Improved GWO Algorithm for UAV Path Planning on Crop Pest Monitoring

Qun Ding[1], Xiaolong Xu[2]*

[1] Jiangsu Key Laboratory of Big Data Security and Intelligent Processing, Nanjing University of Posts and Telecommunications, Nanjing (China)
[2] School of Computer Science, Nanjing University of Posts and Telecommunications, Nanjing (China)

Received 1 December 2021 | Accepted 3 June 2022 | Published 12 July 2022

Abstract

Agricultural information monitoring is the monitoring of the agricultural production process, and its task is to monitor the growth process of major crops systematically. When assessing the pest situation of crops in this process, the traditional satellite monitoring method has the defects of poor real-time and high operating cost, whereas the pest monitoring through Unmanned Aerial Vehicles (UAVs) effectively solves the above problems, so this method is widely used. An important key issue involved in monitoring technology is path planning. In this paper, we proposed an Improved Grey Wolf Optimization algorithm, IGWO, to realize the flight path planning of UAV in crop pest monitoring. A map environment model is simulated, and information traversal is performed, then the search of feasible paths for UAV flight is carried out by the Grey Wolf Optimization algorithm (GWO). However, the algorithm search process has the defect of falling into local optimum which leading to path planning failure. To avoid such a situation, we introduced the probabilistic leap mechanism of the Simulated Annealing algorithm (SA). Besides, the convergence factor is modified with an exponential decay mode for improving the convergence rate of the algorithm. Compared with the GWO algorithm, IGWO has the 8.3%, 16.7%, 28.6% and 39.6% lower total cost of path distance on map models with precision of 15, 20, 25 and 30 respectively, and also has better path planning results in contrast to other swarm intelligence algorithms.

Keywords

Grey Wolf Optimization Algorithm, Path Planning, Pest Monitoring, Simulated Annealing Algorithm, Unmanned Aerial Vehicle.

DOI: 10.9781/ijimai.2022.07.002

I. Introduction

As an aerial vehicle with an independent power system, UAVs (Unmanned Aerial Vehicles) are capable of carrying out various monitoring and exclusion tasks in different environments with a variety of mission equipment. Unmanned Aerial Vehicle, is also called drone, affected by the service demand and business model of various modern industries, has become one of the most promising and fastest-growing industries after decades of development. UAV is more and more relevant to daily life. At present, the main application fields and directions of UAV are agriculture and animal husbandry, electric power, forest fire prevention, military, border defense and so on. As the technology advances rapidly, such as UAV express service and UAV security inspection, these applications are gradually becoming practical as well. In addition, the rise of UAV performance, a more environmentally friendly and free performance form, has replaced the traditional fireworks performance. The market potential of UAV is being tapped. With the miniaturization of UAV's technical characteristics, the battery that UAV could carry is always limited, so the path planning of UAV during flight is a key problem. in modern agriculture, whose application is rapidly expanding for crop drug spraying, pest monitoring, etc. When conducting crop pest monitoring, UAVs patrol over farmland and monitor by using the crop analysis equipment carried. Limited by the shortage of UAVs in terms of endurance and load capacity, UAVs are often required for path planning when assessing the growth status of crops. Previous research has provided a series of traditional path planning algorithms such as the A star algorithm [1] based on direct search for solving shortest paths in static nets, artificial potential field method [2] who simulates the feedback control mechanism of gravitational potential field action, or the Voronoi diagram method [3], visibility-based diagram method [4] and rapid search random tree method (RRT) [5] and so on, which have rapidly advanced the technical development of UAV path planning. However, the traditional planning methods have some unsolvable drawbacks, slow convergence speed and inability to handle high-dimensional space, greatly limiting the path planning of UAVs in complex environments. In contrast, swarm intelligence methods can find global optimal solutions with better convergence in a more complex objective space, so the research of swarm intelligence algorithms is in rapid development. Misra [6] and others used Genetic Algorithm and Particle Swarm Optimization algorithm to find the best path with highly dynamic nature and compared the state space generated between cost functions; Santiago [7] and others used Genetic Algorithm for collision-free navigation in node-connected networks. Since 2014, related scholars proposed the Grey Wolf Optimization algorithm by simulating the hierarchy and hunting pattern of the grey wolf population [8], the algorithm has been applied to a wide range of fields and has been studied and improved by many scholars. Ghorpade

* Corresponding author.

