT-CF-KE	2D, obstacle	=	–	√	–	√	√	–
Zhang DF and Duan (2018)	RT-CF-KE	3D, battlefield	=	–	√	√	√	–	–
Radmanesh et al. (2018a)	RT-CF-UE	2D, civilian airspace	=	√	√	–	–	√	–
Falomir et al. (2018)	RT-DF-KE	2D, urban	=	–	√	–	–	–	–
Chen YB et al. (2015)	RT-DF-KE	3D, battlefield	=	–	√	–	√	–	–
Liu W et al. (2013)	RT-DF-KE	2D, battlefield	≃	–	√	√	–	–	–
Zhang QJ et al. (2015)	RT-DF-UE	2D, battlefield	=	√	–	–	–	√	–
Ma PB et al. (2014)	RT-DF-UE	2D, battlefield	=	√	–	–	–	√	–

RT: rendezvous task; CF: centralized framework; DF: decentralized framework; KE: known environment; UE: unknown environment. 1: real time; 2: collision avoidance among UAVs; 3: connectivity; 4: formation; 5: synchronicity; 6: heading coordination. =: homogeneous; ≃: heterogeneous; √: considered; –: not considered start points and allocated goal points. Then, the gray wolf optimizer (GWO) was used to generate the shortest paths for UAVs. Babel (2019) addressed the engagement of a UAV group against several targets in a 2D obstacle environment, in which UAVs should simultaneously arrive at the destinations while minimizing the total mission time. This problem involves finding an optimal assignment of UAVs to targets and generating curve trajectories. The presented algorithms can solve the problem concurrently without decoupling. Wu JY et al. (2017) combined the harmony search (HS) algorithm and PH curve for a UAV group in a 3D battlefield environment to generate short, collision-free, and smooth PH paths.

Ergezer and Leblebicioğlu (2014) applied a genetic algorithm (GA) and proposed two novel mutation operators to solve path planning for UAVs in a 3D mountain environment to obtain maximum information collection while avoiding forbidden regions (FR) violation. The initial populations were generated from UAV seed paths that were obtained by using the pattern search method and solving the multiple-traveling-salesman problem (mTSP). Then, the authors updated the UAV model, which was based on a real platform and promised more realistic flight paths (Çakıcı et al., 2016).

Sahingoz (2013) combined the GA and Bezier curve to generate curve paths for UAVs visiting a set of areas in a 2D obstacle-free environment, in which the goal was to minimize the total length of flight paths. Parallel GAs were then used to solve this problem in the follow-up study (Sahingoz, 2014). Cekmez et al. (2016) studied CPP of a UAV group in a 2D battlefield environment with radar. A clustering approach was applied to find the subsets of control points. Then, to minimize the makespan, a parallel GA on compute unified device architecture (CUDA) was used to generate a path for each UAV to visit the assigned control points.

Li XH et al. (2016) proposed a variable neighborhood descent (VND) enhanced PSO algorithm to optimize the flight paths in a 2D farmland environment, and paths were generated for a group of UAVs to visit the target farm blocks with the minimum makespan. Li T et al. (2016) studied CPP in a 2D obstacle-free environment, including two subproblems. First, mission allocation was solved using ant colony optimization (ACO) to obtain the largest profit and the lowest cost; then the path planning was solved based on the improved Dubins path to generate the shortest paths. In Manyam et al. (2017), the CPP for a persistent intelligence, surveillance, and reconnaissance (PISR) routing problem in a 2D obstacle-free environment was formulated using mixed-integer linear programming. The branch-and-cut algorithm was used to find the optimal solution with the minimum makespan.

Sørli et al. (2017) studied CPP for a UAV group to deploy several sensors in a 2D obstacle-free environment, and the cooperative co-evolving genetic strategy was used to minimize the makespan by an allocation of sensor placement tasks between UAVs. Harounabadi et al. (2018) applied GA to solve CPP for a UAV group in message ferry networks, in which UAVs act as message ferries to deliver messages among isolated wireless nodes to minimize the message delivery delay. Binol et al. (2018) studied CPP for a UAV group gathering intelligent transportation system (ITS) data from roadside units in a 2D road network. The authors solved the problem by applying modified evolutionary methods based on the GA and HS to obtain the overall shortest path. Ning et al. (2019) studied UAV group trajectory and mission cooperative planning in a 2D battlefield environment based on the Markov model. The authors proposed a two-layer mission planning model based on the simulated annealing (SA) and tabu search (TS) algorithms to ensure the attack effect and to make the flight as short as possible.

