基于自适应变异的多目标鸽群优化的无人机目标搜索

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摘要: 无人机在搜索任务中起着关键的作用, 它能够在复杂环境中寻找到目标. 无人机搜索问题是一个相对复杂的多约束条件下的多目标优化问题. 大多数搜索算法不能满足搜索过程中高效率和低功耗的要求. 本文所采用的目标搜索方法是一种基于Agent路由和光传感器的解耦滚动时域方法. 为了优化目标搜索方法的参数, 本文提出一种基于Agent路由和光传感器的自适应变异多目标鸽群优化(AMMOPIO)算法. 利用自适应飞行机制可以获得较好的鸽群分布, 种群具有多样性和收敛性. 利用变异机制简化了鸽群优化算法中的模型, 提高了搜索效率. 实验仿真结果验证了所提出的AMMOPIO算法在目标搜索问题中的可行性和有效性.

关键词: 目标搜索; 多目标鸽群优化算法; 自适应飞行机制; 变异机制

引用格式: 霍梦真, 段海滨. 基于自适应变异的多目标鸽群优化的无人机目标搜索. 控制理论与应用, 2020, 37(3): 584 – 591

DOI: 10.7641/CTA.2019.80905

An adaptive mutant multi-objective pigeon-inspired optimization for unmanned aerial vehicle target search problem

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Abstract: Unmanned aerial vehicle (UAV) is an indispensable tool for search missions, which can help find targets in critical and complex environments. The search problem of UAVs is a rather intricate multiobjective optimization problem with multiple constraints under complicated conflict environment. Most search algorithms could not meet the requirements of high efficiency and low consumption in combat environment. The target search approach employed in this paper is a decoupling receding horizon approach based on the agent routing and optical sensor tasking. To optimize the parameters of the target search approach, an adaptive mutant multiobjective pigeon-inspired optimization (AMMOPIO) algorithm is proposed for agent routing and optical sensor tasking optimization of target search problem. The utilization of adaptive flight mechanism could obtain the distribution of pigeons with applicable diversity and convergence. The mutation mechanism is used to simplify the model of pigeon-inspired optimization (PIO) to improve the search efficiency. The experimental results validate the feasibility and effectiveness of the proposed AMMOPIO algorithm in target search problem.

Key words: target search; multi-objective pigeon-inspired optimization; adaptive flight mechanism; mutation mechanism

Citation: HUO Mengzhen, DUAN Haibin. An adaptive mutant multi-objective pigeon-inspired optimization for unmanned aerial vehicle target search problem. *Control Theory & Applications*, 2020, 37(3): 584 – 591

1 Introduction

The modern search theory was initially proposed to develop efficient search methods to find enemy marine vessels by Koopman[1], Stone[2] and others. Unmanned aerial vehicles (UAVs) are an indispensable tool for search and rescue of critical, time sensitive missions as they have the advantages of zero casualties, high-speed overload, good stealth performance, short operation time, and low life-cycle cost[3–4]. Search theory has been applied to many fields with great success, encompassing applications such as search and rescue missions, exploration, mining, medicine, and surveillance[5].

Early search theory focused on the allocation of search effort to areas within the search region while finding optimal search paths on these areas is intuitively with unconstrained searcher motion. If it is not that

Received 21 November 2018; accepted 7 August 2019.
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Recommended by Associate Editor: FENG Zu-ren.
Supported by the National Natural Science Foundation of China (91648205).

case, the search problem of finding the optimal paths would become more complicate for searchers. At present, some studies of the search problem as an optimal control problem are conducted in continuous time and space[6], which are generally applied to a very restricted set of initial target distribution. There are many different approaches to solve this problem. Zhang et.al[7] presented a probabilistic path planning method for target search to reduce the expected-time cost in uncertain environments. Tang et.al[8] addressed an improved grouping strategy based on constriction factors particle swarm optimization for multiple targets search in unknown environments. Chen and Chang[9] proposed an agent-based simulation for multi-UAVs coordinative sensing. Sun and Duan[10] presented a restricted-direction target search approach based on coupled routing and optical sensor tasking optimization. To simplify the optimization problem, Qiu and Duan[3] addressed a decoupling receding horizon search approach to agent routing and optical sensor tasking, which was employed in this paper.