E-mail address: xuxl@njupt.edu.cn

et al. [9] designed a multi-objective grey wolf optimization constraint considering the objective function as a topological constraint of distance and geometry, Ge et al. [10] introduced the algorithmic mechanism of Fruit Fly local optimization to regulate the generation of optimal paths. Guo et al. [11] added an individual learning strategy to the standard Grey Wolf Optimization algorithm to balance the exploration and development capabilities of the algorithm. Gu et al. [12] used a trivial nonlinear change function to converge the objective search of the Grey Wolf Optimization algorithm. While another swarm intelligence algorithm achieves the optimal solution search by simulating the principle of solid cooling, i.e., the Simulated Annealing algorithm [13]. Li et al. [14] evaluated the flight control of UAVs over a large range based on Simulated Annealing algorithm, and Hassan et al. [15] collected and analyzed the sensor information of multiple UAVs in the environment by Simulated Annealing algorithm.

It is easy to fall into local optimum when there are many feasible solutions in the solution space by general iterative methods facing with planning scenes, while the Genetic Algorithm seeks the optimal solution by imitating the selection and genetic mechanism in nature, which effectively avoids this problem. However, it takes more time for Genetic Algorithm to get a more accurate solution depending on parameters such as crossover rate and mutation rate, which will greatly increase the risk that may be caused by feedback delay in the flight of UAV. The Simulated Annealing algorithm is optimized by simulating the molecular movement when the solid is cooled down, which has strong global searching ability. This method has similar shortcomings to Genetic Algorithm, the searching ability affected by the cooling rate of temperature will take a long time to find a better solution to the problem. Considering the Grey Wolf Optimization algorithm, the strict strategy of obeying the group rank makes its convergence performance better, but getting a better solution quickly will also increase the risk of the algorithm falling into local optimum.

In view of the above research, in order to balance the global search ability and convergence speed, avoid the algorithm falling into local optimum prematurely, which will lead to the failure of path planning and affect the flight stability of UAV, and at the same time plan a better flight route. In this paper, an Improved Grey Wolf Optimization algorithm (IGWO) is proposed to solve this problem. At the same time, the slow convergence speed in the later period of the algorithm itself is adjusted by increasing the convergence coefficient.

The main contributions of this work are as follows:

(1) In this paper, the path planning problem of UAVs in a multi-obstacle environment is abstracted into a multi-constrained objective planning problem in the context of crop pest monitoring and solved by the Grey Wolf Optimization algorithm.

(2) An improved Grey Wolf Optimization algorithm is proposed to with the Simulate Annealing algorithm which has the sudden leap probabilistically to ensure that the UAV can find the optimal path to a predetermined location.

(3) The effectiveness of the improved algorithm is demonstrated by comparing the Grey Wolf Optimization algorithm, the Simulated Annealing algorithm and the Genetic Algorithm through the designed experiments.

The structure of this paper is as follows: Section II of this paper makes theoretical analysis, establishes the environment model and transforms the UAV path planning problem into a constrained optimization problem, then the next part of this section explores the mechanism of the GWO algorithm and the IGWO algorithm. Section III analyzes the feasibility of its improvement; Section IV gives the relevant results and comparisons of simulation experiments, and concludes in Section V.

II. Methods

A. Preliminaries

For the problem of UAV path planning on crop pest monitoring proposed in this paper, first of all, it is necessary to analyze the problem and establish a model. This problem is essentially a planning constraint problem, which constrains the flight path of UAV to conform to a certain flight trajectory. Therefore, it is necessary to model the flight map of UAV. Secondly, the planning problem is transformed into an optimization problem. In a certain space range, the best flight path of UAV can be found by some methods, which is described by mathematical language, that is, finding a set of optimal solutions in a certain solution space, attaching a certain amount of constraints at the same time.

After the completion of modeling, effective methods and ideas can solve the above problems excellently. In the existing methods, there are some shortcomings, such as the low search rate of GA algorithm and SA algorithm, the problem that the GWO algorithm is easy to fall into local optimum. Therefore, a method to balance search results and search rate is worthy of being proposed. Considering the efficient structure of GWO algorithm and the easy scalability of SA algorithm, it is possible to introduce the structure of SA algorithm into GWO algorithm mechanism. Based on the complex algorithm structure and excellent global searching ability of GA algorithm. Therefore, in the subsequent experiments, it is compared with the original GWO algorithm and SA algorithm as the proposed algorithm for reference analysis.

B. Path Planning Strategies

1. Environment Modeling

The UAV in the crop monitoring [16] not only follows a certain route to cover the target point, but also need to avoid trees, buildings and other obstacles, usually in the flight process, the UAV will have an over-the-horizon area, so the use of relay equipment on the signal tower to establish a communication link for data communication to solve the signal attenuation and interference problems arising from the excessive distance and obstacle blockage, the UAV containing the task crop pest monitoring is shown in Fig. 1. When the UAV is close to the ground vehicle-mounted terminal, the UAV establishes a communication link directly with the terminal; when the flight range is expanded and the distance becomes long, the signal relay is relayed through the relay equipment on the signal tower to establish a communication link.