Cho et al. (2019) studied CPP for heterogeneous UAVs in a 2D obstacle-free environment and formulated the problem as a generalized heterogeneous multiple-depot asymmetric traveling-salesman problem. The authors proposed a sampling-based tour-generation method to find a set of Dubins paths that minimized the sum of costs while every task region was visited exactly once. Zhao M et al. (2017) studied the cooperative multi-target assignment for a UAV group in a 3D battlefield environment. The authors presented a unified gene coding strategy to handle various assignment models in a consistent framework. Then, a discrete mapping differential evolution was proposed to solve the cooperative target assignment, the goal of which was to minimize the total distance of flight paths and the makespan.

Zhang X et al. (2014) addressed path planning for a UAV group performing surveillance of multiple ground targets in a 2D obstacle-free environment, in which the goal was to optimize the makespan and the total length of the UAV paths. The authors proposed a memetic algorithm based on the GA and an approximate gradient based local search to generate high-quality Dubins paths. Qin et al. (2018) studied the fair-energy trajectory planning for UAVs in a 2D reconnaissance scenario, in which the motion, hovering, and communication energy consumption were considered. A heuristic algorithm was proposed to minimize the energy consumption, including the steps of tour calculation and tour splitting.

Yang J et al. (2018) investigated a multi-base UAV cooperative patrol route planning problem in a 2D obstacle-free environment to minimize the UAVs voyage and the mission completion time. The Floyd algorithm was used to obtain the initial routes, and the improved push forward insertion heuristic algorithm was used to obtain the optimal routes. In Quintin et al. (2017), cooperative UAVs were used to visit some designated targets in a predictable dynamic 2D obstacle environment to support unmanned ground vehicle (UGV) situational awareness. A methodology based on TS meta-heuristic was implemented to achieve multiple objectives: smaller number of UAVs, smaller total length of routing, and trade off between the lengths of the different routes. Zhao Z et al. (2019) studied cooperative multi-task online mission planning for a UAV group in a 3D obstacle environment with the goal of minimizing the cost of the whole UAV team and the cost of every UAV team member. A mixed path planning method based on the Dubins curve and B-spline was proposed to generate the curve paths. Then, the Gaussian pseudo-spectral method (GPM) was used to solve the task assignment problem.

6. Allocation task, centralized framework, and unknown environment

Su et al. (2016) studied the cooperative path re-planning in a 3D battlefield environment and proposed a novel multi-stage method based on Q-learning and cooperative fuzzy C-means clustering to guide UAVs in reaching their targets with minimum change.

7. Allocation task, decentralized framework, and known environment

Ma XB et al. (2016, 2018) studied decentralized motion planning for a UAV group moving in a 3D urban-like environment with polygonal obstacles. A prioritized A* algorithm was used to generate the shortest paths for UAVs to reach their targets, and a coordination method based on barrier functions was used to generate collision-free trajectories. Causa et al. (2018) studied CPP for autonomous missions in a real-world 3D scenario with buildings and challenging zones. For the distributed UAV group system, a multi-step strategy was proposed to maximize the task assignment efficiency by distributing the targets among the UAVs, including edge definition and cost evaluation, target assignment, UAV timing, and polynomial path definition.

Chen X et al. (2017) studied CPP for UAVs attacking multiple targets in a 2D battlefield environment. The Voronoi diagram method was used to create a threat field, and a preliminary path was determined based on the established Voronoi diagram and the Dijkstra algorithm. Then, the optimal cooperative path of the UAV group was planned by establishing the path-solving framework and using the consensus algorithm. Ghamry et al. (2017) investigated a forest-fire-fighting application using a UAV group in a 2D plain environment, including the task assignment and trajectory generation problems. The auction-based algorithm was used to minimize the distance between each UAV's initial position and its assigned task. Then, the collision-free trajectory for each UAV was generated by combining the PSO and control parameterization and time discretization (CPTD) algorithms.

Yao WR et al. (2019) presented a distributed mission planning framework for task assignment and path planning of a UAV group. The authors proposed a market-based iterative strategy for UAV group mission planning in a 2D urban environment to optimize the mission execution reward. The proposed strategy can overcome difficulties caused by the information coupling between task assignment and path planning. Yoon et al. (2017) studied CPP using the UAV group as message ferries to deliver delay-sensitive information in a catastrophic 2D disaster scenario. The authors proposed a distributed path planning algorithm to minimize the makespan and maximize the number of nodes that can successfully be serviced within each designated packet deadline.