In the search problem, a single UAV aims to search for several targets in a bounded planar region. The agent is equipped with a gimbaled optical sensor that can be steered around to view a limited area of the search region[10]. The optical sensor will collect information about the environment in the form of automatic target recognition (ATR) data and determine whether the target is located at the specific region or not. The problem mentioned above can be turned into an multi-objective optimization problem (MOP) by selecting the approximate controlling means and mathematical model.

In order to solve MOPs, multi-objective evolutionary algorithms (MOEAs) has been becoming one of the major research topics during recent years. Among the evolutionary algorithms (EAs), pigeon-inspired optimization (PIO) is a novel swarm intelligence algorithm based on the behavior of homing pigeons, invented by Duan and Qiao[11]. Due to the high convergence speed and ease of implementation, PIO algorithm has been applied in many fields such as neural network[12], path planning[13], and so on. However, PIO is easy to be trapped into local optimum and uneven distribution while dealing with complex multi-objective problems. Therefore, this paper presents an improved multi-objective pigeon-inspired optimization algorithm based on the adaptive flight mechanism and mutation mechanism. These two mechanisms are designed to reinitialize the pigeons to improve the search capability of the algorithm and prevent pigeons from falling into local optimum and premature convergence.

The remainder of this paper is organized as follows. Section 2 describes the problem formulation, covering the model description, the design of the multi-objective optimization cost function, and the search approach. Section 3 illustrates the improved MOPIO algorithm. Simulation validation, together with comparison against the traditional approach, is presented in Section 4. Section 5 provides conclusions and some possible paths for future work.

2 Search problem

A single UAV is considered to be tasked with exploring an area of interest in order to search multiple targets in a bounded planar region. The UAV is equipped with a gimbaled optical sensor, which can be steered around to view a limited area of the search region.

This section formulates the target search problem as a discrete-time optimization and the approach that controls the UAV and the optical sensor to find the targets as soon as possible.

2.1 UAV dynamics and sensor model

Denote the controlled variables of a UAV at time k by the velocity $v(k)$ and the heading angle $\theta(k)$,where k is a discrete time variable belonging to the nonnegative integers. Without loss of generality, we assume that the UAV keeps the fixed flight height while performing a search task. Thus, the kinematic equation of the search agent can be expressed as the following discrete time point-mass kinematics model:

$$p(k+1,1) = p(k,1) + v(k) \cdot \sin(\theta(k)). \tag{1}$$

$$p(k+1,2) = p(k,2) + v(k) \cdot \cos(\theta(k)). \tag{2}$$

where $p(k+1,1)$ denotes the horizontal axis in absolute coordinate system of the next current position, $p(k+1,2)$ denotes the vertical axis in absolute coordinate system of the next current position. Due to the maneuverability limitations of the UAV, the velocity has a limited range $[v_{\min}, v_{\max}]$ and the $\Delta\theta$ between two consecutive moments is subject to the minimum turning radius $R_{\min}$. Velocity $v(k)$ together with the turning radius $R_{\min}$ describes the mobility and determines the flight trajectory of the UAV.

During the search process, the region that a sensor can view at a certain moment is called the field of view (FOV), and the subset of the search region viewable by the sensor as it is swept through its entire range of motion is called the sensor's field of regard (FOR)[10]. For each candidate path, the position of UAV can be defined as $p(k) = [x(k), y(k)]$, where $p(k)$ is the waypoint at time k. As shown in the Fig. 1, FOR is considered as the rectangle that takes the current waypoint $p(k)$ as center. FOV is set as a square, whose center can move along the centerline of the rectangle. The center of FOV is stated as the sensor task $q(k)$ that specifies the stare point where the agent will point its optical sensor at time k. Thus, the search problem has been transferred into the problem to obtain the next waypoint $p(k+1)$ and the sensor task $q(k)$.