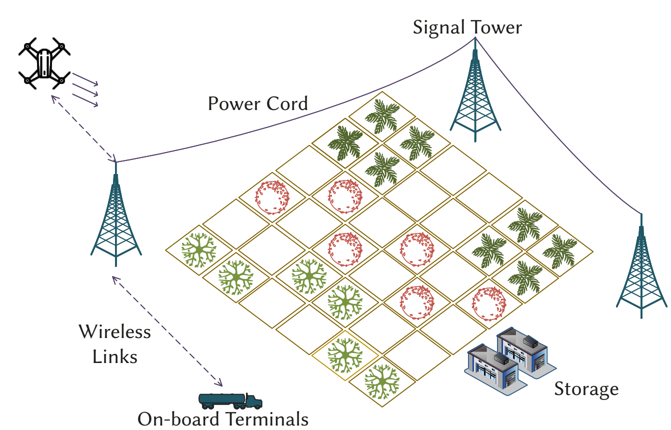


Fig. 1. Crop pest monitoring by UAV in farmland.

In the monitoring process, the UAV flight path is planned, and the first work to be completed before the UAV path planning is the modeling of the environment. In the path planning problem, avoiding obstacles is the benchmark element for the optimized path [17]. In practice, buildings, trees and various facilities in the environment can be considered as obstacle factors on the way of the UAV. In this study, the UAV inspection environment area is defined by the raster method [18], specifying the starting and ending points and quantifying the real obstacles to reduce errors, as shown in Fig. 2. Assuming that the UAV is a particle in the established map environment, the path planning algorithm is used to calculate the best path from the starting point to the end point while avoiding all obstacles.

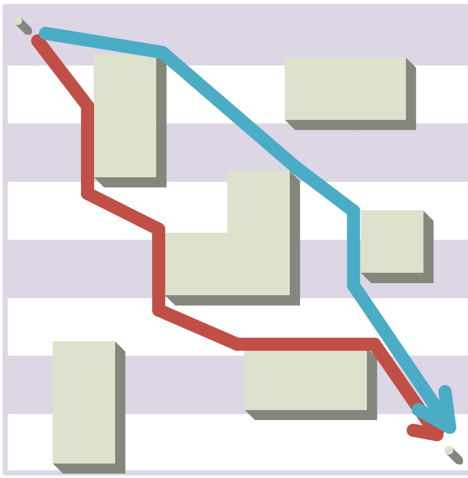


Fig. 2. Rasterized monitoring map by UAV.

The coordinates of the starting point and the end point of the UAV flight are defined as (x_l, y_l) and (x_r, y_c). The r values of $(x_1, x_2, x_3, ..., x_r)$ in the x-axis range correspond to the c values of $(y_1, y_2, y_3, ..., y_c)$ in the y-axis range to form r*c path points. Define the raster map precision as G. Equation in (1) and Equation in (2) define the mapping relationship between each raster coordinate (x_n, y_n) and raster number N in the map(*INT* is defined as rounding operation).

$$x_n = \left(N\% \frac{x_r}{G}\right) * G \tag{1}$$

$$y_n = INT\left(N/\frac{x_r}{G}\right) * G + \frac{G}{2} \tag{2}$$

Based on this definition, each path point $Ln = (x_n, y_n)$ in the UAV travel path forms a set of sequences $S=(L_1, L_2, L_3, ..., L_r)$ as a set of feasible solutions for the UAV path, where each path point can reach the next path point along 8 directions, as shown in Fig. 3. By connecting these path points on each set of sequence, a path line can be formed, and the UAV path planning problem is transformed into an optimization problem of obtaining the optimal coordinate sequence.

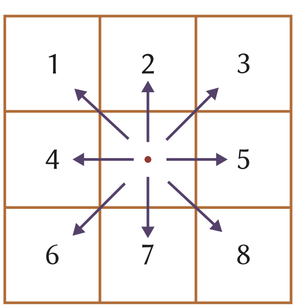


Fig. 3. Flight directions of UAV.

When raster modeling the map, the accuracy of the raster has a critical impact on the path planning. The higher the accuracy, the smaller the raster granularity, the larger the resolution of the environment, and the more information storage, the slower the algorithm decision. When the UAV enters the map environment, the map information is unknown, the UAV traverses the environment, detects the obstacle location, and finds the corresponding grid according to the obstacle location seeking address, and modifies the grid value. The no-obstacle raster value is 1, and the obstacle raster is assigned a value of 0.

