Artificial Intelligence Review (2023) 56:4295–4327
https://doi.org/10.1007/s10462-022-10281-7

Swarm intelligence algorithms for multiple unmanned aerial vehicles collaboration: a comprehensive review

Jun Tang[1] · **Haibin Duan**[2] · **Songyang Lao**[1]

Accepted: 12 September 2022 / Published online: 26 September 2022

Abstract

Over the past decade, unmanned aerial vehicles (UAVs) have demonstrated increasing promise. In this context, we provide a review on swarm intelligence algorithms that play an extremely important role in multiple UAV collaborations. The study focuses on four aspects we consider relevant for the topic: collision avoidance, task assignment, path planning, and formation reconfiguration. A comprehensive investigation of selected typical algorithms that analyses their merits and demerits in the context of multi-UAV collaboration is presented. This research summarises the basic structure of swarm intelligence algorithms, which consists of several fundamental phases; and provides a comprehensive survey of swarm intelligence algorithms for the four aspects of multi-UAV collaboration. Besides, by analysing these key technologies and related applications, the research trends and challenges are highlighted. This broad review is an outline for scholars and professionals in the field of UAV swarms.

Keywords Unmanned aerial vehicle · Swarm intelligence · Collision avoidance · Task assignment · Path planning · Formation reconfiguration

Abbreviations

2D	Two-dimensional
3D	Three-dimensional
ABC	Artificial bee colony
ABCIS	ABC with intellective search and special division
ACO	Ant colony optimization
AEFA	Artificial electric field algorithm
CCA	Cooperative coevolutionary algorithm

✉ Jun Tang
tangjun06@nudt.edu.cn

Haibin Duan
hbduan@buaa.edu.cn

Songyang Lao
laosongyang@vip.sina.com

[1] College of Systems Engineering, National University of Defence Technology, Changsha, China

[2] State Key Laboratory of Virtual Reality Technology and Systems, Beihang University, Beijing, China

CPTD	Control parametrization and time discretization
CM	Cauchy mutant
DBF	Dynamic Bayesian framework
DBVF	Distance-based value function
DE	Differential evolution
EKF	Extended Kalman filter
EP	Evolutionary programming
ES	Evolutionary strategy
FESGA	Fuzzy elite strategy genetic algorithm
GA	Genetic algorithm
GAP	Generalized assignment problem
GH	Greedy heuristic
GS	Greedy strategy
GSA	Gravitational search algorithm
GWO	Grey wolf optimizer
IBA	Inspired bat algorithm
IoT	Internet-of-things
LSO	Lion swarm optimisation
MFOA	Multi-swarm fruit fly optimization algorithm
MOSFLA	Multi-objective shuffled frog-leaping algorithm
MPGA	Multi-population GA
MTS	Minimum time search
NNA	Nearest neighbour algorithm
PIO	Pigeon-inspired optimization
PRM	Probabilistic roadmap
PSO	Particle swarm optimization
SAA	Simulated annealing algorithm
SCA	Sine cosine algorithm
SMC	Sequential Monte Carlo
SOS	Symbiotic organisms search
SSA	Sparrow search algorithm
TSP	Travelling salesman problem
UAV	Unmanned aerial vehicle
UGV	Unmanned ground vehicle
WOA	Whale optimization algorithm

1 Introduction

In nature, different organisms usually benefit from group behaviours. The swarm intelligence concept first proposed by Beni and Wang (1993) is a subdiscipline of computational intelligence which is used to resolve problems by modelling populations of agents that can self-organize and interact with each other. Through the research on the characteristics of individuals and their relationships with the group, the algorithm of the corresponding mechanism, called 'swarm intelligence', has evolved, and it has become an extremely important part of a new field of artificial intelligence (Chakraborty and Kar 2017). A swarm consists of multiple artificial agents, which could exchange heuristic information using local interaction. And this interaction coupled with certain stochastic elements can produce adaptive search behaviour that ultimately leads to global optimization. These swarm intelligence algorithms are essentially inspired by biology; have the characteristics of self-organization, parallelization, distribution, flexibility and robustness; and are gradually being applied in many ways (Garnier et al. 2007; Pham et al. 2020; Tang et al. 2021a; Shaikh et al. 2020). For example, swarm intelligence algorithms are used in optimization problems such as simulation, image processing, system identification, scheduling problems, and unmanned systems in the engineering field. Therefore, further research on swarm intelligence technology has extremely important academic and practical value.

Regarded as an advanced technology, multi-UAV collaboration is widely applied in the military and civilian fields, including target surveillance, remote sensing, multi-target tracking, striking targets, etc. (Zhou et al. 2021a; Tang et al. 2021b). As the key steps in the operation of multi-UAV cooperative missions, collision avoidance ensures that UAVs in the same cluster keep a safe distance from each other and obstacles; task assignment assigns different subtasks and their order to each UAV while achieving the task requirements and UAV capabilities; path planning generates near-optimal paths that meet certain constraints, ensures that each UAV can arrive the mission area rapidly and reduces the probability of being captured and damaged by the opposing side; and formation reconfiguration refers to a certain number of UAVs moving according to the requirements of the transformation to form a new formation shape which aims at adapting to the environment or perform related tasks.

The collective systems of swarm intelligence algorithms can complete difficult tasks in dynamic and varied environments without any external guidance or control and with no central coordination, and this capability is very suitable for multi-UAV collaboration. To enhance the intelligence and environmental adaptability of multi-UAV control, we review the application of swarm intelligence algorithms in the field of multi-UAV collaboration. The main contributions of this paper are as follows:

- The basic framework of swarm intelligence algorithms is summarised, and it comprises of several fundamental phases. Although the algorithms utilise different mechanisms, these general phases are common to all these algorithms.
- The trend indicator of swarm intelligence in multi-UAV collaboration is provided. Clearly, much in-depth research and application of swarm intelligence algorithms have been conducted in this field.
- A comprehensive survey of swarm intelligence algorithms for multi-UAV collaboration is represented. Applying the proposed swarm intelligence framework, different approaches, techniques, methods, settings and implications for use are discussed and summarized for collision avoidance, task assignment, path planning, and formation reconfiguration.
- The trends and challenges of using swarm intelligence algorithms for multi-UAV collaboration in the future are systematically outlined.

The remainder of this paper is organized as follows. Section 2 summarises the basic framework of swarm intelligence algorithms and briefly describes typical algorithms. Section 3 reviews the multi-UAV applications in which swarm intelligence algorithms are used. Section 4 discusses future research issues and directions on swarm intelligence algorithms for multiple UAV collaborations. The conclusions that can be derived from this review are summarized in Sect. 5.

2 Swarm intelligence algorithms

Swarm intelligence algorithms are decentralized and self-organising by definition and provide a viable solution for the multiobjective optimization of (expensive) black-box functions. Swarm intelligence algorithms were successfully evaluated on multiobjective optimization and feature extraction, which suggests that they may also be suitable for complex multi-UAV scenarios and UAV collaboration situations. In Table 1, we comprehensively show swarm intelligence algorithms according to four categories. The most representative algorithms, the middle transition algorithms and the latest algorithms are selected respectively. At the same time, we summarize these algorithms from many aspects, including algorithm name, author, inspiration source, establishment time.

2.1 Swarm intelligence in multi-UAV collaboration

In essence, swarm intelligence algorithms are on the basis of an iterative random search algorithm, and heuristic information is shared globally in the iterative process to perform subsequent iterative searches. In the past few decades, many swarm intelligence algorithms have been proposed and improved. Based on the source of inspiration for creating these technologies, they can basically be divided into four categories (Sotoudeh-Anvari et al. 2009; Kennedy 2006): evolutionary phenomena, biological swarm intelligence, physical rules, and concepts related to humans. Among the numerous swarm intelligence algorithms, a basic framework can be abstracted and shown in Fig. 1 (Tan and Ding 2015; Khan and Ling 2020). The first step is the initialization operation, including the definition of the relevant parameter values, setting the termination conditions, and randomly generating agents. Then, according to the initially set evaluation function, the agents in the group are evaluated. Then, the intelligence is evaluated according to the set unique rules, and the agents are updated. Finally, whether the termination condition is met is judged so as to loop or end the iterative process.

In order to analyse the application of the above four types of swarm intelligence technologies in the field of multi-UAV collaboration more comprehensively, we selected more classical, applied papers to determine their statistics. The selected genetic algorithm (GA) and differential evolution (DE) algorithm are based on evolutionary phenomenon; the selected particle swarm optimization (PSO), ant colony optimization (ACO) and artificial bee colony (ABC) are biological-based swarm intelligence algorithms; the gravitational search algorithm (GSA) is based on physical rules; and the others that are less used in this field are classified as other. In addition, algorithms based on human concepts are rarely used in the UAV field, and typical algorithms of this type are not selected. Figure 2 illustrates the number of studies in the field of multi-UAV collaboration that we have retrieved based on Google Scholar data and Web of Science data since 1950. The results show that in the past few decades, much in-depth research and application of swarm intelligence algorithms have been conducted in this field.

Due to the increasingly complex application environment of unmanned aerial vehicles (UAV), the increasingly diverse tasks performed, and the limited capabilities of a single UAV, the need for multi-UAV collaboration technology is becoming increasingly more urgent and has become an increasingly important development trend. Over the years, a large number of studies have further solved the current concerns by analysing the group behaviours of creatures in nature, such as mimicking bird migration, bee foraging, etc., to

Table 1 Classification of swarm intelligence algorithms

Category	Algorithm	Author	Inspiration	Year
Evolution-based	Genetic algorithms (GA) (Holland 1975)	Holland	The process of natural evolution	1975
	Shuffled complex evolution (SCE) (Duan et al. 1993)	Duan et al	A synthesis of four concepts	1993
	Differential evolution (DE) (Storn and Price 1997)	Storn and Price	The Simulation of biological evolution	1997
	Queen-bee Evolution (QBE) (Jung 2003)	Jung	The reproduction process of queen-bee	2003
	Diferential Search Algorithm (DSA) (Civicioglu 2012)	Civicioglu	The concept transfer of stable motion	2012
	Bull Optimization Algorithm (BOA) (Findik 2015)	Findik	The basic evolutionary operators	2015
Biology-based	Particle swarm optimization (PSO) (Kennedy and Eberhart 1995)	Eberhart and Kennedy	The behavior of bird focking	1995
	Ant colony optimization (ACO) (Dorigo and Caro 1999)	Dorigo	The foraging of ant colonies	1996
	Artificial bee colony (ABC) (Karaboga and Basturk 2007)	Karaboga and Basturk	The foraging of bee colony	2007
	Grey wolf optimize (GWO) (Mirjalili et al. 2014)	Mirjalili et al	The predation of gray wolves	2014
	Sailfish optimizer (SFO) (Shadravan et al. 2019)	Shadravan et al	The behavior simulation of swordfish and sardine	2019
	Sparrow search algorithm (SSA) (Xue and Shen 2020)	Xue and Shen	The foraging and anti-predation of sparrows	2020
Physics-based	Simulated annealing (SA) (Kirkpatrick et al. 1983)	Kirkpatrick et al	The process of solid annealing	1983
	Central force optimization (CFO) (Formato 2007)	Formato	The metaphor of gravitational kinematics	2007
	Gravitational search algorithm (GSA) (Rashedi et al. 2009)	Rashedi et al	Law of gravity and Newton's second law	2009
	Charged system search (CSS) (Kaveh and Talatahari 2010)	Kaveh and Talatahari	The principles from physics and mechanics	2010
	Sine cosine algorithm (SCA) (Mirjalili 2016)	Mirjalili	The theorems of sine and cosine	2016
	Artificial electric field algorithm (AEFA) (Yadav 2019a)	Anita and Yadav	Coulomb's law and Newton's second law	2019
Human-based	Tabu search (TS) (Glover and Laguna 1998)	Glover and Laguna	The taboo of memory	1986
	Harmony search algorithm (HSA) (Geem et al. 2001)	Geem et al	The simulation of music performance	2001
	Human-inspired algorithm (HIA) (Zhang et al. 2009)	Zhang et al	The search strategies of mountain climbers	2009
	Wisdom of artificial crowds (WOAC) (Yampolskiy and El-Barkouky 2011)	Yampolskiy and El-Barkouky	The phenomenon of wisdom of crowds	2011
	Exchange market algorithm (EMA) (Ghorbani and Babaei 2014)	Ghorbani and Babaei	The procedure of trading the shares on stock market	2014
	Student psychology-based optimization (SPBO) (Das et al. 2020)	Das et al	The psychology of the students in the class	2020

maximise the efficiency of a single UAV and control the decision making and management of multiple UAVs. As a result, tasks such as collision avoidance, task assignment, path planning, and formation reconfiguration can be completed safer, more reliably and stabler.