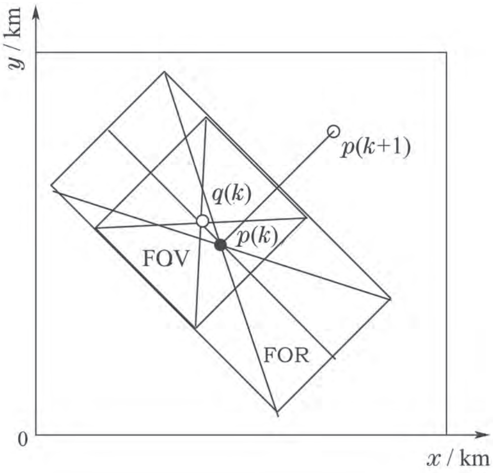

Fig. 1 Diagram of the sensor model

2.2 Search map

The graph-based model method is employed to depict the environment information in allusion to searching process. The search region is divided into $M \times N$ cells. The coordinate of each two-dimension discrete cell is denoted as (x, y), $x \in \{1, 2, \cdots, M\}$, $y \in \{1, 2, \cdots, N\}$. For the convenience of the following exposition, the cells are numbered by the following equation in a sequence as $m \in \{1, 2, \cdots, M \times N\}$:

$$m = x + (y-1) \times M. \tag{3}$$

Denote the information structure of each cell as $\boldsymbol{I}_m(k)$, including the target occupancy probability $\rho_m(k)$ that describes the probability that the search targets exist in the $m_{\rm th}$ cell at time k and the environment certainty $\chi_m(k)$ that describes the certainty of the $m_{\rm th}$ cell for the UAV. $\boldsymbol{I}_m(k)$ can be stated as follow:

$$\boldsymbol{I}_m(k) = [\rho_m(k) \ \ \chi_m(k)], \tag{4}$$

where $\rho_m(k) \in [0, 1]$ and $\chi_m(k) \in [0, 1]$. If the target exists in the $m_{\rm th}$ cell, $\rho_m(k) = 1$; On the contrary, $\rho_m(k) = 0$ while there is no target in the $m_{\rm th}$ cell. Similarly, if the UAV fully understands the environment information, $\chi_m(k) = 1$; On the contrary, $\chi_m(k) = 0$ while the UAV knows nothing about the information in the cell.

Consider there exist n targets in the search region whose initial positions are unknown. It is reasonable to assume that the position of the target is uniformly distributed. Thus, we can obtain the following equations:

$$\begin{cases} \rho_m^i(0) = \dfrac{1}{M \times N}, \\ \chi_m^i(0) = 0, \end{cases} \tag{5}$$

where $m \in \{1, 2, \cdots, M \times N\}$ and $i \in \{1, 2, \cdots, n\}$.

During the dynamic search, the search map at time $k+1$ is updated dynamically based on the state of the agent and the detection results of the sensor at time constantly. The updating principle of the $\rho_m^i(k+1)$ is stated as follows:

Case 1 The $i_{\rm th}$ target is detected:

$$\begin{cases} \rho_m^i(k+1) = \rho_m^i(k), \ m \in \text{FOV}, \\ \rho_m^i(k+1) = 0, \qquad m \notin \text{FOV}. \end{cases} \tag{6}$$

Case 2 The $i_{\rm th}$ target is not detected:

$$\begin{cases} \rho_m^i(k+1) = 0, \qquad m \in \text{FOV} \\ \rho_m^i(k+1) = \rho_m^i(k), \ m \notin \text{FOV}. \end{cases} \tag{7}$$

The updating principle of the $\chi_m^i(k+1)$ is stated as follows:

$$\begin{cases} \chi_m^i(k+1) = 1, \qquad m \in \text{FOV} \\ \chi_m^i(k+1) = \chi_m^i(k), \ m \notin \text{FOV}. \end{cases} \tag{8}$$

2.3 Cost function

The search problem of the UAV is a rather intricate multi-objective optimization problem. It is crucial to select the multi-objective cost functions associated with each candidate path. The introduction of the set of cost functions are shown below:

F_1 describes the probability of finding target on the candidate path under the action of the control $v(k)$ and $\theta(k)$.

F_2 describes the entire environment certainty for agent which could be increased by probing the region unknown away from the cells with $\chi_m(k) = 1$.

F_3 describes the time cost or fuel cost between two continuous waypoints.

F_4 reflects the behavior of avoiding the threating regions composed of natural threats, missiles threats, and no-fly zone. The value of this function represents the cost to be paid by the drone crossing the threat zone.