8. Allocation task, decentralized framework, and unknown environment

Sun XL et al. (2015) studied the real-time mission planning of a UAV group in a 3D dynamic environment. The shortest path to the assigned task of each UAV was estimated using the A* algorithm, and a cluster-based decentralized task assignment was carried out at every planning horizon. Then, the shortest path was further calculated using the A* algorithm, and the cubic B-spline curve was used to smooth the paths. Kothari et al. (2009) generated the curve paths for UAVs from given starting locations to goal locations in a dynamic 2D obstacle-rich environment. The environment includes many static, pop-up, and dynamic obstacles. The rapidly exploring random trees (RRTs) algorithm was used to generate the shortest and collision-free paths for UAVs in real time. During the flight, each UAV can exchange some information with others when they are in the communication range. Wu ZY et al. (2018) focused on effective planning for a UAV group in a 2D obstacle environment. Considering the communication noise among UAVs, the Kalman filter and collision probability were combined to generate collision-free and smooth trajectories for leading UAVs to reach their own targets.

Moon et al. (2013) presented a hierarchical framework for task assignment and path planning of multiple UAVs in a 3D dynamic environment. An intersection-based algorithm for generating the shortest path and a negotiation-based algorithm for task assignment were proposed. In addition, the potential field was used to avoid pop-up threats. Yao WR et al. (2016) proposed a hierarchical path-generation scheme to improve the adaptability and performance of the distributed mission planning system of a UAV group. The distributed mission planning in a 2D dynamic environment with pop-up tasks includes rough path planning, task allocation, and refined path planning. The objective is to find the appropriate allocation mappings for global reward value maximization. Jang et al. (2019) proposed an integrated decision-making framework of a heterogeneous UAV group to execute cooperative tasks in a 2D dynamic environment. The goal was to find an assignment set that can maximize the minimum value of the requirement satisfaction index of tasks. Note that some of the UAVs may be lost during the mission, and to reduce the difficulty in solving the problem, the problem was approximated and decoupled into three sub-problems: coalition formation, position allocation, and path planning.

9. Allocation task, hybrid framework, and known environment

Yan et al. (2019a) studied the coupled task allocation and path planning problem for a heterogeneous UAV group performing an attack mission in a 2D obstacle environment. The leader solved the task allocation optimization problem in the decentralized framework to determine the maximum system utility of the group to destroy a target. The system utility was calculated by combining the reward of the target and the total range of the UAV group. Then, the cooperative path planning for the UAV group was implemented using the DCPSO algorithm and PH curve to generate simultaneous arrival paths with the optimization objectives of the total path length and the smoothness of paths. In the follow-up research, Yan et al. (2019b) studied a more complex situation, where each target required a UAV group, and each UAV can attack a set of targets. Thus, the task sequence of UAVs should be considered.

The features of the studied CPP problems in allocation tasks are shown in Table 7.

10. Coverage task, centralized framework, and known environment

Lin et al. (2018) studied track planning for a UAV group to execute an exploration task in a 3D mountain environment, the goal of which was to complete coverage of the whole area in the minimum execution time and at the maximum coverage rate. By rasterizing an actual mountain map, a co-evolutionary algorithm based on ACO was proposed to generate the visiting sequence of grids for UAVs. Li JD et al. (2018) studied the cooperative coverage path planning in a 3D plateau and mountain environment. The authors solved the problem in two phases. First, a parallel search strategy was used to solve the global route planning issue with the goal of optimizing the path length of each UAV. Second, GA was applied to divide the search area and to optimize the number of required UAVs.