The excellent performance of swarm intelligence algorithms in solving optimization problems is reflected in both simple static problems and complex dynamic problems (Gogna and Tayal 2013). Algorithms with static objective function usually maintain the previously given objective function in the optimization process, while the objective function will change in the search process of other algorithms. There are many different factors affecting the classification of swarm intelligence algorithms. The core is based on the number of random solutions generated by the algorithm in each iteration: single solution-based algorithms and population solution-based algorithms (Hussain et al. 2019). In the former, only one candidate solution is randomly generated and iterated continuously in the optimization process; the latter will generate multiple candidate solutions, which is more conducive to sharing information about the search space and has stronger space exploration ability.

2.2 Typical swarm intelligence algorithms

These descriptive swarm intelligence algorithms are very efficient swarm optimization algorithms, and they have been validated on a massive academic and real-world problems. They possess several faults since they converge slowly to the solution and are prone to stagnation because of the search to a certain extent. Therefore, the basic swarm intelligence algorithms have been improved accordingly to avoid such problems when combined with specific applications. In this subsection, we discuss and represent the distinct types of swarm intelligence algorithms for multi-UAV collaboration.

2.2.1 Genetic algorithm

The heuristic algorithm based on the law and process of biological genetics and population evolution in nature is an evolutionary algorithm (GA). According to the development history, there are four main branches of evolutionary algorithms. The most popular is the genetic algorithm developed by Holland to simulate Darwinian evolution (Holland 1992). The algorithm was created when studying the similarities between biological genetic phenomena and the behaviour of artificial adaptive systems. The algorithm starts from a random initial population; mainly uses random selection, crossover, and mutation operations to obtain a new group of individuals who are more adaptable to the environment; and finally converges to the optimal individual generation by generation to generate the optimal solution to the problem (Chen and Liu 2007).

After evaluating the fitness of the individual, the selection operator is used to determine how to choose the individual from the parent population as the offspring. Common methods include roulette wheel selection, the stochastic tournament, excepted value selection, etc. (Katoch et al. 2021). Through the crossover operator, the genetic algorithm can retain the original characteristics of the population, that is, it can imitate the gene recombination process of sexual reproduction in nature. For example, in the one-point crossover operator, for individuals $X_{i,t} = \left(x_{i,t}^1,\ x_{i,t}^2, \dots,\ x_{i,t}^j,\ \dots, x_{i,t}^D\right)$ and

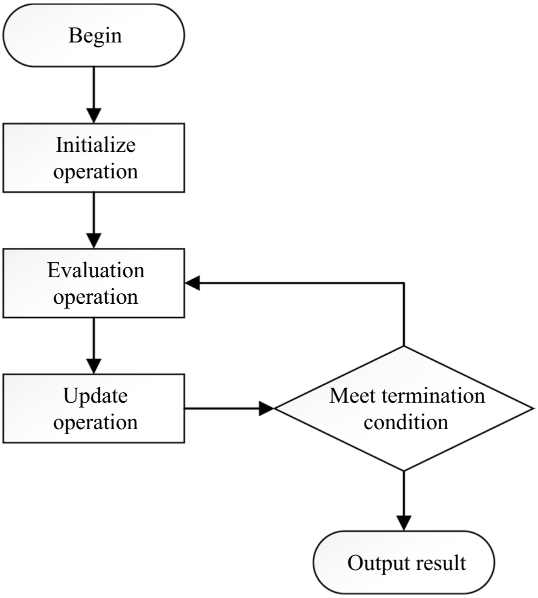

Fig. 1 The basic framework of swarm intelligence algorithms

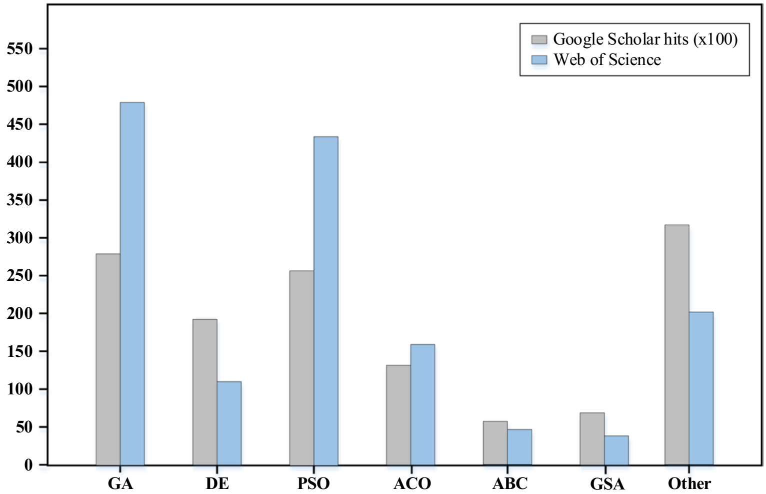

Fig. 2 The trends of swarm intelligence in multi-UAV collaboration

$X_{i+1,t} = \left(x_{i,t}^1,\ x_{i,t}^2, \ldots,\ x_{i,t}^j,\ \ldots, x_{i,t}^D\right)$, only one intersection point is randomly set in the D-dimensional code string. That is, a random number is specified from 1 to D, and the codes of the two individuals are exchanged. In addition, there are two-point crossovers, multipoint crossovers, uniform crossovers and arithmetic crossovers (Holland 1975). The last operation is the mutation operation. To the mutation operation selects a certain bit or several of the individuals with a certain probability and randomly changes the gene values of those bits.

2.2.2 Differential evolution

Differential evolution (DE) was jointly proposed by Rainer Storn and Kenneth Price in 1995 to solve the Chebyshev polynomial (Storn and Price 1997). In essence, it is a random search algorithm on the basis of population. Similar to the genetic algorithm, it mainly simulates the biological evolution process through the three operation operators of mutation, crossover and selection so as to evolve the initial solution to the global optimal solution (Wang et al. 2011). In the development process of the past few decades, DE has attracted increasingly more attention from researchers and has been successfully used in various scientific and engineering fields.

The selection and crossover operations in differential evolution are similar to the genetic algorithm introduced above, and the most important operation is the mutation operation. If the target individual in the parent is $X_{i,t} = \left(x_{i,t}^1,\ x_{i,t}^2, \ldots,\ x_{i,t}^j,\ \ldots, x_{i,t}^D\right)$, it corresponds to the mutant individual $V_{i,t+1} = \left(v_{i,t+1}^1,\ v_{i,t+1}^2, \ldots, v_{i,t+1}^D\right)$. The most basic mutation strategy is "DE/rand/1"; and the strategy is widely used, simple and robust (Wang et al. 2011):

$$V_{i,t+1} = X_{r1,t} + F \cdot \left(X_{r2,t} - X_{r3,t}\right)$$

where $r_1,\ r_2, r_3 \in \{1, 2, \ldots, NP\}$ are randomly selected positive integers that are different from each other, and $X_{ri,t}$ is called the basis vector. $X_{r2,t} - X_{r3,t}$ is called the difference vector. F is the mutation factor or scaling factor. Some well-known mutation strategies in the literature are summarized as follows (Bi and Xiao 2012):

$$DE/rand/2 \quad V_{i,t+1} = X_{r1,t} + F \cdot \left(X_{r2,t} - X_{r3,t}\right) + F \cdot \left(X_{r4,t} - X_{r5,t}\right)$$

$$DE/best/2 \quad V_{i,t+1} = X_{best,t} + F \cdot \left(X_{r1,t} - X_{r2,t}\right) + F \cdot \left(X_{r3,t} - X_{r4,t}\right)$$

$$DE/current-to-best/1 \quad V_{i,t+1} = X_{i,t} + F \cdot \left(X_{best,t} - X_{i,t}\right) + F \cdot \left(X_{r1,t} - X_{r2,t}\right)$$

$$DE/rand-to-best/1 \quad V_{i,t+1} = X_{r1,t} + F \cdot \left(X_{best,t} - X_{r1,t}\right) + F \cdot \left(X_{r2,t} - X_{r3,t}\right)$$

where the parameters $r_1,\ r_2,\ r_3,\ r_4,$ and r_5 are positive integers in the range $[1, NP]$, and $X_{best,t}$ is the individual with the optimal fitness in the t^{th} generation. Essentially, the mutation process of the DE algorithm adds the weighted difference vector of different individuals in the parent to the base vector, which can also be said to add a random disturbance to the base vector.

2.2.3 Particle swarm optimization

On account of the study of bird flock behaviour, Kennedy and Eberhart proposed the PSO algorithm in 1995 (Kennedy and Eberhart 1995). In this algorithm, a group of particles update their speed and position by constantly interacting with their neighbours' information to find the global optimal value. The initial state of the algorithm is a solution group composed of random particles, and each particle has only two attributes: speed and position. The particles constantly adjust their speed and position based on the current individual optimal value and the current global optimal solution. The update process of the above speed and position can be expressed as (6) and (7) (Poli et al. 2007), respectively, as follows:

$$v_{t+1} = c_1 v_t + c_2 r_1 (p_{i,t} - x_t) + c_3 r_2 (p_{g,t} - x_t)$$

$$x_{t+1} = x_t + v_{t+1}$$

where v_t and x_t are the velocity and position of particle i at time t, respectively; $p_{i,t}$ is the individual optimal value of particle i found before time t; $p_{g,t}$ indicates the global optimal solution of the particle swarm found before time t; c_1, c_2, andc_3 are the respective cognition coefficients; and r_1 andr_2 are the random parameters within $[0, 1]$ $[0, 1]$. The first part of is the "memory term", which represents the velocity vector of the particle in the current state. The second part is the "self-cognition item", which represents the vector from the current value to the optimal value. It expresses the influence of historical experience. The third part is the "global cognition item", which represents the vector from the current value to the global optimal solution. It shows the cooperation between particles and global information sharing (Wei and Qiqiang 2004).

2.2.4 Ant colony optimization

The ant colony optimization algorithm was first proposed by Marco Dorigo in 1992 on the basis of his doctoral research (Dorigo 1992). Its core idea is to learn from the behaviour of ants in searching paths when searching for food or avoiding risk. The ACO algorithm has the characteristics of being distributed, using positive feedback and conducting heuristic searches (Dorigo 1992). Specifically, it mimics the processing of pheromones by ants. Ants can leave a substance called a pheromone on their path, and other ants can perceive the strength of this substance to guide their direction of action during foraging (Dorigo and Blum 2005). First, m ants start randomly, and the initial values of their pheromone concentrations are all equal. Then, the ant selects the next position to be transferred according to the random ratio rule, and its selection probability is as follows (Dorigo and Caro 1999):

$$p_{ij}^k(t) = \begin{cases} \frac{\left[\tau_{ij}(t)\right]^\alpha \left[\eta_{ij}(t)\right]^\beta}{\sum_{s \in allowed_k} \left[\tau_{is}(t)\right]^\alpha \left[\eta_{is}(t)\right]^\beta}, j \in allowed_k \\ 0, Otherwise \end{cases}$$

where τ_{ij} represents the pheromone of the edge, $\eta_{ij} = \frac{1}{d_{ij}}$ represents the factor of transferring from location i to location j, d_{ij} is the distance, and $allowed_k$ is the location set that the kth ant is allowed to visit next. After a certain period of time, all the ants completed an action. Then, the path length of each ant is computed; and the shortest path length, which is the contemporary optimal solution, is saved. Furthermore, considering the volatilization of pheromones and the release of pheromones by ants at the edge, the pheromone data are updated for the next iteration.