2. Problem Formulation

The path planning problem by the UAV for crop monitoring in agricultural fields is described in this paper as a constrained optimization problem [19] with the shortest flight distance from the starting point of travel to the end point, and Equation in (3) defines the general constrained optimization problem form.

$$\begin{cases} \min\limits_{x\in X} f(x) \\ \quad s.t. \\ g_i(x) \le 0 \\ h_j(x) = 0 \\ i, j = 1,2,3, \dots \end{cases} \tag{3}$$

where *f*(*x*) is the objective function, which represents the shortest distance of the UAV flight path in the constraint problem; X is the objective function feasible domain, which is the coordinate limit of the path point located in the map during the UAV flight; g_i and h_i are the equation constraint and inequality constraint in the constraint optimization in the UAV path planning problem, it is desirable to limit the flight distance and obstacle avoidance of the UAV through the constraint, which can shorten the UAV flight time as well as ensure the safety of the device.

In the planning problem, the path length of the UAV flight is a critical factor in the overall planning objective. So Equation in (4) defines the objective function that is the UAV flight path length function as follows.

$$f(x) = \sum_1^r \sqrt{(x_{k+1} - x_k)^2 + (y_{k+1} - y_k)^2} \tag{4}$$

The constraints that can be placed on the UAV flight during path planning are: the total direction of travel of the UAV is the end direction, which limits the fold back path points; another constraint is the collision avoidance constraint, where the flight path does not pass within or on the boundary of the defined obstacle. Equation in (5) defines the collision avoidance constraint. The distance between the UAV's position for each travel and the previous position to avoid the obstacle, ζ is defined as the safe range of the obstacle.

$$\frac{y_{ii} - y_i}{x_{ii} - x_i} * x_k + \zeta - y_k \ne 0 \tag{5}$$

C. Algorithmic Mechanism

1. Grey Wolf Optimization Algorithm

The Grey Wolf Optimization algorithm proposed by Mirjalili et al. in 2014 is a newer swarm intelligence optimization algorithm [20], inspired by the hunting behavior of grey wolf packs. In the algorithm, the wolves set up a hierarchy of ranks, as shown in Fig. 4, and the first four of the ranks are defined as α wolves, β wolves, γ wolves, and ω wolves. The head wolf, i.e. rank of wolf α, is at the highest position and makes the decision of the whole pack intelligence optimization, and wolf β is responsible for assisting with the hierarchical differentiation. When there is a vacancy of α in the wolf pack, wolf β becomes wolf α, and each rank behind rises one level at a time. GWO achieves the purpose of optimization by simulating the predatory behavior of the grey wolf pack based on the mechanism of wolf pack collaboration. The GWO algorithm is characterized by simple structure, few parameters to be adjusted and easy implementation, in which there exists a convergence factor that can be adjusted adaptively and an information feedback mechanism that can achieve a balance between local search for excellence and global search, so it has good performance in terms of solution accuracy and convergence speed for the problem.

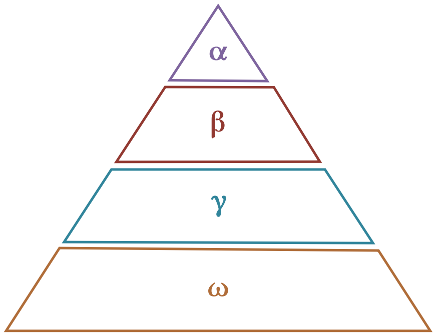


Fig. 4. Hierarchy of the grey wolf.

When path planning is carried out through the Grey Wolf Optimization algorithm, the hierarchical system is strictly implemented, and the low-level wolves are close to the high-level wolves, while the "prey" is captured by the distance, that is, the algorithm searches for the global optimal solution: it will select and determine the wolf α, β and γ with the highest rank according to the distance from the prey (global optimal solution). Under the leadership of the top three, the whole wolf pack will identify and surround the prey, and constantly update the level of the wolf pack. After determining the prey, the hunting of the wolf pack will be finished, and the algorithm will get the optimal feasible solution of the plan. Each individual grey wolf has its own location in the solution space, i.e., corresponding to the path feasible solution, and the optimal feasible solution of the whole optimization is the location of wolves α, and in turn wolves β and wolves γ are considered to be the second and third optimal solutions of the optimization algorithm. The number of path points in the path line of the location map environment is regarded as the sub-element of each feasible solution, i.e., the solution space dimension.