Mansouri et al. (2018) studied cooperative coverage path planning for inspection of a complex 3D infrastructure using a UAV group, in which the goal was to minimize the completion time. The infrastructure was sliced in horizontal planes, and the surface of the infrastructure was divided into several areas. Then, each area could be assigned to a UAV, and the problem was formulated as an mTSP. After the assignment by a proposed heuristic algorithm, trajectories were generated by applying the

Table 7 Features of the studied cooperative path planning problems in allocation tasks

Reference	Classification	Environment	UAVs	1	2	3	4	5	6
Wang et al. (2019)	AT-CF-KE	2D, obstacle	=	–	√	–	–	√	–
Shi et al. (2017)	AT-CF-KE	2D, battlefield	=	–	–	–	–	–	–
Dewangan et al. (2019)	AT-CF-KE	3D, obstacle	=	–	√	–	–	–	–
Babel (2019)	AT-CF-KE	2D, obstacle	=	–	√	–	–	√	√
Wu JY et al. (2017)	AT-CF-KE	3D, battlefield	=	–	√	–	–	–	–
Ergezer and Leblebicioğlu (2014)	AT-CF-KE	3D, mountain	=	–	–	–	–	–	–
Çakıcı et al. (2016)	AT-CF-KE	3D, mountain	=	–	–	–	–	–	–
Sahingoz (2013, 2014)	AT-CF-KE	2D, obstacle-free	=	–	–	–	–	–	–
Cekmez et al. (2016)	AT-CF-KE	2D, battlefield	=	–	–	–	–	–	–
Li XH et al. (2016)	AT-CF-KE	2D, farmland	=	–	–	–	–	–	–
Li T et al. (2016)	AT-CF-KE	2D, obstacle-free	=	–	–	–	–	–	–
Manyam et al. (2017)	AT-CF-KE	2D, obstacle-free	=	–	–	–	–	–	–
Sørli et al. (2017)	AT-CF-KE	2D, obstacle-free	=	–	–	–	–	–	–
Harounabadi et al. (2018)	AT-CF-KE	2D, obstacle-free	=	–	–	–	–	–	–
Binol et al. (2018)	AT-CF-KE	2D, road network	=	–	–	–	–	–	–
Ning et al. (2019)	AT-CF-KE	2D, battlefield	=	–	–	–	–	–	–
Cho et al. (2019)	AT-CF-KE	2D, obstacle-free	≃	–	–	–	–	–	–
Zhao M et al. (2017)	AT-CF-KE	3D, battlefield	=	–	–	–	–	√	–
Zhang X et al. (2014)	AT-CF-KE	2D, obstacle-free	=	–	–	–	–	–	–
Qin et al. (2018)	AT-CF-KE	2D, obstacle-free	=	–	–	–	–	–	–
Yang J et al. (2018)	AT-CF-KE	2D, obstacle-free	=	–	–	–	–	–	–
Quintin et al. (2017)	AT-CF-KE	2D, obstacle	≃	–	–	–	–	–	–
Zhao Z et al. (2019)	AT-CF-KE	3D, obstacle	=	√	–	–	–	–	–
Su et al. (2016)	AT-CF-UE	3D, battlefield	=	√	√	–	–	–	–
Ma XB et al. (2016, 2018)	AT-DF-KE	3D, urban-like	=	–	√	–	–	–	–
Causa et al. (2018)	AT-DF-KE	3D, urban	=	–	–	–	–	√	–
Chen X et al. (2017)	AT-DF-KE	2D, battlefield	=	–	–	–	–	√	–
Ghamry et al. (2017)	AT-DF-KE	2D, obstacle-free	=	–	√	–	–	–	–
Yao WR et al. (2019)	AT-DF-KE	2D, urban	=	–	–	–	–	–	–
Yoon et al. (2017)	AT-DF-KE	2D, obstacle-free	=	–	–	–	–	–	–
Sun XL et al. (2015)	AT-DF-UE	3D, obstacle	=	√	–	–	–	–	–
Kothari et al. (2009)	AT-DF-UE	2D, obstacle-rich	=	√	√	–	–	–	–
Wu ZY et al. (2018)	AT-DF-UE	2D, obstacle	=	√	√	–	–	–	–
Moon et al. (2013)	AT-DF-UE	3D, obstacle	=	√	√	–	–	–	–
Yao WR et al. (2016)	AT-DF-UE	2D, obstacle	=	√	–	–	–	–	–
Jang et al. (2019)	AT-DF-UE	2D, obstacle	≃	√	√	–	–	–	–
Yang et al. (2019a, 2019b)	AT-HF-KE	2D, obstacle	≃	√	–	–	–	√	–

AT: allocation task; CF: centralized framework; DF: decentralized framework; HF: hybrid framework; KE: known environment; UE: unknown environment. 1: real time; 2: collision avoidance among UAVs; 3: connectivity; 4: formation; 5: synchronicity; 6: heading coordination. =: homogeneous; ≃: heterogeneous; √: considered; –: not considered

switching model predictive controller cascaded over an attitude-thrust controller. Collision avoidance was solved as an integer linear programming problem to ensure a safe distance between UAVs. Maza and Ollero (2007) focused on cooperatively searching in a 2D obstacle-free environment to detect objects of interest using a heterogeneous UAV group. The goal was to minimize the number of turns needed using a zig-zag pattern. A heuristic algorithm was presented to divide the whole area by considering the relative capabilities and initial locations of UAVs, and a zig-zag pattern was used to generate the coverage path for each UAV.