2.2.5 Artificial bee colony

Inspired by the intelligent foraging behaviour of bee colonies, Karaboga developed the ABC algorithm in 2005 to deal with multivariate optimization problems (Karaboga 2005).

Bee populations can effectively collect nectar from food sources by cooperating with each other. The original ABC algorithm includes three types of bees: hired bees, bystander bees, and scout bees. Each type of bee has its own division of labour. More formally, the hired bee will look for a richer food source d_m near the original food source x_m (Tsai et al. 2009). Previous research compared the fitness of the food to be mined with the original fitness and found a new food source by using the following process (Kaur and Goyal 2011):

$$d_{mi} = x_{mi} + \omega_{mi}(x_{mi} - x_{ki})$$

$$fit_m(\vec{x}_m) = \begin{cases} \frac{1}{1+f_m(x_m)} & iff_m(x_m) \geq 0 \\ 1 + abs(f_m(x_m)) & iff_m(x_m) < 0 \end{cases}$$

where each food source could be regarded as the solution vector of the problem to be optimized. The bees use greedy selection and decide which food source to mine according to the fitness value. The fitness can be calculated based on. In the equation, $f_m()$ is the objective function for this optimization problem.

2.2.6 Gravitational search algorithm

The gravitational search algorithm was created by Esmat Rashedi, Hossein Nezamabadi-pour and others in 2009 (Xing and Gao 2014). In this algorithm, each agent is considered as the solution of the problem, and the performance of the solution is measured by quality. All these agents will be attracted or repelled by gravity. Through this direct communication form, after a certain number of iterations, they will tend to move to agents with higher quality, that is, better agents (Rashedi et al. 2009):

$$F_{ij}^d(t) = G(t) \times (x_j^d - x_i^d)/(R_{ij}(t) + \varepsilon)$$

where $G(t)$ is the gravitational constant at time t, $(x_j^d - x_i^d)$ is the mass difference between the two individuals, $R_{ij}(t)$ is the Euclidean distance between agent i and agent j, and $F_{ij}^d(t)$ represents the gravitational action between individuals. In addition, the agent's next time velocity is considered to be a small part of its current velocity jerk. Thus, its position and speed can be calculated as follows (Rashedi et al. 2009):

$$v_i^d(t+1) = rand_i() \times v_i^d(t) + a_i^d(t)$$

$$x_i^d(t+1) = x_i^d(t) + v_i^d(t+1)$$

which shows that the update of $v_i^d(t+1)$ requires acceleration $a_i^d(t)$. The acceleration is obtained by dividing the force $F_i^d(t)$ obtained by combining and the mass M_i of the agent based on Newton's second law.

2.2.7 Others

In addition to the abovementioned applications in multi-UAV collaboration, there are many other crowd intelligence optimization algorithms. For example, there are two other branches based on evolutionary thinking: the evolutionary strategy (ES) (Beyer and

Schwefel 2002) and evolutionary programming (EP) (Fogel 1998). Based on the behaviours of biological groups, the sparrow search algorithm is on the basis of the foraging behaviour and anti-predation behaviour of sparrows (Xue and Shen 2020), the inspired bat algorithm (IBA) is influenced by the echolocation of microbats (Yang 2010), the grey wolf optimizer (GWO) is inspired by the composition and hierarchy of wolves (Mirjalili et al. 2014), and the whale optimization algorithm (WOA) simulates the behaviour of humpback whale groups (Mirjalili and Lewis 2016). Other algorithms are based on physical rules. The simulated annealing algorithm (SAA) is based on the annealing process (Kirkpatrick et al. 1983), the sine cosine algorithm (SCA) is influenced by sine and cosine functions (Abualigah and Diabat 2021), and the artificial electric field algorithm (AEFA) is inspired by Coulomb's law of electrostatic force (Yadav 2019b).

These swarm intelligence algorithms are still mainly inspired by biological groups in nature, especially insects and animals, through artificially designing information exchange mechanisms to simulate the process of information exchange among individuals in biological communities so as to optimize the problem using directed iteration (Zhang et al. 2007). In recent years, most of the new swarm intelligence algorithms proposed are enhancements to traditional algorithms and mainly focus on optimizing parameters, improving the speed, and fusing known algorithms (Yang et al. 2018).

3 Literature review

Compared to a single UAV, the advantages of multiple UAVs are reflected in the performances of complex missions, and collaboration could improve the detection, localization and perception abilities. Most swarm intelligence algorithms have been proposed to deal with stationary optimization problems, and therefore, they could converge on the (near) optimum solution fleetly. In this section, major swarm intelligence algorithms which tackle multi-UAV collaboration will be reviewed for several classes of problems divided as follows:

- Swarm intelligence in collision avoidance
- Swarm intelligence in task assignment
- Swarm intelligence in path planning
- Swarm intelligence in formation reconfiguration

Since the four classes have been extensively studied, they are further classified by application (see Tables 2, 3, 4 and 5) and by the relevant parameters of representative algorithms.

3.1 Swarm intelligence algorithms in collision avoidance

Collision avoidance approaches play an extremely important role in the reliable and safe operations of collaborative and noncollaborative UAVs in a common airspace. There are a large number of approaches to the collision avoidance problem; and in different environments, the approaches have their own advantages and disadvantages during threat resolution.

3.1.1 Collision avoidance

Separation assurance, which is at the core of aviation safety, is a multilayered process; and collision avoidance capability is considered the last line of defence against collisions with other aircraft or obstacles. Generally, collision avoidance technology could be divided into two steps: conflict detection and conflict resolution. Figure 3 shows the conflict scenarios that may occur during the flight of multiple drones. UAV_1, UAV_2, and UAV_3 are fixed-wing drones, and UAV_4 and UAV_5 are rotor drones. Where the flight paths of UAV_1 and UAV_2 overlap, if they still follow the established route, $Collision_1$ will occur; furthermore, $Collision_2$, $Collision_3$ and $Collision_4$ indicate that UAV_3, UAV_4 and UAV_5 conflict with obstacles O_1, O_2 and O_3 on their respective flights.

3.1.2 Representative applications

This review summarises and analyses the typical swarm intelligence algorithms used for collision avoidance problems between multiple UAVs in Table 2. At the top of this table, 'UAV category' is utilised to express whether the research objects are fixed-wing or rotary UAVs, 'Cooperative detection' is used to distinguish whether the UAV entities cooperate during conflict detection, 'Avoidance category' is used to confirm whether the collision avoidance algorithm can act on the UAV or the obstacle, 'Number of objects' is used to confirm whether the collision avoidance algorithm is applied to a single entity or multiple entities, 'Uncertainties' is used to express whether the algorithm considers relevant uncertain factors, 'Security restriction' is used to indicate whether the detection of conflicts is based on time or distance constraints, 'Spatial dimension' is used to illustrate the functional airspace of the algorithm, 'Algorithms' indicates the applied algorithms, and 'Year' expresses the year of publication.

For the collision avoidance problem in two-dimensional (2D) space, to search ways of calculating state trajectories for dynamic systems subject to computational constraints, obstacles and priority assignment, Greiff and Robertsson (2017) developed the derived algorithms for miniature UAVs in a modular fashion and included a traditional GA for handling the travelling salesman problem (TSP) problem with respect to priorities and static obstacle avoidance. To ensure the flight safety of rotary UAVs, Chen et al. (2019) employed the Dijkstra approach to explore the feasible paths and applied the standard PSO algorithm to obtain the global optimal path as the obstacle avoidance strategy. To optimize the link quality and energy consumption in the concerned UAV system, Mood et al. (2021) proposed a novel constrained GSA in which a multiple constraint ranking method is applied to handle the constraints, e.g., collision constraints.

For the collision avoidance problem in three-dimensional (3D) space without cooperative detection, Hawary and Razak (2018) proposed an easy and practical path optimizer on the basis of the traditional TSP, adopted a brute force search method to reoptimize the route in the event of collisions adopting a range finder sensor, and combined the GA and the nearest neighbour algorithm (NNA) to optimize the route and avoid collisions at once. Using comparative experiments regarding 3D terrain environments with static obstacles that should be avoided, Bagherian (2018) concluded that PSO obtains a good trajectory that is not as suitable as that of the GA but better than that of the fuzzy system in a relatively shorter time than the GA. Responding to specific application cases, Xue et al. (2020) developed an improved ACO algorithm with the grid method establishing the environment

Table 2 Summary and analysis of typical swarm intelligence algorithms used in collision avoidance

Literatures	UAV category	Cooperative detection	Avoidance category		Number of objects	Object state	Uncertainties	Security restriction		Spatial dimension	Algorithms	Year
			UAV	obstacle				time	distance			
Greiff and Robertsson (2017)	Unspecified	×	×	√	Single	Static	×	×	√	2D	Traditional GA	2017
Chen et al. (2019)	Rotary	×	×	√	Single	Static	×	×	√	2D	Traditional PSO	2019
Mood et al. (2021)	Rotary	√	√	×	Single	Dynamic	×	√	√	2D	Constrained GSA	2021
Hawary and Razak (2018)	Fixed-wing	×	√	√	Single	Static, dynamic	×	√	√	3D	GA + NNA	2018
Bagherian (2018)	Rotary	×	×	√	Single	Static	×	×	√	3D	Traditional PSO	2018
Xue et al. (2020)	Unspecified	×	×	√	Single	Static	×	√	√	3D	ACO + grid method	2020
Pérez-Carabaza et al. (2019)	Rotary	×	√	×	Multiple	Dynamic	√	√	√	3D	Traditional ACO	2019
Zhang et al. (2020)	Fixed-wing	√	√	√	Multiple	Static, dynamic	×	√	√	3D	Adaptive DE	2020
Legowo et al. (2017)	Unspecified	√	√	√	Multiple	Static, dynamic	×	×	√	3D	DE + EKF	2017
Skrzypecki et al. (2019)	Unspecified	√	√	×	Multiple	Dynamic	×	×	√	3D	Improved PSO	2020
Dentler et al. (2019)	Rotary	√	√	√	Multiple	Static, dynamic	×	√	√	3D	Chaotic ACO	2019
Poudel and Moh (2021)	Rotary	√	√	√	Multiple	Static, dynamic	×	√	√	3D	Traditional ABC	2021
Qiu and Duan (2020)	Unspecified	√	√	√	Multiple	Static, dynamic	×	√	√	3D	Modified PIO	2020
Radmanesh et al. (2018)	Unspecified	√	√	√	Multiple	Static, dynamic	√	√	√	3D	GWO + DBVF + DBF	2018

Table 2 (continued)

Literatures	UAV category	Cooperative detection	Avoidance category		Number of objects	Object state	Uncertainties	Security restriction		Spatial dimension	Algorithms	Year
			UAV	obstacle				time	distance			
Wang et al. (Yingxun et al. 2020)	Unspecified	√	√	√	Multiple	Static, dynamic	√	√	√	3D	Chaotic GWO	2020

The symbol '√' indicates that this item is met, and the symbol '×' indicates that this item is not met

Table 3 Summary and analysis of typical swarm intelligence algorithms used in task assignment