F_5 is designed to estimate whether the trajectory of UAV is within the limited search region.

The better results of search task require larger value of cost functions F_1, F_2, F_3 and lower value of cost functions F_4, F_5. Therefore, to unify the optimization, we adopt the inverse value of cost functions F_1, F_2 and F_3.

2.4 Receding horizon control search approach

The receding horizon control (RHC) search approach with the advantage of online processing constraints on control input and output could describe the control problem as a constrained optimization problem of finite time[14]. The primary steps of the RHC search controller are as follows:

Step 1 Initialize the agent waypoint p_0 at time k, optimize five cost functions based on the search map information and obtain a set of the optimal control variables $v(k)$ and $\theta(k)$ in N steps;

Step 2 Choose the first item of control variables as the agent RHC inputs and abandon the others;

Step 3 Reach the next waypoint p_1 at next time $(k+1)$ by the control inputs;

Step 4 Obtain the search result by sensor at waypoint p_1 and update the search map information structure $\boldsymbol{I}_m(k)$;

Step 5 Update the current time and the agent waypoint as initial value, return to Step 1.

The whole process of RHC search approach is illustrated in Fig. 2.

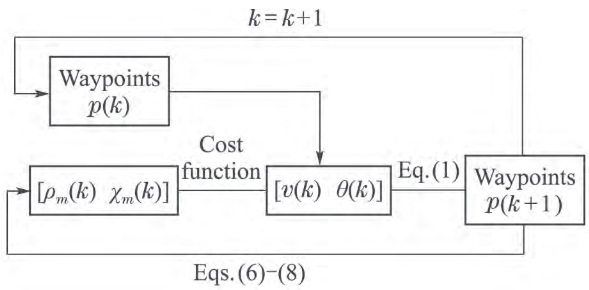

Fig. 2 Process of RHC search approach

3 Search problem

Pigeon-inspired optimization is a population-based bio-inspired swarm intelligence optimization algorithm based on the special navigation behavior of the homing pigeons. In this algorithm, two operators (map and compass operator, landmark operator) are employed to guide the pigeons to find the destination. When pigeons start their journey, they may rely more on compass-like tools. While in the middle of their journey, they could switch to using landmarks when they need to reassess their route and make corrections[11]. Due to the imperfection of the basic multi-objective pigeon-inspired optimization algorithm[16], two mechanisms are employed to strengthen the capability of global exploration and local exploitation.

3.1 Main algorithm

The basic PIO algorithm adopts two independent useful cycles to mimic the characteristics of the homing pigeons. To improve the efficiency of the optimization process, the two cycles are integrated to one main cycle using two adaptive flight parameters k_1 and k_2. The velocity $\boldsymbol{V}_i$ and position $\boldsymbol{X}_i$ of each pigeon at time $t+1$ are updated according to the following equations:

$$\begin{aligned}&\boldsymbol{V}_i(t+1)=\\&\mathrm{e}^{-Rt}\cdot\boldsymbol{V}_i(t)+k_1\cdot(\boldsymbol{X}_{\mathrm{gbest},i}(t)-\boldsymbol{X}_i(t))+\\&k_2\cdot(\boldsymbol{X}_{\mathrm{center}}(t)-\boldsymbol{X}_i(t)),\end{aligned}\tag{9}$$

$$\boldsymbol{X}_i(t+1)=\boldsymbol{X}_i(t)+\boldsymbol{V}_i(t+1),\tag{10}$$

where R is map and compass factor, t is the time of iteration, i is the number of pigeons in the swarm and $i\in\{1,2,\cdots,N\}$, $\boldsymbol{X}_{\mathrm{gbest},i}$ represents the best position in the flight path of the pigeon. $\boldsymbol{X}_{\mathrm{center}}$ is the center of the pigeon's position used as the reference direction during the last period of flight. The adaptive flight parameters and center position $\boldsymbol{X}_{\mathrm{center}}$ are obtained by the following mechanisms.