In Bouzid et al. (2019), the optimal coverage planning for quadrotors in a damaged 2D area was considered. The area includes a set of points of interest (POIs), and when all POIs are accessed, the coverage mission is completed. Thus, the coverage planning problem was formulated as a capacitated vehicle routing problem (CVRP), and a modified savings heuristic approach was proposed to determine the best sequence of POIs for each quadrotor. Then, an improved RRT approach, called multi-RRT* fixed node (RRT*FN), was developed to generate the shortest paths for the quadrotors. Avellar et al. (2015) studied a UAV group routing problem for area coverage and remote sensing in an obstacle-free 2D environment. The problem was solved as a VRP, and the Yalmip toolbox and Gorubi solver were used to optimize the maximum flight time and the number of required UAVs. Zheng et al. (2018) studied CPP for 3D fine-resolution building model reconstruction with the goal of improving the data-collection speed while minimizing redundant image datasets. This problem was formulated as a VRP and solved using the Yalmip toolbox and Gorubi solver.

Govindaraju et al. (2014) studied coverage path planning for a UAV group surveillance over forested regions to enhance ground visibility and minimize the mission completion time. The authors proposed a probabilistic sensing model, and applied the centroidal Voronoi tessellation and clustered spiral-alternating algorithm to determine the waypoints and plan the paths, respectively. Yao P et al. (2017) focused on solving the cooperative searching problem in a 3D urban environment. The goal was to obtain effective and collision-free coverage paths for UAVs, by which the maximum probability of finding the target during the given flight time can be obtained. A three-layer distributed control structure based on the Gaussian mixture model (GMM) and receding horizon control (RHC) was presented to solve the problem.

Balampanis et al. (2017) studied the division and coverage of a coastal region using a heterogeneous UAV group. Multiple heuristic algorithms were proposed to find the optimal partition and allocation of the area that can minimize the coverage path length of each UAV. Hoang et al. (2018) proposed an angle-encoded particle swarm optimization ($\theta-$PSO) algorithm to generate paths to guide a UAV group through several pre-determined waypoints. The ultimate goal was to optimize the total range of the UAV group while avoiding obstacles and maintaining the shape of the UAV formation.

11. Coverage task, centralized framework, and unknown environment

Lazarus et al. (2010) studied CPP for UAV group by searching and mapping the complex obstacles in a 2D environment. The circle packing search algorithm was used to minimize the number of repeated searches of the explored region, while the UAV trajectories were generated using Dubins path planning. Luo et al. (2019) studied the cooperative search for a UAV group in an uncertain 2D environment, and proposed a co-evolution pigeon-inspired optimization (CPIO) algorithm based on the cooperation-competition mechanism to maximize the target existence probability and to minimize the environmental uncertainty. Then, the search tracking approach was used to ensure that the UAVs safely returned to the starting base.

Yang F et al. (2017) focused on the cooperative search by a UAV group in an uncertain 2D environment. An improved ACO (IACO) algorithm was proposed to maximize the coverage rate and search efficiency. The proposed IACO uses the feedback mechanism of pheromone to integrate the information among UAVs, which can avoid the overlap of waypoints and achieve higher coverage.

12. Coverage task, decentralized framework, and known environment

Gupta et al. (2017) studied coverage path planning for a UAV group in a 2D obstacle environment to survey a given region with the minimum makespan. The authors proposed a spiral search method to cover the given area, and the A* algorithm was used to generate the shortest paths for UAVs when returning to the base after completing the mission. Ji et al. (2015) studied the distributed cooperative search for a UAV group with limited sensing and communication capabilities in a non-convex 2D environment, and proposed a distributed cooperative search algorithm. The goal was to control UAVs in finding several unknown targets deployed in a given region with the minimum search time while avoiding obstacles.