Literatures	UAV category	Cooperative allocation	UAV formation		Number of targets	Uncertainties	Target requirements		Spatial dimension	Algorithms	Year
			Uniform	Heterogeneous			Priority	Time			
Ghamry et al. (2017)	Unspecified	√	√	×	Multiple	×	×	√	2D	PSO + CPTD	2017
Schwarzrock et al. (2018)	Unspecified	√	×	√	Multiple	×	√	√	2D	Swarm-GAP	2018
Kim et al. (2021)	Fixed-wing	×	×	√	Multiple	√	×	√	2D	Social-learning PSO	2021
Wu et al. (2018)	Unspecified	√	×	√	Multiple	√	√	√	2D	Dynamic ACO	2018
Zhang et al. (2016)	Unspecified	√	×	√	multiple	×	×	√	2D	GSA + GA	2016
Amorim et al. (2020)	Unspecified	√	√	×	Multiple	×	√	√	2D	Swarm-GAP	2020
Ye et al. (2020)	Fixed-wing	√	×	√	Multiple	×	×	×	3D	Modified GA	2020
Xu et al. (2020)	Rotary	√	√	×	Multiple	×	√	×	3D	GA + MOSFLA	2020
Han et al. (2021)	Unspecified	√	×	√	Multiple	×	√	√	3D	Fuzzy elite strategy GA	2021
Zhao et al. (Ming et al. 2017)	Unspecified	√	×	√	Multiple	×	×	×	3D	Discrete mapping DE	2017
Yang et al. (2020)	Rotary	√	×	√	Multiple	×	×	√	3D	Traditional DE	2020
Liu et al. (2019a)	Unspecified	√	×	√	Single	×	×	√	3D	improved ACO	2019
Hu et al. (2020)	Unspecified	√	√	×	Multiple	×	×	√	3D	ABCIS	2020
Lu et al. (2020)	Unspecified	√	√	×	Multiple	×	×	√	3D	GWO + PSO + GA	2020
Dong et al. (2020)	Unspecified	√	√	×	Multiple	×	×	√	3D	LSO + SMC	2020
Luo et al. (2020)	Fixed-wing	√	×	√	Multiple	√	√	√	3D	MFOA	2020

The symbol '√' indicates that this item is met, and the symbol '×' indicates that this item is not met

Table 4 Summary and analysis of typical swarm intelligence algorithms used in path planning

Literatures	UAV category	Cooperative planning	UAV formation		Number of targets	Uncertainties	Objective functions		Spatial dimension	Algorithms	Year
			Uniform	Heterogeneous			Safety	Cost			
Chen et al. (2021)	Rotary	√	×	√	Multiple	×	×	√	2D	GA + ACO	2021
Kyriakakis et al. (2021)	Rotary	√	√	×	Multiple	×	×	√	2D	Multi-swarm framework	2021
Yu et al. (2020)	Unspecified	×	√	×	Single	×	√	×	2D	Constrained DE	2020
Gonzalez et al. (2020)	Unspecified	×	√	×	Single	×	√	√	2D	Traditional DE	2020
Tian et al. (2018)	Rotary	×	√	×	Single	×	√	√	2D	Improved ABC	2018
Wu et al. (2020)	Unspecified	×	√	×	Single	×	√	√	2D	Fast convergent ABC	2020
Silva Arantes et al. (2017)	Fixed-wing	√	×	√	Multiple	√	√	√	3D	Modified GA	2017
Adhikari et al. (2017)	Unspecified	×	√	×	Multiple	√	√	√	3D	Fuzzy adaptive DE	2017
Huang and Fei (2018)	Fixed-wing	×	√	×	Single	×	√	√	3D	Global best PSO	2018
Xu et al. (Zhen et al. 2020)	Rotary	×	√	×	Single	×	√	√	3D	Multi-objective PSO	2020
Shao et al. (2020)	Unspecified	×	√	×	Multiple	×	√	√	3D	Comprehensively improved PSO	2020
Phung and Ha (2021)	Rotary	×	√	×	Single	×	√	√	3D	Spherical vector-based PSO	2021
Xu et al. (2021)	Unspecified	×	√	×	Single	×	√	√	3D	Mixed-strategy based GSA	2021
Liu et al. (2021)	Unspecified	×	√	×	Single	×	√	√	3D	Modified SSA	2021
Tong et al. (2021)	Unspecified	×	√	×	Single	×	√	√	3D	Multi-objective PIO + DE	2021
Qu et al. (2020)	Unspecified	×	√	×	Single	×	√	√	3D	Hybrid GWO	2020
Zhou et al. (2021b)	Unspecified	×	√	×	Single	×	√	√	3D	BA + ABC	2021
Liu et al. (2019b)	Unspecified	×	√	×	Single	×	×	√	3D	Optimal SA	2019

The symbol '√' indicates that this item is met, and the symbol '×' indicates that this item is not met

to deal with the obstacle avoidance problem of UAVs, and the feasibility was validated by simulation. Pérez-Carabaza et al. (2019) proposed a minimum time search (MTS) planner on the basis of ACO that contains communication and collision avoidance constraints, and the method ensured that UAVs were able to generate the optimized search trajectories without the risk of collision or communication loss with the ground control station.

For the collision avoidance problem in 3D space with cooperative detection, Zhang et al. (2020) studied the adaptive DE-based distributed model predictive control method to address multi-UAV flight, the method achieved simultaneous obstacle/collision avoidance and formation maintaining in a complex environment, and the local optimization problem could be resolved by the adaptive DE algorithm. Legowo et al. (2017) combined the DE algorithm and extended Kalman filter (EKF) to develop a detection and tracking system, which is regarded to be the main challenge in sensing and avoidance systems; and the system could detect any obstacles either in static or moving conditions and reply with proper avoidance manoeuvres to keep minimum separation distances. For the predicted collision avoidance method, Skrzypecki et al. (2019) used the improved PSO with the global neighbourhood and included maximum speed and search area limits such as the maximal remembered signal value resetting for a specific UAV and for all UAVs once a source was detected. To improve the area coverage of UAV swarms, Dentler et al. (2019) proposed a novel mobility model combining the ACO algorithm with chaotic dynamics, and they improved this model with a CA mechanism to obtain high efficiency on the basis of area coverage by a UAV swarm. Poudel and Moh (2021) proposed the probabilistic roadmap (PRM) to obtain the shortest and collision-free roadmap and followed it with the conventional ABC to dynamically find the position coordinates if some threats or obstacles arise during the flight time. Qiu and Duan (2020) developed a distributed optimization control frame to transform UAV flocking control to a multiobjective optimization problem, and improved pigeon-inspired optimization (PIO) was used to assist each UAV in handling it. The results show that the UAV flocking control algorithm could coordinate UAVs to operate in a stable formation through complex environments. Radmanesh et al. (2018) applied a distance-based value function (DBVF) and a dynamic Bayesian framework (DBF) to build a risk map and proposed a GWO-based algorithm to search the optimal UAV trajectory in the presence of fixed/moving obstacles in an uncertain environment. To enhance the performance of multi-UAV coordination control, including collision avoidance, Wang et al. (Yingxun et al. 2020) developed the chaotic GWO method based on chaotic initialization and chaotic search to resolve the local finite horizon optimal control problem, and the method achieved better performance than the classical PSO-based method.

3.2 Swarm intelligence algorithms in task assignment

Multiple UAVs generally cooperate in teams to improve the mission execution efficiency. UAVs are equipped with different sensors with complementary functions to adjust to complex mission constraints. In the scenario with a large number of tasks, the optimization effect of task assignment affects straight the work effectiveness of a multi-UAV system.

3.2.1 Task assignment

The task allocation problem of multi-UAVs owns the intrinsic attributes of complexity, such as being highly nonlinear, dynamic, highly adversarial and multimodal. The objective of the problem is to maximize the total reward generated by achieving different targets that

Table 5 Summary and analysis of typical swarm intelligence algorithms used in formation reconfiguration

Literatures	UAV category	Cooperative reconfiguration	UAV formation		Number of targets	Uncertainties	Reconstruction form		Spatial dimension	Algorithms	Year
			Uniform	Heterogeneous			Synchronous	Leader–follower			
Mousavi et al. (2019)	Unspecified	√	×	√	Multiple	×	×	√	2D	Quantum-inspired GA	2019
Ceccarelli et al. (2020)	Rotary	×	√	×	Multiple	×	√	×	2D	Iterative GA	2020
Han et al. (2020)	Unspecified	√	√	×	Single	×	√	×	2D	Traditional ACO	2020
Zhong et al. (Yun et al. 2018)	Fixed-wing	√	×	√	Single	√	√	×	2D	Quantum ABC	2018
Li et al. (2021)	Unspecified	√	√	×	Multiple	×	×	√	2D	Pigeon behavior	2021
Bian et al. (2019)	Fixed-wing	√	√	×	Multiple	×	×	√	3D	Pre-DMPC-DE	2019
Zhang et al. (2019)	Fixed-wing	√	√	×	Multiple	×	×	√	3D	Adaptive DE	2019
Hoang et al. (2019)	Rotary	√	√	×	Single	×	√	×	3D	Angle-encoded PSO	2019
Ali and Han (2021)	Fixed-wing	√	√	×	Multiple	×	×	√	3D	PSO + CM	2021
Zhang et al. (2014)	Unspecified	×	√	×	Multiple	×	√	×	3D	PIO + CPTD	2014
Li et al. (2016)	Unspecified	√	√	×	Single	×	√	×	3D	Distributed CCA	2016

The symbol '√' indicates that this item is met, and the symbol '×' indicates that this item is not met

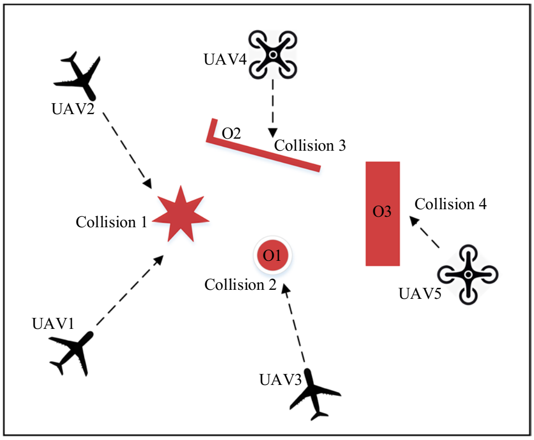

Fig. 3 A conceptual model of the multi-UAV collision avoidance case

have various attributes and maximize the overall effectiveness of UAV formation under the premise of achieving a variety of indicators. When assigning tasks to multiple drones, corresponding tasks are assigned according to the types and characteristics of the drones. Figure 4 shows the mission assignment scenario for multiple drones to perform reconnaissance and strike missions. As shown in Fig. 4a, three reconnaissance drones UAV_1, UAV_2, and UAV_3 are dispatched to perform reconnaissance tasks and are responsible for the three task subareas $TaskArea1$, $TaskArea2$, and $TaskArea3$, respectively. After reconnaissance, it is known that there are five key strike targets $\{T_1, T_2, T_3, T_4, T_5\}$ in the mission area. As shown in Fig. 4b, after algorithm evaluation, UAV_4 is assigned the task to strike targets T_1 and T_2, UAV_5 is assigned to perform the strike mission on target T_3, and UAV_6 will execute strikes on targets T_4 and T_5. However, in most cases the background is more complex, for example, (Stolfi et al. 2021) proposed a Predator–Prey approach to protect a restricted area from a number of intruders, and utilised a coevolutionary genetic algorithm to optimise the UAV parameters to maximise the intruder detection.

3.2.2 Representative applications

This review summarises and analyses typical swarm intelligence algorithms used for the task assignment problems between multiple UAVs in Table 3. At the type of this table, 'UAV category' is utilised to express whether the research objects are fixed-wing or rotary UAVs, 'Cooperative allocation' is used to distinguish whether the UAV entities cooperate during mission allocation, 'UAV formation' is used to indicate whether the UAVs are uniform or heterogeneous, 'Number of targets' is used to confirm whether the task assignment algorithm is applied with a single target or multiple targets, 'Target requirements' is used to indicate whether there are priority or time window requirements on the targets, 'Uncertainties' is applied to express whether the algorithm considers relevant uncertain factors, 'Spatial dimension' is used to illustrate the functional airspace of the algorithm, 'Algorithms' indicates the applied algorithms, and 'Year' expresses the year of publication.