3.2 Adaptive flight mechanism

In the flight process of pigeons, the balance of the $\boldsymbol{V}(t)$, $\boldsymbol{X}_{\mathrm{gbest}}$, and $\boldsymbol{X}_{\mathrm{center}}$ is crucial to the tradeoff between the exploration and exploitation for the evolutionary properties, such as convergence, diversity, and optimal solution. There exist some challenges on the optimization of the flight parameters. Thus, the adaptive flight mechanism is proposed in this paper to balance the global exploration with local exploitation by utilizing the diversity information and population SP information[17]. The calculation of the population SP information of the i_{th} pigeon at $(t+1)$ iteration is shown below:

$$\mathrm{SP}(t+1)=\sqrt{\frac{\sum\limits_{i=1}^{N}(\bar{d}(t+1)-d_i(t+1))^2}{N-1}},\tag{11}$$

where $d_i(t+1)$ is the minimum Manhattan distance between the position of the i_{th} pigeon and other pigeons, $\bar{d}(t+1)$ represents the average value of the $d_i(t+1)$ for all pigeons. During the optimization process, the pigeons are with nonlinear characteristics intricately [15]. Thus, a special nonlinear function is proposed to describe this process:

$$\varGamma(t+1)=\mathrm{e}^{1/(\mathrm{SP}(t+1)+1)-1},\tag{12}$$

where $\varGamma(t+1)$ is the adaptive nonlinear function of the flight process. The initial values of adaptive flight parameters are random numbers created according to the uniform distribution. Considering the value of $\varGamma(t+1)$, the adaptive flight parameters are updated as follows:

Case 1 $\mathrm{SP}(t+1)=\mathrm{SP}(t)$:

$$\begin{cases}k_1(t+1)=k_1(t)\\k_2(t+1)=k_2(t).\end{cases}\tag{13}$$

Case 2 $\mathrm{SP}(t+1)>\mathrm{SP}(t)$:

$$\begin{cases} k_1(t+1) = k_1(t) \cdot (\Gamma(t+1)+1), \\ k_2(t+1) = k_2(t) \cdot \Gamma(t+1). \end{cases} \tag{14}$$

Case 3 $\mathrm{SP}(t+1) < \mathrm{SP}(t)$:

$$\begin{cases} k_1(t+1) = k_1(t) \cdot \Gamma(t+1), \\ k_2(t+1) = k_2(t) \cdot (\Gamma(t+1)+1). \end{cases} \tag{15}$$

The variation of the population SP information reflects the distribution of the pigeon flock. That is to say, the increasing value of SP means the inhomogeneity of the pigeon flock, and the decreasing value of SP means the suitable distribution of the pigeon flock.

At the beginning of the optimization, the solutions obtained are far from the true Pareto fronts (PF) with uneven distribution. Based on the above equations, we can see that the parameter k_1 becomes larger to increase the diversity of the pigeon flock and enhances the exploration ability. During the second half of the optimization, large number of the non-dominated solutions close to the PF are obtained and distributed more evenly. Thus, the parameter k_2 gets larger to improve the exploitation ability.

As the parameter k_1 increases, the searching process of the optimization mainly depends on the $\boldsymbol{X}_{\mathrm{gbest}}$. While the parameter k_2 rises, the center position $\boldsymbol{X}_{\mathrm{center}}$ plays a major role in the searching process. This demonstrates that the optimization process of the improved MOPIO algorithm corresponds to the navigation mechanism of the pigeon flocks, which illustrates the rationality of the adaptive flight mechanism.

3.3 Mutation mechanism

The center position $\boldsymbol{X}_{\mathrm{center}}$ of the PIO algorithm is calculated by following:

$$\boldsymbol{X}_{\mathrm{center}}(t) = \frac{\sum_{i=1}^{N} \boldsymbol{X}_i(t) \cdot \mathrm{fitness}(\boldsymbol{X}_i(t))}{N \cdot \sum_{i=1}^{N} \mathrm{fitness}(\boldsymbol{X}_i(t))}. \tag{16}$$

The fitness is the function to be optimized:

$$N(t) = \mathrm{ceil}(\frac{N(t-1)}{2}), \tag{17}$$

$$\begin{cases} \mathrm{fitness}(\boldsymbol{X}_i(t)) = f_{\max}(\boldsymbol{X}_i(t)), & \text{Case 1}, \\ \mathrm{fitness}(\boldsymbol{X}_i(t)) = \dfrac{1}{f_{\min}(\boldsymbol{X}_i(t)) + \epsilon}, & \text{Case 2}, \end{cases} \tag{18}$$

where Case 1 represents the maximization problem, Case 2 represents the minimization problem.