Park et al. (2018) studied network reconstruction through connectivity probing and relay deployment by a UAV group in ad hoc networks. The authors proposed a novel distributed coverage path planning algorithm based on adaptive zig-zag patterns and proposed an iterative heuristic algorithm to minimize duplicate coverage. Yao P et al. (2018) focused on the optimal search for a marine target using a UAV group, in which the goal was to optimize the local and future search reward. The authors formulated the target probability map, and consensus theory with a state predictor was adopted to fuse the updated target probability maps. Then, the UAV paths were optimized in real time by distributed model predictive control (DMPC).

Azpùrua et al. (2018) studied coverage path planning for geophysical surveys in a 2D plain environment using a UAV group to minimize the survey time. The authors used regular hexagons to decompose the region of interest, and the sub-region allocation was solved by the k-means clustering algorithm. Then, the paths for each UAV were generated in a lawn-mower pattern.

13. Coverage task, decentralized framework, and unknown environment

Chen J et al. (2013) studied cooperative area reconnaissance for a UAV group in a dynamic 2D battlefield environment. Receding horizon optimization for efficient online cooperative route planning was provided, and an improved PSO algorithm based on SA was proposed to obtain the optimal route predictive control series in each prediction time domain. Zhen et al. (2018) studied the cooperative search-attack mission planning for a UAV group, in which the goal was to optimize the coverage rate and the attack benefit. An improved distributed ACO algorithm was proposed employing the Dubins curve, and cooperation Dubins paths were generated for UAVs.

Wu QP et al. (2014) focused on a cooperative region surveillance strategy for a UAV group, in which UAVs planned their coverage trajectories in an uncertain 2D environment to obtain maximum rewards. The expected rewards for a UAV include target detection, environment exploration, cooperation reward, and swerve avoidance reward. The authors divided the expansive environment into several sub-regions and presented a limited model predictive search policy to accomplish cooperative region surveillance. Liu Z et al. (2018) studied cooperative search and coverage for a given bounded rectangular region using a UAV group. The authors designed cognitive maps and developed a controllable revisit mechanism. Then, in the frame of distributed receding horizon optimization, a minimum spanning tree (MST) topology optimization strategy was proposed to optimize the cooperative search and coverage time.

Hu et al. (2017) studied optimal search for moving targets in an uncertain 2D environment using a UAV group. The coverage search path planning optimization model was constructed based on the model predictive control (MPC) method, and a hybrid PSO (HPSO) was proposed to solve the problem. The goal was to maximize the cumulative probability of target discovery. Yang YL et al. (2007) studied the coverage search problem using a UAV group in an uncertain 2D environment to minimize the uncertainty of the entire environment within a finite time horizon. The authors presented a more formal formulation of this problem using a discretized cellular space with UAVs moving synchronously at a constant speed, and presented an opportunistic cooperative learning method to achieve coordination among UAVs.

14. Coverage task, hybrid framework, and unknown environment

Long and Zhu (2011) focused on a UAV cooperative reconnaissance mission in a 2D obstacle environment. The problem was solved by combining centralized pre-planning and distributed re-planning. In the pre-planning stage, grid disintegration was applied to divide the area into several task nodes, and the fuzzy C-means clustering algorithm was used to execute the clustering division. Then, the spanning-tree coverage (STC) was applied to generate the shortest flight path for each UAV. In online re-planning, the unfinished tasks of failed UAVs were completed by other UAVs automatically, which ensures good robustness to failures.

The features of the studied CPP problems in coverage tasks are shown in Table 8.

4.2 Analysis of existing research

Key issues in the studied literature are summarized in Fig. 7. From the perspective of the organizational framework, centralized global planning is beneficial in obtaining a better solution. More than half of the investigated studies to date have been carried out in centralized frameworks. Moreover, because of the high flexibility, decentralized frameworks are adopted in about one-third of the

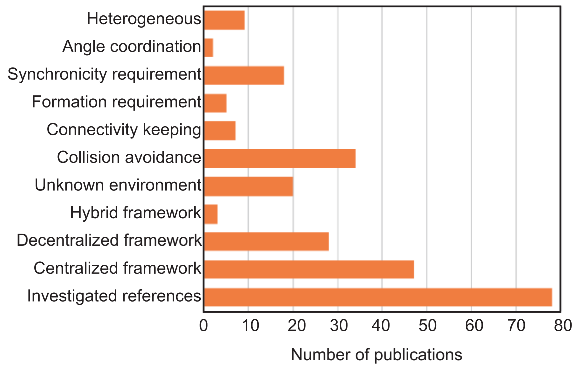


Fig. 7 Statistics of key issues in the literature in Web of Science from 2007 to 2019