For the task assignment problem in 2D space, to assign each UAV to each fire spot in view of their relative distances, Ghamry et al. (2017) utilised the PSO and control parametrization and time discretization (CPTD) approach to calculate the optimal mission allocation for multiple UAVs in forest firefighting while considering the control input constraints. Schwarzrock et al. (2018) developed a solution from the Swarm-GAP (generalized assignment problem) algorithm to the task allocation for multiple UAVs in a decentralized way. It assumes that the missions are generated by a central entity, such as during a military operation that monitoring an area with the objective of detecting different targets. Considering the computation time and nonconvex nature of the optimization problem in hostile environments, Kim et al. (2021) proposed social-learning PSO to maximize the objective function that estimated the overall damage to vessels as the engagement outcome. On the basis of the complete analysis of the classic ant colony's labour division, Wu et al. (2018) proposed the dynamic ant colony labour division and the implementation to handle the task allocation problem in a dynamic environment for UAV swarm combat, and the results showed that the method has better practicability in various multiagent systems. Considering the assignment problem where heterogeneous UAVs operate in collaborative teams, Zhang et al. (2016) developed a hybrid GSA-GA that adopted the selection, crossover and mutation operations in the GA for the position update strategy of the GSA particles, and the experiments demonstrated its performance improvement. Amorim et al. (2020) combined a swarm intelligence thought with the generalized assignment problem (GAP) approach to develop a heuristic method, i.e., swarm-GAP, to resolve the task allocation problem among agents expressing multiple UAVs and optimise the resource usage in dynamic environments.

For the task assignment problem in 3D space, to address this issue of suppressing enemy air defence missions against multiple ground stationary targets, Ye et al. (2020) developed an improved GA with multitype gene chromosome encoding strategy for the synergic task assignment problem of heterogeneous fixed-wing UAVs without priority or time window requirements on the multiple targets. Xu et al. (2020) studied a multiobjective shuffled frog-leaping algorithm (MOSFLA) and GA-based task assignment and sequencing model for multiple rotary UAV plant protection operation optimization, and the results showed that using the GA with a known assignment matrix would greatly shrink the total operating time. Considering the resource consumption, the mission completion effect, and the workload balance, Han et al. (2021) used the proposed fuzzy elite strategy genetic algorithm (FESGA) with commendable computational efficiency to address the task assignment problem of heterogeneous UAV systems with restricted resources and task priority constraints. By generating reasonable DE offspring, Zhao et al. (Ming et al. 2017) proposed a discrete mapping DE algorithm with a unified gene coding strategy to not only solve the cooperative multitarget assignment problem availably but also improve the accuracy and scale of the multitarget assignment. With the goals of balancing the global load and minimising the slowdown, Yang et al. (2020) introduced the DE algorithm to explore for near-optimal positions of UAVs in ground internet of things (IoT) networks, and the simulation results showed the method's feasibility and superiority. Liu et al. (2019a) compared standard ACO with multiple-inspired ACO and artificial potential field ACO in the simulation of mission allocation, and the results showed that the strengthen strategies used by the two enhanced algorithms effectively speed up the ant path search, thereby reducing the UAV track planning time. To optimize the 3D position of aerial base stations under different scenarios, Hu et al. (2020) proposed a modified ABC with intellective search and special division (ABCIS) to improve the performance, and the results showed that the method can obtain significant enhancements on both unimodal and multimodal functions. Lu et al. (2020) improved the application of GWO in high-dimensional task assignment using PSO and a GA to accelerate the convergence speed, and the simulations confirmed the developed approach using three ground attack scenarios. Dong et al. (2020) introduced a sequential Monte Carlo (SMC) method resampling mechanism to enhance the performance of standard lion swarm optimisation (LSO); and the results showed that the proposed method could avoid excessive concentration, extend the search area and improve the search ability. With the specification of simultaneously reducing the completion and total mission times, Luo et al. (2020) developed a multiswarm fruit fly optimization algorithm (MFOA) with dual method switching to deal with the multifunctional heterogeneous UAV cooperative task allocation problem.

3.3 Swarm intelligence algorithms in path planning

The goal of multi-UAV cooperative path planning is to explore for a preferable flight path for each UAV from its starting point to the terminal point under the conditions of minimizing the total flight costs and meeting the constraints of the distance between the UAVs, arrival time, safety requirements and the UAV performance.

3.3.1 Path planning

As UAVs operate in the sky, they can travel via any path; therefore, it is not feasible to search forcibly through all possible combinations to calculate the set of optimal routes reaching the final destination safely. Thus, there is a need for an efficient optimization technique to plan the optimal path, and it plays a vital role in multi-UAV systems. As shown in Fig. 5a, three different types of drones are ordered to fly to a destination and need to cross the complex terrain containing obstacles O_1 and O_2. Thus, path planning is performed to obtain an efficient and convenient flight path. The planned path is shown in Fig. 5b. There is an impenetrable obstacle O_1 on the straight path from UAV_2 to the destination, so it needs to detour from one side. First, UAV_2 could fly straight to vertex P_1 of obstacle O_1, then follow O_1 to vertex P_2, and finally fly straight to the destination from P_2. Similarly, there is an impenetrable obstacle O_2 on the straight path from UAV3 to the destination, so the planned path is $\{P_3, P_4, Destination\}$. Finally, UAV_1 can travel between O_1 and O_2; and obviously, this straight path is the most efficient. Path planning is regarded as a fundamental aspect of autonomous UAV guidance, and the overview can be seen in Goerzen et al. (2010), including key terminology, definitions, problem types, algorithm performance and algorithm constraints, etc. If the problem discussed the path planning which covers the entire destination environment considering the UAV's motion restrictions, sensor's characteristics and obstacle avoidance, it can be called coverage path planning (CPP) and the detailed survey is provided in Cabreira et al. (2019). Unlike a pure CPP problem, Kyriakakis et al. (2021) introduced a Moving Peak Drone Search Problem (MPDSP) and its objective is

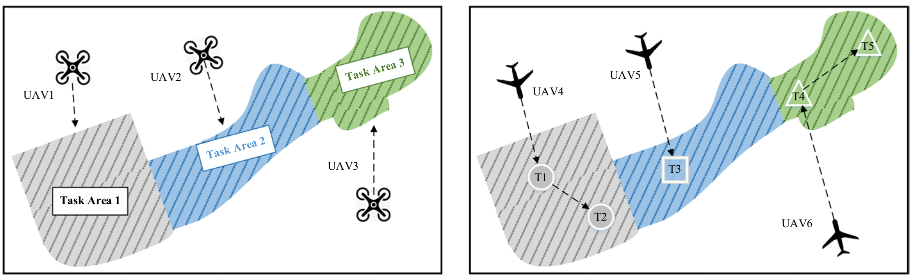

Fig. 4 A conceptual model of the multi-UAV task assignment case

to cover as many locations as possible with the highest possible search value, as relevant resources allow.

3.3.2 Representative applications

This review summarises and analyses typical swarm intelligence algorithms used for the path planning problems between multiple UAVs in Table 4. At the top of this table, 'UAV category' is utilised to express whether the research objects are fixed-wing or rotary UAVs, 'Cooperative planning' is used to distinguish whether the UAV entities cooperate during path planning, 'UAV formation' is used to indicate whether the UAVs are uniform or heterogeneous, 'Number of targets' is used to confirm whether the path planning algorithm is applied with a single target or multiple targets, 'Uncertainties' is applied to express whether the algorithm considers relevant uncertain factors, 'Objective functions' is used to indicate whether the safety and cost functions are considered, 'Spatial dimension' is used to illustrate the function airspace of the algorithm, 'Algorithms' indicates the applied algorithms, and 'Year' expresses the year of publication.

For the path planning problem in 2D space, considering the air-ground cooperation problem of unmanned ground vehicles (UGVs) and UAVs, Chen et al. (2021) combined the GA with ACO to decouple their routes, and the results verified that this method could effectively handle the heterogeneous delivery problem and obtain their optimal routes. Kyriakakis et al. (2021) introduced a novel dynamic optimization problem applied to UAV search and rescue scenarios, and a multi-swarm framework was developed with additional UAV constraints. In addition, seven optimization algorithms are evaluated to resolve this problem, and among them the PSO was proved to be the most effective. Yu et al. (2020) developed an adaptive selection mutation constrained DE algorithm to deal with the optimization problem. In the proposed method, the fitness functions contain the travel distance and risk of a UAV; and the three constraints include the height of a UAV, the angle of a UAV, and the limited UAV slope. To plan the feasible path covering an entire area for a UAV that keeps a flight level with respect to the ground, Gonzalez et al. (2020) developed a coverage algorithm to generate the resulting paths and used DE to evaluate them paths to choose the best path in terms of the distance costs. To address the track planning problem of quad-rotor UAV formations, Tian et al. (2018) used the improved ABC to optimize the track initialization strategy and update alterable dimensions, and the results verified that the real-time performance of the method is better than that of the standard ACO with respect of the shortest path, execution time and total costs. To obtain the optimal path from the starting point to the end point based on the conflicts and constraints in the battlefield environment, Wu et al. (2020) developed an enhanced fast convergent ABC algorithm in which the physical constraint information of UAVs is fully considered when searching the solution space.

For the path planning problem in 3D space, to study the path planning problem of landing UAVs under different types of critical situations, Silva Arantes et al. (2017) utilised the GA and the multipopulation GA (MPGA) for path planning. These methods were evaluated using a greedy heuristic (GH) to initialize paths, and the results showed that the developed approach could minimize the damage while increasing safety during emergency landings. Adhikari et al. (2017) provided a fuzzy adaptive differential DE for 3D UAV path planning, which is constructed as a multiobjective unconstrained optimization that aims to minimize the fuel and threat costs and search for the shortest path. To develop a global best PSO to improve the performance of 3D path planning for fixed-wing UAVs, Huang and Fei (2018) introduced the competition strategy into the classical PSO to enhance the convergence speed and the search ability of the particles during the particle evolution process. Considering the path planning of rotary UAVs in a known static rough terrain environment, Xu et al. (Zhen et al. 2020) developed an improved multiobjective PSO algorithm to calculate collision-free and feasible trajectories with the minimum altitude, length and angle variable rates; and a vibration function was introduced to improve the algorithm efficiency. To promote the rapidity and optimality of automatic path planners, Shao et al. (2020) provided a 3D path planning algorithm for UAV formation based on comprehensively improved PSO, which not only speeds up the convergence but also enhances the solution optimality. To address the problem of path planning for multiple UAVs in complicated environments subject to multiple conflicts, Phung and Ha (2021) proposed the spherical vector-based PSO, which generates the optimal path minimizing the cost function by efficiently exploring the configuration space of UAVs. Xu et al. (2021) developed a mixed strategy-based GSA, which is an adaptive adjustment method for the gravitational constant attenuation factor alpha; and it could adaptively balance the exploration and exploitation. To construct a highly efficient path planning method for this complex optimization problem in a complex 3D flight environment, Liu et al. (2021) developed a modified sparrow search algorithm (SSA) in which an adaptive inertia weight is used to balance the convergence rate and exploration capabilities of the algorithm. Considering the optimisation problem of path planning with three indices (path length, path sinuosity and path risk), Tong et al. (2021) integrated the PIO and DE mutation strategies to generate feasible paths, and Pareto dominance was used to choose the global best location of a pigeon. Qu et al. (2020) combined hybrid GWO and modified symbiotic organism search (SOS). In the method, the GWO phase was simplified to improve the convergence rate and maintain the exploration ability of the population, and the SOS phase algorithm was synthesized with GWO to enhance the exploitation ability. Zhou et al. (2021b) combined the standard bat algorithm (BA) and ABC algorithm to obtain the global search ability; and the simulation results showed that the method could plan faster, shorter, safer, accident-free flight UAV paths. Liu et al. (2019b) designed an optimized algorithm on the basis of the SAA to generate the optimized path of a UAV in view of the selected sampling points, and the extensive simulation results demonstrated that the method could decrease data redundancy and increase the lifetime compared with the randomly selected sampling point scheme.