Due to the single cost function, there exists the single maximum or minimum value of the function. However, in the multi-objective optimization problems, there exist multiple cost functions. And a single solution which can find the maximum or minimum value for all the objectives at the same time does not exist. Thus, a mutation mechanism is developed to generate the center position $\boldsymbol{X}_{\mathrm{center}}$ in the multi-objective optimization problems.

Firstly, restore the nondominated solutions in the repository. Then, choose one solution $\boldsymbol{X}_{\mathrm{rep}}$ in the repository randomly and employ the mutation mechanism to improve the chosen solution based on the step mutation operator in Eqs. (19)–(21):

$$\boldsymbol{X}_{\mathrm{center}}(t, j) = \boldsymbol{X}_{\mathrm{rep}}(j) + \Delta d \cdot (ub - lb), \tag{19}$$

$$\Delta d = \mathrm{sum}(\frac{a(k)}{2^k}), \tag{20}$$

$$\begin{cases} a(k) = 0, \ \mathrm{rand} < 1/m, \\ a(k) = 1, \ \mathrm{rand} \geqslant 1/m, \end{cases} \tag{21}$$

where m is the mutation operator and $k = 0, 1, \cdots, m$.

The chosen solution is expanded in D dimensions respectively. While the solution with certain dimension j mutated could obtain the better function value, then the j_{th} dimension of $\boldsymbol{X}_{\mathrm{center}}$ is updated. The pseudocode of mutation mechanism is introduced in following steps:

Step 1 Initialize the flight parameters, population size, repository size, map and compass operator, mutation operator, and maximal iterations.

Step 2 Initialize the position $\boldsymbol{X}(0)$ and velocity $\boldsymbol{V}(0)$ of the pigeon flock.

Loop.

Step 3 Calculate the value of cost functions.

Step 4 Obtain the non-dominated solutions and store the non-dominated solutions in repository.

Step 5 Select one solution $\boldsymbol{X}_{\mathrm{rep}}$ randomly in repository, use the mutation mechanism Eq. (19).

Step 6 Calculate the population SP information of the pigeons Eq.(11).

Step 7 Calculate two flight parameters Eqs. (13)–(15).

Step 8 Update the position and velocity Eqs. (9)–(10).

End loop.

4 Simulation results

The receding horizon control search approach is utilized to solve the search problem and the AMMOPIO algorithm is designed to optimize the parameters of RHC search approach. The holistic search process is depicted in Fig. 3.

In the simulation, suppose there is a single UAV agent searching for three stationary targets whose positions are unknow in the bounded planar region. The UAV is expected to search the targets as many as possible in the shortest time with multiple goals, consisting of improving the certainty of environment, reducing fuel cost, avoiding the threats, and staying in the task search region.

The sampling time is set to be 20 s, and 30 RHC circles are conducted in one simulation. In one single circle, the AMMOPIO algorithm runs 100 times. The parameters and constraints of the simulation are shown in Table 1. The initial states are shown in Table 2. The control parameters of AMMOPIO are given in Table 3.