Table 8 Features of the studied CPP problems in coverage tasks

Reference	Classification	Environment	UAVs	1	2	3	4	5	6
Lin et al. (2018)	CT-CF-KE	3D, mountain	=	–	√	–	–	–	–
Li JD et al. (2018)	CT-CF-KE	3D, plateau and mountain	=	–	–	–	–	–	–
Mansouri et al. (2018)	CT-CF-KE	3D, urban	=	–	√	–	–	–	–
Maza and Ollero (2007)	CT-CF-KE	2D, obstacle-free	$\simeq$	–	–	–	–	–	–
Bouzid et al. (2019)	CT-CF-KE	2D, obstacle	=	–	√	–	–	–	–
Avellar et al. (2015)	CT-CF-KE	2D, obstacle-free	=	–	–	–	–	–	–
Zheng et al. (2018)	CT-CF-KE	3D, urban	=	–	√	–	–	–	–
Govindaraju et al. (2014)	CT-CF-KE	2D, forest	=	–	–	–	–	–	–
Yao P et al. (2017)	CT-CF-KE	3D, urban	=	–	√	–	–	√	–
Balampanis et al. (2017)	CT-CF-KE	2D, coastland	$\simeq$	–	√	–	–	–	–
Hoang et al. (2018)	CT-CF-KE	3D, urban	=	–	√	–	√	–	–
Lazarus et al. (2010)	CT-CF-UE	2D, obstacle	=	√	√	–	–	–	–
Luo et al. (2019)	CT-CF-UE	2D, obstacle	=	√	√	–	–	–	–
Yang F et al. (2017)	CT-CF-UE	2D, obstacle-free	=	√	–	–	–	–	–
Gupta et al. (2017)	CT-DF-KE	2D, obstacle	=	–	–	–	–	–	–
Ji et al. (2015)	CT-DF-KE	2D, obstacle	=	–	–	√	–	–	–
Park et al. (2018)	CT-DF-KE	2D, obstacle-free	=	–	–	√	–	–	–
Yao P et al. (2018)	CT-DF-KE	2D, ocean	=	√	–	–	–	–	–
Azpùrua et al. (2018)	CT-DF-KE	2D, plain	=	–	–	√	–	–	–
Chen J et al. (2013)	CT-DF-UE	2D, battlefield	$\simeq$	√	√	√	–	–	–
Zhen et al. (2018)	CT-DF-UE	2D, battlefield	$\simeq$	√	√	–	–	–	–
Wu QP et al. (2014)	CT-DF-UE	2D, obstacle-free	=	√	√	–	–	–	–
Liu Z et al. (2018)	CT-DF-UE	2D, obstacle-free	=	√	√	√	–	–	–
Hu et al. (2017)	CT-DF-UE	2D, obstacle-free	=	√	–	–	–	–	–
Yang YL et al. (2007)	CT-DF-UE	2D, obstacle-free	=	√	–	–	–	–	–
Long and Zhu (2011)	CT-HF-UE	2D, obstacle	=	√	–	–	–	–	–

CT: coverage task; CF: centralized framework; DF: decentralized framework; HF: hybrid framework; KE: known environment; UE: unknown environment. 1: real time; 2: collision avoidance among UAVs; 3: connectivity; 4: formation; 5: synchronicity; 6: heading coordination. =: homogeneous; $\simeq$: heterogeneous; √: considered; –: not considered

investigated studies. However, studies on hybrid frameworks are relatively few at present.

To make CPP more practical, the synchronicity requirement among UAVs is considered in about one-quarter of the investigated studies, and most of these studies involve CPP rendezvous and allocation tasks. The unknown environment is taken into account in nearly one-third of the investigated studies, and collision avoidance among UAVs is considered in almost half of the investigated studies. In contrast, connectivity maintenance, formation requirements, and heading coordination among UAVs are considered in exceedingly few investigated studies. Also, although the cooperation of heterogeneous UAVs is necessary for many practical applications, fewer than one-tenth of the investigated studies involve the CPP of homogeneous UAVs.

5 Future research directions

As shown in the above literature review, numerous studies have been conducted on the CPP of UAV groups, and various problems and algorithms have been explored. However, there are still many issues remaining for further study. In the following, several challenging CPP problems and interesting topics for future research are highlighted.