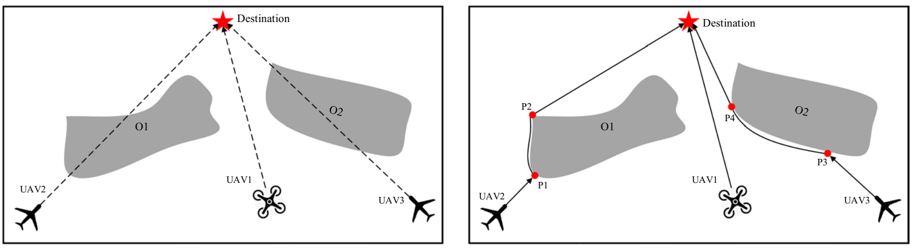

Fig. 5 A conceptual model of multi-UAV path planning case

3.4 Swarm intelligence algorithms in formation reconfiguration

UAV formation flies in some uncertain environments. The appearance of threats and obstacles is random in time and space, and UAVs may experience accidents or man-made attacks during missions and be damaged. When this type of situation occurs, it is necessary to reconstruct the formation to ensure the survivability and mission completion ability of the UAV formation.

3.4.1 Formation reconfiguration

Formation reconfiguration refers to the need to reorganize a formation when a UAV formation encounters unexpected situations during its flight. Compared with formation assembly, formation reconstruction has more constraints. It not only imposes stringent requirements on the modelling and control of UAV dynamics but also requires UAVs to change their relative locations to meet the multitasking needs. For example, when a member retreats, a reasonable formation must be redesigned; and when an obstacle is encountered, not only a reasonable formation must be designed but also the position of the formation must be reasonably set so that every drone can pass obstacles safely. As shown in Fig. 6a, a heterogeneous UAV group consisting of seven UAVs flies in a triangular formation and then passes through a series of obstacles $\{O_1, O_2, O_3\}$. Since the channel formed between O_1 and O_2 only allows a single UAV to pass, a heterogeneous UAV group is required for formation reconstruction. Figure 6b shows the formation reconstruction process. Seven UAVs manoeuvre in sequence, and the entire formation is transformed into a formation that can pass through the channel. Besides, in the UAV formation, there are often the situation of the leader and the member vehicles. Xie et al. studied the adaptive formation tracking problems using the grey wolf tracking strategy in Xie et al. (2021) for swarm systems with multiple leaders and switching topologies based on neighboring relative state information. Note that the optimal formation reconfiguration of UAV swarm can complete missions faster especially when several UAVs break off during the mission. Its mission reliability is the swarm capability to achieve the intended tasks under specified conditions for an expected period of time (Dui et al. 2021).

3.4.2 Representative applications

This review summarises and analyses typical swarm intelligence algorithms used for the formation reconfiguration problems between multiple UAVs in Table 5. At the top of this table, ‘UAV category’ is utilised to express whether the research objects are fixed-wing or rotary UAVs, ‘Cooperative reconfiguration’ is used to distinguish whether the UAV entities cooperate during formation reconfiguration, ‘UAV formation’ is used to indicate whether the UAVs are uniform or heterogeneous, ‘Number of targets’ is used to confirm whether the formation reconfiguration algorithm is applied with a single target or multiple targets, ‘Uncertainties’ is applied to express whether the algorithm considers relevant uncertain factors, ‘Reconstruction form’ is used to indicate whether the reconstruction form is a synchronous structure or leader–follower structure, ‘Spatial dimension’ is used to illustrate the functional airspace of the algorithm, ‘Algorithms’ indicates the applied algorithms, and ‘Year’ expresses the year of publication.

For the formation reconfiguration problem in 2D space, to obtain several efficient coalitions of UAVs, Mousavi et al. (2019) proposed a coalition formation algorithm on the basis of a version of the GA, the quantum-inspired GA, to search the solution of the multiobjective formation alteration problem. Ceccarelli et al. (2020) presented an iterative GA that computes the most efficient coverage for a subset of or every user in a known map to supply an optimized layout for the UAVs to arrange, and the testing results illustrated that the developed method calculated optimal results more frequently than the k-means clustering algorithm. To elaborately design the multipath establishment and maintenance scheme with frequent local topological changes of the UAV formation, Han et al. (2020) used the classic ACO to reduce the routing reconstruction costs under frequent local topological changes. To address the formation and adjustment problem of manned/unmanned combat aerial vehicles, Zhong et al. (Yun et al. 2018) proposed corresponding mathematical models and applied the quantum ABC algorithm, greedy strategy (GS) and two-stage GS to resolve it; and the effectiveness and superiority of the developed method were validated. Li et al. (2021) integrated the formation decision function into the UAV virtual point formation control mode, and classified it at the expected angle based on the track planning model of pigeon swarm behavior, and put forward a hierarchical early warning mechanism.

For the formation reconfiguration problem in 3D space, compared with the standard GA, DE, and PSO algorithms, Bian et al. (2019) developed an enhanced DE algorithm on the basis of a distributed model predictive control framework (Pre-DMPC-DE), and the results was verified that the enhanced algorithm improved the iterative rate and reduced the computational consumption with a better convergence ability for the UAV formation. To handle multi-UAV flight while simultaneously achieving collision avoidance and formation retaining in a complex environment, Zhang et al. (2019) studied adaptive DE that aims at resolving the local optimization problem to generate stable flight for each UAV in formation reconfiguration. Through the derivation of a uniform cost function considering the constraints on collision avoidance, flight altitude, communication range, and visual inspection requirements, Hoang et al. (2019) proposed angle-encoded PSO for intermediate waypoint reconfiguration, which could be accomplished in an alignment, rotation, or shrinking fashion. To improve the fitness function of the formation, Ali and Han (2021) provided 3D formation control for a fixed-wing UAV swarm using PSO with Cauchy mutant (CM) operators, and the results showed that the developed method enhanced the convergence rate and the solution optimality. Under the terminal status and control action energy constraints, Zhang et al. (2014) developed a controller that combines PIO with CPTD, which aims to search for the best values of UAV inputs (thrust, load factor, and bank angle) to complete the formation reconfiguration task. For the discretization of the multi-UAV formation reconfiguration process, Li et al. (2016) developed a distributed cooperative coevolutionary algorithm (CCA) with a grouping strategy for the control parameters to be optimized, and the simulations verified that the approach performed better than the existing approaches, e.g., PSO and DE.

4 Trends and challenges

Profiting from the capabilities of strong risk tolerance, low manufacturing costs and good manoeuvrability, various UAVs have been widely utilised in both military and civil fields. Among the related challenges, multi-UAV collision avoidance, task assignment, path planning, and formation reconstruction stand out as the core scientific problems of autonomous control for different UAVs (Tang et al. 2021c; Pan et al. 2021). The task could be fully completed with sufficient attention and effort focused on the main orientation of multi-UAV collaboration. This section highlights future research directions in this area.

4.1 Transforming ways for information exchange

When controlling the flight of a UAV cluster, it is usually assumed that the information can be received continuously, but this requires sufficient computing resources and an ideal communication environment. However, in the actual flight process, many problems, such as limited transmission speed and delay in obtaining information from sensors, will be encountered. Therefore, how to better use swarm intelligence algorithms to further change the information transmission and interaction method between drones and between systems and drones has become one of the key issues to be resolved urgently. Aiming at achieving this transformation, it is necessary to ensure information quality, be less susceptible to interference, and improve control performance while significantly reducing the excessive consumption of communication and computing resources to design a more appropriate swarm intelligence program.

4.2 Control using a distributed method

Distributed control has played an important role in the coordination of multiple tasks and has become one of the cores of UAV cluster coordination technology. However, this distributed control strategy can further integrate swarm intelligence algorithms and develop more advanced control schemes. Simply put, this fusion technology can be applied to multiple functions, such as autonomous formations, situational awareness, global planning, etc., to better model the individual behaviour of a single UAV in a cluster and the overall behaviour of the UAV system. We are familiar with centralized control. Although centralized control is more efficient, once the central drone is damaged, the entire drone cluster will collapse. In contrast, if the distributed swarm intelligent control method is adopted, the costs of the entire system can be effectively reduced, and the robustness and flexibility of the system could be further improved.

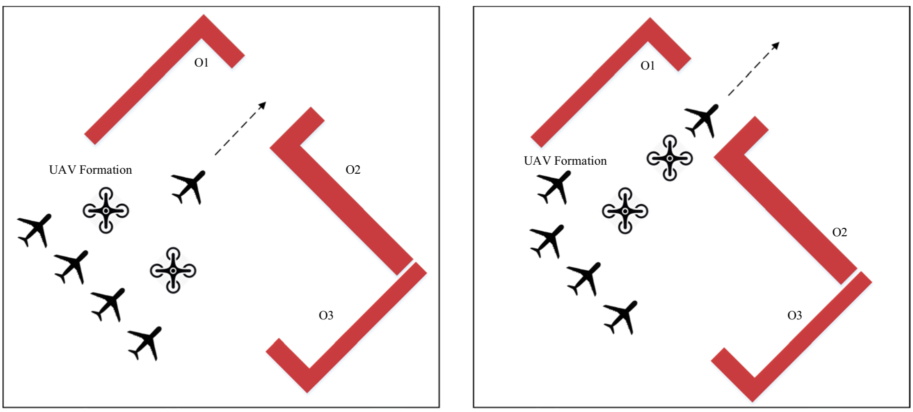

Fig. 6 A conceptual model of the multi-UAV formation reconfiguration case

4.3 Convenient development and transplantation

In order to adapt to more complex application scenarios, different types of UAVs with different system functions are often required for effective integration and comprehensive integration of new technologies. This is also one of the important trends in the research and development of UAV collaborative. To achieve this goal, it is necessary to learn from the inspiration of group intelligence behaviour and vigorously develop a more open system architecture for different types of UAVs. This is also to provide unified standards and tools for components and platforms for mutual exchange or comprehensive integration so that different types or platforms of drone clusters can also be quickly upgraded or replaced. Heterogeneous UAV clusters are composed of UAVs on multiple platforms equipped with different functional modules, which means that platforms and functions are more diverse and integrated. Distribution means that the overall function of the UAV cluster is broken down into multiple homogeneous or heterogeneous subfunctions, which are distributed in different single UAVs at the same time through information interaction, communication and cooperation, to achieve equality or greater strong overall performance. The types and performance of UAVs on various platforms are often very different, resulting in differences in their motion and payload characteristics, so they are suitable for different swarm intelligence algorithms. A single swarm intelligence algorithm cannot meet the needs of heterogeneous UAV clusters, and the comprehensive ensemble of multiple swarm intelligence algorithms would be a feasible solution. The ensemble algorithm can be applied to the selection of motion and communication modes for each UAV in heterogeneous UAV swarm. In this process, it is necessary to design the ensemble methods of multiple swarm intelligence algorithms according to the system architecture, so that heterogeneous UAV swarm can exchange information and cooperate in various ways. The performance of the ensemble swarm intelligence algorithm will be restricted by the system architecture. Therefore, the realization of heterogeneous and distributed swarm intelligence algorithms requires a more open system architecture that can support convenient transplantation and development.

4.4 Human–machine collaboration mode

When performing various tasks in multiple fields, close cooperation between humans and machines is sometimes required. Human–machine collaboration is a key technology to further enhance the collaborative capabilities of UAVs. Generally, when UAVs are organized in clusters, they can perform tasks such as air interception and ground strikes together with manned aircraft formations. This form of marshalling UAVs and manned aircraft emphasizes close cooperation, comprehensive integration, system support and complementary advantages between the two, thereby improving the overall effectiveness of the formation. Human–machine marshalling puts forward higher requirements for the autonomous capabilities of drones. For different mission scenarios, hierarchical swarm intelligence algorithms are designed to match the autonomous capabilities required by UAVs. Among these capabilities, it is necessary to further reduce human intervention in drones, and it is necessary to use swarm intelligence algorithms to make higher-level swarm intelligence decisions to improve the overall formation reaction speed.