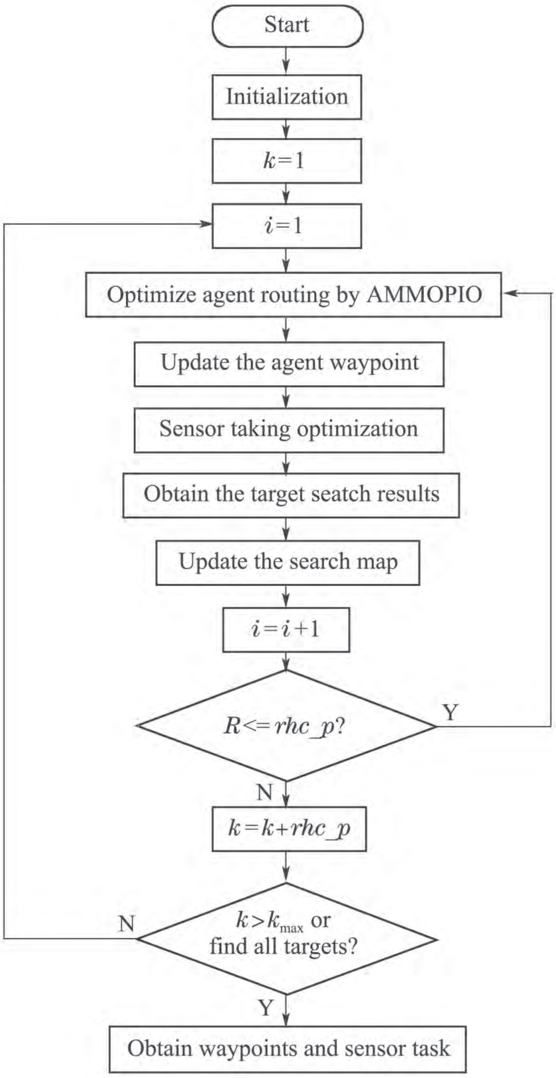

Fig. 3 Process of target search

Table 1 Optimization parameters and constraints

Variables	Description	Value
$v/(\mathrm{km}\cdot\mathrm{s}^{-1})$	The UAV velocity	$[\frac{L_{\min}}{ts},\ 0.2]$
ϕ/rad	The heading angular velocity	$\Delta\phi_{\max}$
T	Simulation time	600 s
t/s	Sampling time	20 s
rhc_p	Length of the prediction horizon	3
rhc_m	Length of the control horizon	3
R	Bounded planar region	$[0,60]^2$
M	The row number	60
N	The column number	60
$R_{\min}$/km	The minimum turning radius	3
$L_{\min}$/km	The shortest direct flight distance	3

Table 2 Initial states

Variables	Description	Value
p/km	The position of UAV	$[5,0]$
ϕ/rad	The heading angle	0
P_t/km	The position of targets	$\{[40,25],\ [30,45],\ [20,10]\}$

Table 3 Control parameters of AMMOPIO algorithm

Variables	Description	Value
$T_{\max}$	Maximum number of the iteration	100
N	Number of the pigeon flock	100
R	The map and compass operator	0.2
m	The mutation operator	20

The performances of the AMMOPIO algorithm are compared with the basic MOPIO algorithm and other two state-of-the-art methods, including multiobjective particle swarm optimization (MOPSO) and multi-objective brain storm optimization (MOBSO). The basic MOPIO algorithms is composed of two cycles and the center position $\boldsymbol{X}_{\mathrm{center}}$ is randomly selected in the non-dominated solutions without mutation mechanism. The best results of four algorithms in 20 simulation cycles are illustrated in Figs. 4–7.