1. CPP for a large-scale UAV swarm

In a large-scale UAV swarm, it is almost unrealistic to use a centralized framework to solve CPP problems (Ajlouni et al., 2018). Usually, a decentralized or hybrid framework should be adopted. Thus, distributed behavior optimization for UAV groups, including cooperative path planning, decision making, and control, will become imperative. Because the role of UAVs in a large swarm may be different and the information for each UAV is asymmetric, conflicts will arise in cooperative decision making. How to design an appropriate conflict-resolution mechanism and how to combine CPP and cooperative control effectively to generate feasible flight paths are subjects worth in-depth study.

2. CPP in the cooperation of heterogeneous vehicles

As the literature review reflects, only a few studies considered the CPP of heterogeneous UAVs (Maza and Ollero, 2007; Chen J et al., 2013; Liu W et al., 2013; Balampanis et al., 2017; Quintin et al., 2017; Zhen et al., 2018; Cho et al., 2019; Jang et al., 2019; Yan et al., 2019a). Due to the differences in performance, functions, and roles of heterogeneous UAVs, their cooperation generally involves more problems, such as coalition formation and role assignment (Jang et al., 2019), which are closely related to their cooperative path planning. Also, UAVs may cooperate with other categories of vehicles, such as ground vehicles and underwater vehicles, to achieve multi-domain coordination in complex tasks (Sujit et al., 2009; Quintin et al., 2017; Ding et al., 2019b). Their coordination in various dimensions, e.g., task, time, and space, will bring about behavioral dependence and thus new constraints, posing more challenges to the CPP in a larger heterogeneous group (Chen J et al., 2016).

3. CPP in swarm-versus-swarm UAV games

Recently, the dynamic offense-defense confrontation for a swarm-versus-swarm combat has emerged as a hot research direction (Jia et al., 2019). In Xing et al. (2019), the target allocation and social-force-based swarm motion decision were studied, leading to emergent offensive and defensive actions in swarm combat. This work focuses on the behavior decisions of swarming UAVs rather than path planning. How to plan and generate the best cooperative attack or defense paths for swarming UAVs from a game-theoretical perspective is undoubtedly a very challenging problem.

4. CPP with variable communication topology

Currently, most research considers only the communication connectivity of UAVs, and the communication topology is usually assumed to be fixed or just neglected (Chen J et al., 2013; Liu W et al., 2013; Ji et al., 2015; Azpùrua et al., 2018; Liu Z et al., 2018; Park et al., 2018; Zhang DF and Duan, 2018). To adapt to environment and task requirements, the UAV group may change the topology to gain more flexibility in cooperative motion planning. In this sense, the topology will become a design variable in CPP, which will increase the complexity of CPP problem solving, especially in a decentralized framework.

5. CPP in complex mixed environments

With the maturation of UAV technology in the future, wide applications of UAVs in urban areas can be anticipated, including express delivery and disaster relief. The environment for UAVs to perform these tasks may become very complex, because UAVs may need to shuttle between buildings in an open but crowded block, and even get into buildings with complex and even uncertain indoor environments. Safety will become a more serious issue for UAV path planning due to humans, public transport, and other factors. On the other hand, the environment may provide powerful support for UAV groups, e.g., reliable links (relays) for inter-UAV communication and a distributed energy supply for persistent flying. How to use these resources will also be reflected in the CPP of UAV groups. Many challenging CPP problems will emerge with extensive UAV applications.

6 Conclusions

This paper provides a systematic overview of the current research on cooperative UAV group path planning by focusing on the three elements of the system (i.e., task, UAV group, and environment) and the three elements of the CPP problem (i.e., UAV paths, objectives, and constraints). A taxonomy of various CPP problems has been proposed and used as clues to classify the existing research and identify their features. A comparative statistical analysis regarding various issues in CPP reveals some shortcomings and gaps in current research. A collection of challenging CPP problems and interesting topics have been presented for future research.

Contributors

Hao ZHANG conceived the idea of this review. Hao ZHANG and Li-hua DOU did literature research. Hao ZHANG drafted the manuscript. Bin XIN and Kaoru HIROTA helped organize the manuscript. Hao ZHANG, Bin XIN, and Jie CHEN revised and finalized the paper.

Compliance with ethics guidelines

Hao ZHANG, Bin XIN, Li-hua DOU, Jie CHEN, and Kaoru HIROTA declare that they have no conflict of interest.

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