4.5 Strengthening the self-organization level

Self-organization is a procedure in which the various components in a system automatically coordinate according to certain rules agreed with each other to form a relatively stable structure. It can be said that drone collaboration is an important manifestation of the level of self-organization. In addition to its own state, a single drone must consider the behaviour of other intelligent individuals when making decisions. Due to the support of information, networks, platforms and other technologies, clusters can share information; therefore, this consideration can be a broader global consideration so that individual drones in the cluster can achieve common goals. Behaviour selection is more precise and optimized. In the future, if UAV clusters are more collaborative in applications, it will be necessary for swarm intelligence algorithms to shift the local perspective to the global perspective in the self-organizing mode of UAV systems. Furthermore, in the observation, judgement, decision-making and action process, swarm intelligence algorithms should take global information as the core and conduct comprehensive trade-offs and global control from the overall perspective.

5 Conclusions

With the rapidly high-level development of UAV technology, the representative one of the emerging fields is to apply multiple UAVs as a formation under autonomous control in a complex situation. Among the challenges in achieving autonomous control, collision avoidance, task assignment, path planning, and formation reconfiguration stand out as the key functions. In this review, various classical swarm intelligence algorithms for UAVs have been systematically summarized and analysed.

The search was implemented using recognized scientific databases, i.e., the Web of Science, Elsevier, IEEE Xplore, Science Direct, SpringerLink, Scopus and Google Scholar, using terms such as 'genetic algorithm' and 'collision avoidance'/'task assignment'/'path planning'/'formation reconfiguration'. The same search format was used for differential evolution instead of genetic algorithm and similarly for the other swarm intelligence algorithms. The literature retrieved contains journal articles, conference papers, book chapters and technical reports. Generally, most swarm intelligence algorithms have been used for multi-UAV collaboration, and this paper discusses the commonly used and representative algorithms. The main contributions of this review are summarized as follows: this paper provides the basic framework of swarm intelligence algorithms, and it consists of several fundamental phases and represents the distinct types of swarm intelligence algorithms for multi-UAV collaboration. Using the proposed swarm intelligence framework, different approaches, techniques, methods, settings and implications for application are discussed and summarized for collision avoidance, task assignment, path planning, and formation reconfiguration. In addition, this review provides suggestions for future research directions on these topics. We hope that this paper can provide information and inspiration for researchers and related practitioners, and contribute to the advancement of the UAV application industry.

Acknowledgements The authors would like to express their sincere thanks to the members of the editorial team and anonymous reviewers whose valuable comments and contributions contributed to significantly improve this paper. This work is supported by National Natural Science Foundation of China (No. 62073330).

Declarations

Conflict of interest The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

Abualigah L, Diabat A (2021) Advances in sine cosine algorithm: a comprehensive survey. Artif Intell Rev 54:1–42
Adhikari D, Kim E, Reza H (2017) A fuzzy adaptive differential evolution for multi-objective 3D UAV path optimization. In: 2017 IEEE congress on evolutionary computation (CEC), IEEE, pp 2258–2265
Ali ZA, Zhangang H (2021) Multi-unmanned aerial vehicle swarm formation control using hybrid strategy. Trans Inst Measur Control 43:2689
Amorim JC, Alves V, de Freitas EP (2020) Assessing a swarm-GAP based solution for the task allocation problem in dynamic scenarios. Expert Syst Appl 152:113437
Bagherian M (2018) Unmanned aerial vehicle terrain following/terrain avoidance/threat avoidance trajectory planning using fuzzy logic. J Intell Fuzzy Syst 34:1791–1799
Beni G, Wang J (1993) Swarm intelligence in cellular robotic systems. In: Dario P, Sandini G, Aebischer P (eds) Robots and biological systems: towards a new bionics? Springer, Berlin
Beyer H-G, Schwefel H-P (2002) Evolution strategies: a comprehensive introduction. Nat Comput 1:3–52
Bi X, Xiao J (2012) Classification-based self-adaptive differential evolution and its application in multilateral multi-issue negotiation. Front Comput Sci 6:442–461
Bian L, Sun W, Sun T (2019) Trajectory following and improved differential evolution solution for rapid forming of UAV formation. IEEE Access
Cabreira TM, Brisolara LB, Ferreira PR Jr (2019) Survey on coverage path planning with unmanned aerial vehicles. Drones 3(1):1–38
Ceccarelli N, Regis PA, Sengupta S, Feil-Seifer D (2020) Optimal UAV positioning for a temporary network using an iterative genetic algorithm. In: 2020 29th wireless and optical communications conference (WOCC), IEEE, pp 1–6
Chakraborty A, Kar AK (2017) Swarm intelligence: a review of algorithms. Nature-inspired computing and optimization, pp 475–494
Chen M, Liu S (2007) An improved adaptive genetic algorithm and its application in function optimization. J Harbin Eng Univ 28:875–879
Chen Z, Luo F, Zhai C (2019) Obstacle avoidance strategy for quadrotor UAV based on improved particle swarm optimization algorithm. In: 2019 Chinese control conference (CCC), IEEE, pp 8115–8120
Chen Y, Chen M, Chen Z, Cheng L, Yang Y, Li H (2021) Delivery path planning of heterogeneous robot system under road network constraints. Comput Electr Eng 92:107197
Civicioglu P (2012) Transforming geocentric Cartesian coordinates to geodetic coordinates by using differential search algorithm. Comput Geosci 46:229–247
da Silva Arantes J, Motta Toledo CF, Júnior OT, Williams BC (2017) Heuristic and genetic algorithm approaches for UAV path planning under critical situation. Int J Artif Intell Tools 26:176
Das B, Mukherjee V, Das D (2020) Student psychology based optimization algorithm: a new population based optimization algorithm for solving optimization problems. Adv Eng Softw 146:102804
Dentler J, Rosalie M, Danoy G, Bouvry P, Kannan S, Olivares-Mendez M, Voos H (2019) Collision avoidance effects on the mobility of a UAV swarm using chaotic ant colony with model predictive control. J Intell Rob Syst 93:227–243
Dong S, Jiang M, Yuan D (2020) Joint task planning of UAV groups using improved multi-objective lion swarm optimization. In: 2020 39th Chinese control conference (CCC), IEEE, pp 1408–1413
Dorigo M (1992) Optimization, learning and natural algorithms. PhD Thesis, Politecnico Di Milano
Dorigo M, Blum C (2005) Ant colony optimization theory: a survey. Theoret Comput Sci 344:243–278
Dorigo M, Di Caro G (1999) Ant colony optimization: a new meta-heuristic. In: Proceedings of the 1999 congress on evolutionary computation-CEC99 (Cat. No. 99TH8406), IEEE, pp 1470–1477
Duan QY, Gupta VK, Sorooshian S (1993) Shuffled complex evolution approach for effective and efficient global minimization. J Optim Theory Appl 76:501–521
Dui H, Zhang C, Bai G, Chen L (2021) Mission reliability modeling of UAV swarm and its structure optimization based on importance measure. Reliab Eng Syst Saf 215:1–12
Findik O (2015) Bull optimization algorithm based on genetic operators for continuous optimization problems. Turk J Electr Eng Comput Sci 23:2225–2239

Fogel DB (1998) Artificial intelligence through simulated evolution. Wiley, Chichester
Formato RA (2007) Central force optimization: a new metaheuristic with applications in applied electromagnetics. Prog Electromag Res 77:425–491
Garnier S, Gautrais J, Theraulaz G (2007) The biological principles of swarm intelligence. Swarm Intell 1:3–31
Geem ZW, Kim JH, Loganathan GV (2001) A new heuristic optimization algorithm: harmony search. Simulation 76:60–68
Ghamry KA, Kamel MA, Zhang Y (2017) Multiple UAVs in forest fire fighting mission using particle swarm optimization. In: 2017 international conference on unmanned aircraft systems (ICUAS), IEEE, pp 1404–1409
Ghorbani N, Babaei E (2014) Exchange market algorithm. Appl Soft Comput 19:177–187
Glover F, Laguna M (1998) Tabu search-Handbook of combinatorial optimization. Springer, Boston, pp 2093–2229
Goerzen C, Kong Z, Mettler B (2010) A survey of motion planning algorithms from the perspective of autonomous UAV guidance. J Intell Rob Syst 57(1):65–100
Gogna A, Tayal A (2013) Metaheuristics: review and application. J Exp Theor Artif Intell 25:503–526
Gonzalez V, Monje C, Garrido S, Moreno L, Balaguer C (2020) Coverage mission for UAVs using differential evolution and fast marching square methods. IEEE Aerosp Electron Syst Mag 35:18–29
Greiff M, Robertsson A (2017) Optimisation-based motion planning with obstacles and priorities. IFAC-PapersOnLine 50:11670–11676
Han C, Yin J, Ye L, Yang Y (2020) NCAnt: a network coding-based multipath data transmission scheme for multi-UAV formation flying networks. IEEE Commun Lett 25:1041–1044
Han S, Fan C, Li X, Luo X, Liu Z (2021) A modified genetic algorithm for task assignment of heterogeneous unmanned aerial vehicle system. Meas Control 5:994
Hawary A, Razak N (2018) Real-time collision avoidance and path optimizer for semi-autonomous UAVs. In: IOP conference series: materials science and engineering. IOP Publishing, p 012043
Hoang VT, Phung MD, Dinh TH, Zhu Q, Ha QP (2019) Reconfigurable multi-UAV formation using angle-encoded PSO. In: 2019 IEEE 15th international conference on automation science and engineering (CASE), IEEE, pp 1670–1675
Holland JH (1975) Adaptation in natural and artificial systems: an introductory analysis with applications to biology, control, and artificial intelligence. University of Michigan Press, Oxford
Holland JH et al (1992) Adaptation in natural and artificial systems: an introductory analysis with applications to biology, control, and artificial intelligence. MIT Press, Cambridge
Hu B, Sun Z, Hong H, Liu J (2020) UAV-aided networks with optimization allocation via artificial bee colony with intellective search. EURASIP J Wirel Commun Netw 2020:1–17
Huang C, Fei J (2018) UAV path planning based on particle swarm optimization with global best path competition. Int J Pattern Recognit Artif Intell 32:1859008
Hussain K, Mohd Salleh MN, Cheng S, Shi Y (2019) Metaheuristic research: a comprehensive survey. Artif Intell Rev 52:2191–2233
Jung SH (2003) Queen-bee evolution for genetic algorithms. Electron Lett 39:575–576
Karaboga D (2005) An idea based on honey bee swarm for numerical optimization, Technical report-tr06, Erciyes University, Engineering Faculty
Karaboga D, Basturk B (2007) A powerful and efficient algorithm for numerical function optimization: artificial bee colony (ABC) algorithm. J Global Optim 39:459–471
Katoch S, Chauhan SS, Kumar V (2021) A review on genetic algorithm: past, present, and future. Multimed Tools Appl 80:8091–8126
Kaur A, Goyal S (2011) A survey on the applications of bee colony optimization techniques. Int J Comput Sci Eng 3:3037
Kaveh A, Talatahari S (2010) A novel heuristic optimization method: charged system search. Acta Mech 213:267–289
Kennedy J (2006) Swarm intelligence. In: Zomaya AY (ed) Handbook of nature-inspired and innovative computing. Springer, Berlin
Kennedy J, Eberhart R (1995) Particle swarm optimization. In: Proceedings of ICNN'95-international conference on neural networks, IEEE, pp 1942–1948
Khan TA, Ling SH (2020) A survey of the state-of-the-art swarm intelligence techniques and their application to an inverse design problem. J Comput Electron 19:1606–1628
Kim J, Oh H, Yu B, Kim S (2021) Optimal task assignment for UAV swarm operations in hostile environments. Int J Aeronaut Space Sci 22:456–467
Kirkpatrick S, Gelatt CD, Vecchi MP (1983) Optimization by simulated annealing. Science 220:671–680

Kyriakakis NA, Marinaki M, Matsatsinis N, Marinakis Y (2021) Moving peak drone search problem: an online multi-swarm intelligence approach for UAV search operations. Swarm Evol Comput 66:1–19

Legowo A, Ramli MFB, Shamsudin SS (2017) Development of sense and avoid system based on multi sensor integration for unmanned vehicle system. In: IOP conference series: materials science and engineering, IOP Publishing, p 012006

Li S, Fang X (2021) A modified adaptive formation of UAV swarm by pigeon flock behavior within local visual field. Aerosp Sci Technol 114:1–15