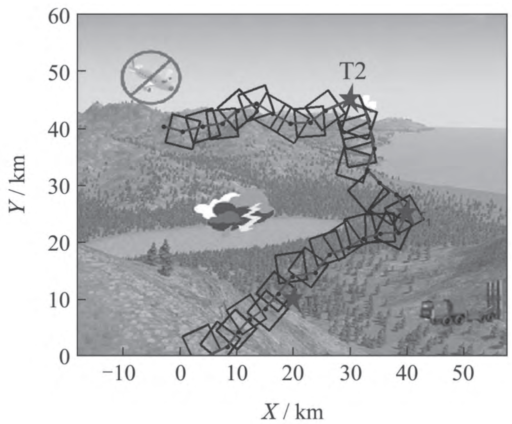

Fig. 4 Search results of AMMOPIO algorithm

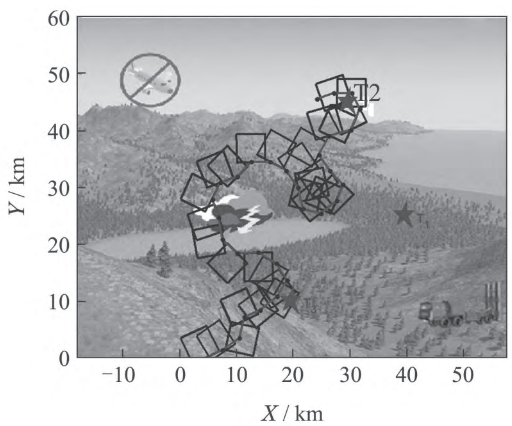

Fig. 5 Search results of MOPIO algorithm

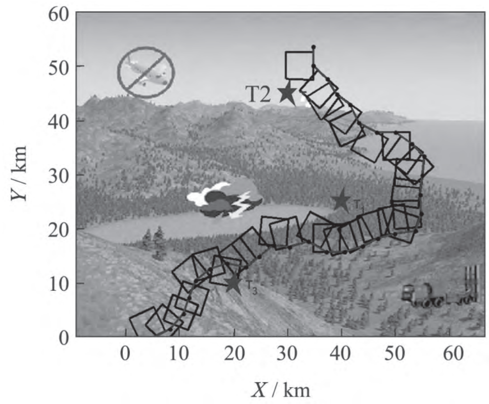

Fig. 6 Search results of MOPSO algorithm

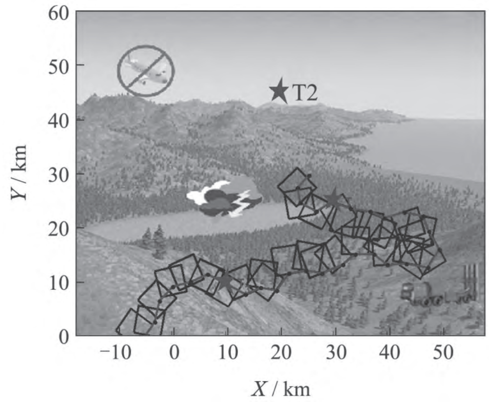

Fig. 7 Search results of MOBSO algorithm

Table 4 Statistic data of four algorithms

Algorithm	n_{ave}	t_{ave}
AMMOPIO	1.95	33.75
MOPIO	0.65	6.073
MOPSO	1.05	117.2
MOBSO	1.06	587.9

In Fig. 4, three signal represents the threat region, respectively, no-fly zones, bad weather region, and missiles threat. T1–T3 denotes three stationary targets to be found. The red short lines between the adjacent dots are the paths of the UAV. The blue squares are FOV. The average number of the targets n_{ave} found in 20 simulation cycles is recorded in Table 5 and the t_{ave} represents the average running time of the simulations.

Observed that the agent in Fig. 4 found three stationary targets, while successfully avoiding the threats and remaining in the search task region. On the contrary, the results in the Figs. 5–7 show that the agent could only find two of the three targets with winding flight path in the simulation. Compared with other three algorithms, the AMMOPIO method gives a good performance in less valid paths.

The statistic data in Table 5 illustrates that the search target optimization with AMMOPIO algorithm could find more than double targets compared with the basic MOPIO algorithm although more time is needed. The MOPSO and MOBSO approaches could only find one target approximately in much more simulation time in contrast to the AMMOPIO algorithm. The average number of the targets could reflect the stability of the algorithms. The statistic data shows the feasibility of our proposed algorithm in the practical environment.

As we can see in the results above, our proposed AMMOPIO algorithm could find most targets in the finite time. It could be estimated that it could find more targets as there are more than three targets. Therefore, it is clearly that the performance of AMMOPIO algorithm is superior to other three methods. Contrast to the algorithm in [3], this paper employed the multi-objective optimization algorithm to solve the target finding problem. That is to consider all requirements simultaneously rather than scaling down the value of requirements. Even though there is a gap between the number of targets found and the number of targets existing, a preliminary evaluation can be still given that the optimization purposes of searching targets has a basic implementation.

5 Conclusion

This paper presented an AMMOPIO algorithm for the optimization of target search problem. The adaptive flight mechanism could improve the distribution of pigeons with applicable diversity and convergence. The mutation mechanism is used to simplify the model of PIO to improve the search efficiency. From the comparative results in simulation, it can be concluded that our proposed AMMOPIO algorithm does perform superiority in the number of targets found and the time taken to find targets compared with other three approaches. We will also develop more theoretical research on multi-objective optimizations to enhance the ability of unmanned system in the process of performing missions.

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