Li X, Zhang X, Liu H, Guan X (2016) Formation reconfiguration based on distributed cooperative coevolutionary for multi-UAV. In: 2016 12th world congress on intelligent control and automation (WCICA), IEEE, pp 2308–2311

Liu R, Liang J, Alkhambashi M (2019a) Research on breakthrough and innovation of UAV mission planning method based on cloud computing-based reinforcement learning algorithm. J Intell Fuzzy Syst 37:3285–3292

Liu X, Liu Y, Zhang N, Wu W, Liu A (2019b) Optimizing trajectory of unmanned aerial vehicles for efficient data acquisition: a matrix completion approach. IEEE Internet Things J 6:1829–1840

Liu G, Shu C, Liang Z, Peng B, Cheng L (2021) A modified sparrow search algorithm with application in 3d route planning for UAV. Sensors 21:1224

Lu Y, Ma Y, Wang J, Han L (2020) Task assignment of UAV swarm based on Wolf Pack algorithm. Appl Sci 10:8335

Luo R, Zheng H, Guo J (2020) Solving the multi-functional heterogeneous UAV cooperative mission planning problem using multi-swarm fruit fly optimization algorithm. Sensors 20:5026

Ming Z, Lingling Z, Xiaohong S, Peijun M, Yanhang Z (2017) Improved discrete mapping differential evolution for multi-unmanned aerial vehicles cooperative multi-targets assignment under unified model. Int J Mach Learn Cybern 8:765–780

Mirjalili S (2016) SCA: a sine cosine algorithm for solving optimization problems. Knowl-Based Syst 96:120–133

Mirjalili S, Lewis A (2016) The whale optimization algorithm. Adv Eng Softw 95:51–67

Mirjalili S, Mirjalili SM, Lewis A (2014) Grey wolf optimizer. Adv Eng Softw 69:46–61

Mood SE, Ding M, Lin Z, Javidi MM (2021) Performance optimization of UAV-based IoT communications using a novel constrained gravitational search algorithm. Neural Comput Appl 1–12

Mousavi S, Afghah F, Ashdown JD, Turck K (2019) Use of a quantum genetic algorithm for coalition formation in large-scale UAV networks. Ad Hoc Netw 87:26–36

Pan Q, Tang J, Wang H, Li H, Chen X, Lao S (2021) SFSADE: an improved self-adaptive differential evolution algorithm with a shuffled frog-leaping strategy. Artif Intell Rev

Pérez-Carabaza S, Scherer J, Rinner B, López-Orozco JA, Besada-Portas E (2019) UAV trajectory optimization for Minimum Time Search with communication constraints and collision avoidance. Eng Appl Artif Intell 85:357–371

Pham Q-V, Huynh-The T, Alazab M, Zhao J, Hwang W-J (2020) Sum-rate maximization for UAV-assisted visible light communications using NOMA: swarm intelligence meets machine learning. IEEE Internet Things J 7:10375–10387

Phung MD, Ha QP (2021) Safety-enhanced UAV path planning with spherical vector-based particle swarm optimization. Appl Soft Comput 107:107376

Poli R, Kennedy J, Blackwell T (2007) Particle swarm optimization. Swarm Intell 1:33–57

Poudel S, Moh S (2021) Hybrid path planning for efficient data collection in UAV-aided WSNs for emergency applications. Sensors 21:2839

Qiu H, Duan H (2020) A multi-objective pigeon-inspired optimization approach to UAV distributed flocking among obstacles. Inf Sci 509:515–529

Qu C, Gai W, Zhang J, Zhong M (2020) A novel hybrid grey wolf optimizer algorithm for unmanned aerial vehicle (UAV) path planning. Knowl-Based Syst 194:105530

Radmanesh M, Kumar M, Sarim M (2018) Grey wolf optimization based sense and avoid algorithm in a Bayesian framework for multiple UAV path planning in an uncertain environment. Aerosp Sci Technol 77:168–179

Rashedi E, Nezamabadi-Pour H, Saryazdi S (2009) GSA: a gravitational search algorithm. Inf Sci 179:2232–2248

Schwarzrock J, Zacarias I, Bazzan AL, de Araujo Fernandes RQ, Moreira LH, Freitas (2018) Solving task allocation problem in multi unmanned aerial vehicles systems using swarm intelligence. Eng Appl Artif Intell 72:10–20

Shadravan S, Naji HR, Bardsiri VK (2019) The Sailfish optimizer: a novel nature-inspired metaheuristic algorithm for solving constrained engineering optimization problems. Eng Appl Artif Intell 80:20–34

Shaikh PW, El-Abd M, Khanafer M, Gao K (2020) A review on swarm intelligence and evolutionary algorithms for solving the traffic signal control problem. IEEE Trans Intell Transp Syst
Shao S, Peng Y, He C, Du Y (2020) Efficient path planning for UAV formation via comprehensively improved particle swarm optimization. ISA Trans 97:415–430
Skrzypecki S, Tarapata Z, Pierzchala D (2019) Combined PSO methods for UAVs swarm modelling and simulation. In: MESAS, pp 11–25
Sotoudeh-Anvari A, Hafezalkotob A (2018) A bibliography of metaheuristics-review from 2009 to 2015. Int J Knowl-Based Intell Eng Syst 22:83–95
Stolfi DH, Brust MR, Danoy G, Bouvry P (2021) A competitive predator-prey approach to enhance surveillance by UAV swarms. Appl Soft Comput 111:107701
Storn R, Price K (1997) Differential evolution–a simple and efficient heuristic for global optimization over continuous spaces. J Global Optim 11:341–359
Tan Y, Ding K (2015) A survey on GPU-based implementation of swarm intelligence algorithms. IEEE Trans Cybern 46:2028–2041
Tang J, Liu G, Pan Q (2021a) A review on representative swarm intelligence algorithms for solving optimization problems: applications and trends. IEEE/CAA J Automat Sin 8:1627–1643
Tang J, Lao SY, Wan Y (2021b) A systematic review of collision avoidance approaches for unmanned aerial vehicles. IEEE Syst J 1–12
Tang J, Liu G, Pan Q (2021c) Review on artificial intelligence techniques for improving representative air traffic management capability. J Syst Eng Electron 1–21
Tian G, Zhang L, Bai X, Wang B (2018) Real-time dynamic track planning of multi-UAV formation based on improved artificial bee colony algorithm. In: 2018 37th Chinese control conference (CCC), IEEE, pp 10055–10060
Tong B, Chen L, Duan H (2021) A path planning method for UAVs based on multi-objective pigeon-inspired optimisation and differential evolution. Int J Bio-Inspir Comput 17:105–112
Tsai PW, Pan JS, Liao BY, Chu SC (2009) Enhanced artificial bee colony optimization. Int J Innov Comput Inf Control 5:5081–5092
Wang Y, Cai Z, Zhang Q (2011) Differential evolution with composite trial vector generation strategies and control parameters. IEEE Trans Evol Comput 15:55–66
Wei Y, Qiqiang L (2004) Survey on particle swarm optimization algorithm. Eng Sci 5:87–94
Wu H, Li H, Xiao R, Liu J (2018) Modeling and simulation of dynamic ant colony's labor division for task allocation of UAV swarm. Physica A 491:127–141
Wu C, Huang X, Luo Y, Leng S (2020) An improved fast convergent artificial bee colony algorithm for unmanned aerial vehicle path planning in battlefield environment. In: IEEE 16th international conference on control & automation (ICCA), IEEE, pp 360–365
Xie Y, Han L, Dong X, Li Q, Ren Z (2021) Bio-inspired adaptive formation tracking control for swarm systems with application to UAV swarm systems. Neurocomputing 453:272–285
Xing B, Gao WJ (2014) Gravitational search algorithm. Springer, Berlin
Xu Y, Sun Z, Xue X, Gu W, Peng B (2020) A hybrid algorithm based on MOSFLA and GA for multi-UAVs plant protection task assignment and sequencing optimization. Appl Soft Comput 96:106623
Xu H, Jiang S, Zhang A (2021) Path planning for unmanned aerial vehicle using a mix-strategy-based gravitational search algorithm. IEEE Access 9:57033–57045
Xue J, Shen B (2020) A novel swarm intelligence optimization approach: sparrow search algorithm. Syst Sci Control Eng 8:22–34
Xue Y, Huang H, Ren S, He Z, Ran J (2020) Research on obstacle avoidance of UAV for optical cable route inspection. In: Journal of Physics: Conference Series, IOP Publishing, p 012059
Yadav A (2019a) AEFA: artificial electric field algorithm for global optimization. Swarm Evol Comput 48:93–108
Yadav A (2019b) AEFA: artificial electric field algorithm for global optimization. Swarm Evol Comput 48:93–108
Yampolskiy RV, El-Barkouky A (2011) Wisdom of artificial crowds algorithm for solving NP-hard problems. Int J Bio-Inspired Comput 3:358–369
Yang X-S (2010) A new metaheuristic bat-inspired algorithm. In: Nature inspired cooperative strategies for optimization (NICSO 2010), Springer, pp 65–74
Yang X-S, Deb S, Zhao Y-X, Fong S, He X (2018) Swarm intelligence: past, present and future. Soft Comput 22:5923–5933
Yang L, Yao H, Wang J, Jiang C, Benslimane A, Liu Y (2020) Multi-UAV-enabled load-balance mobile-edge computing for IoT networks. IEEE Internet Things J 7:6898–6908

Ye F, Chen J, Tian Y, Jiang T (2020) Cooperative multiple task assignment of heterogeneous UAVs using a modified genetic algorithm with multi-type-gene chromosome encoding strategy. J Intell Rob Syst 100:615–627
Yingxun W, Zhang T, Zhihao C, Jiang Z, Kun W (2020) Multi-UAV coordination control by chaotic grey wolf optimization based distributed MPC with event-triggered strategy. Chin J Aeronaut 33:2877–2897
Yu X, Li C, Zhou J (2020) A constrained differential evolution algorithm to solve UAV path planning in disaster scenarios. Knowl-Based Syst 204:106209
Yun Z, Peiyang Y, Jieyong Z, Lujun W (2018) Formation and adjustment of manned/unmanned combat aerial vehicle cooperative engagement system. J Syst Eng Electron 29:756–767
Zhang D, Xie G, Yu J, Wang L (2007) Adaptive task assignment for multiple mobile robots via swarm intelligence approach. Robot Auton Syst 55:572–588
Zhang LM, Dahlmann C, Zhang Y (2009) Human-inspired algorithms for continuous function optimization. In: IEEE international conference on intelligent computing and intelligent systems, pp 318–321
Zhang X, Duan H, Yang C (2014) Pigeon-inspired optimization approach to multiple UAVs formation reconfiguration controller design. In: Proceedings of 2014 IEEE Chinese guidance, navigation and control conference, IEEE, pp 2707–2712
Zhang Y, Hu B, Li J-W, Zhang J-D (2016) Heterogeneous multi-UAVs cooperative task assignment based on GSA-GA. In: 2016 IEEE international conference on aircraft utility systems (AUS), IEEE, pp 423–426
Zhang B, Sun X, Liu S, Deng X (2019) Adaptive differential evolution-based receding horizon control design for Multi-UAV formation reconfiguration. Int J Control Autom Syst 17:3009–3020
Zhang B, Sun X, Liu S, Deng X (2020) Adaptive differential evolution-based distributed model predictive control for multi-UAV formation flight. Int J Aeronaut Space Sci 21:538–548
Zhen X, Enze Z, Qingwei C (2020) Rotary unmanned aerial vehicles path planning in rough terrain based on multi-objective particle swarm optimization. J Syst Eng Electron 31:130–141
Zhou W, Liu Z, Li J, Xu X, Shen L (2021a) Multi-target tracking for unmanned aerial vehicle swarms using deep reinforcement learning. Neurocomputing 466:285–297
Zhou X, Gao F, Fang X, Lan Z (2021b) Improved bat algorithm for UAV path planning in three-dimensional space. IEEE Access 9:20100–20116