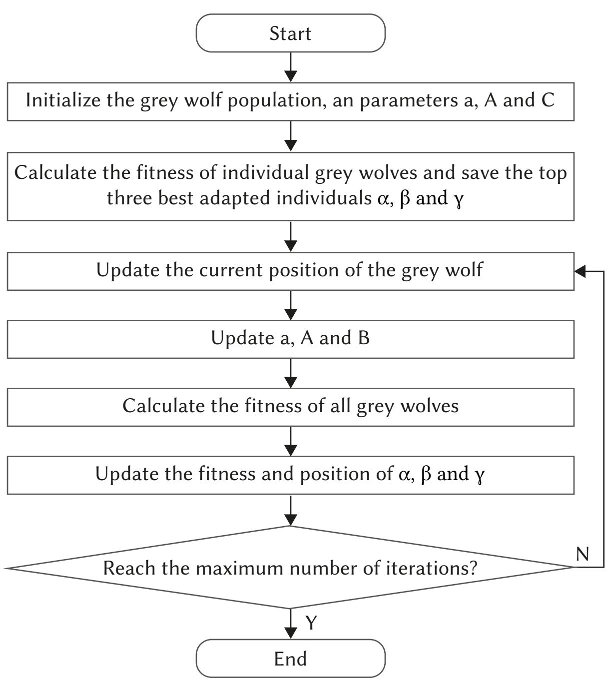


Fig. 5. Flow chart of the GWO algorithm.

The flow of Grey Wolf Optimization algorithm is shown in Fig. 5. In the whole iterative process of the algorithm, the Grey Wolf Optimization algorithm has the following defects: the wolf α searched by the algorithm as the current optimal solution of the algorithm may not be the global optimal point, and in the continuous iteration, the wolf ω gradually approaches the α, β and γ wolves, resulting in the whole optimal search falling into the local optimal; in the algorithm mechanism, the wolves mainly judge the distance to the top three wolves of the rank based on the distance to the search mechanism of judging the solution by distance causes the convergence rate of the algorithm to become slower in the later period. Based on this consideration, the second subsection of this chapter explores how to overcome the shortcomings of the Grey Wolf Optimization algorithm itself and the analysis of its rationality.

2. Improved Grey Wolf Optimization Algorithm

From the perspective of simulating wolf hunting behavior, the core behavior of the whole Grey Wolf Optimization algorithm is hunting, and Equation in (6) defines the hunting behavior as follows. D indicates the distance between the individual and the prey, and the current grey wolf moves toward the target, and the grey wolf position is updated as shown in Fig. 6. Besides, Equation in (7) defines the coordinates of wolves. t is the number of iterations of the algorithm, and there are two random vectors C and A defined in this equation for the update of the grey wolf position and the convergence of the algorithm when iterating as a whole (a is the improved convergence factor, r_1 and r_2 vectors modulo random numbers between 0 and 1).

$$D = \left|C * X_p(t) - X(t)\right| \\ C = 2 * r_1 \tag{6}$$

$$X(t+1) = X_p(t) - \mathrm{A} * \mathrm{D} \\ \mathrm{A} = 2a * r_2 - a \\ a = 2\left(1 - \frac{t^2}{T^2}\right) \tag{7}$$

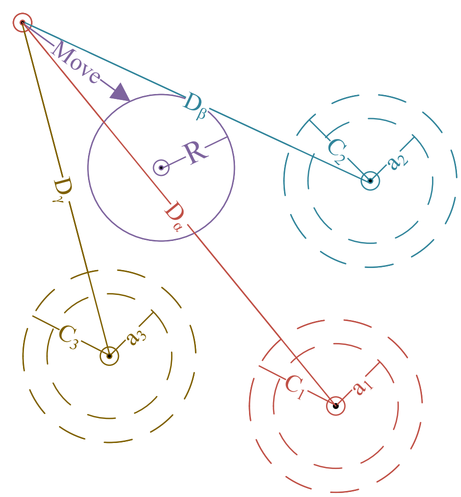


Fig. 6. Update schematic of the location for grey wolf.

Equation in (8) defines the distance at which each grey wolf performs hunting. D_α, D_β, and D_γ denote the distances between wolves α, β, γ and other individual grey wolves respectively; X_α, X_β, and X_γ denote the current positions of wolves α, β, and γ; X is the current position of the grey wolf, while C_1, C_2, and C_3 in Equation are random vectors.

$$\begin{cases} D_\alpha = \left|C_1 * X_\alpha - X\right| \\ D_\beta = \left|C_2 * X_\beta - X\right| \\ D_\gamma = \left|C_3 * X_\gamma - X\right| \end{cases} \tag{8}$$

During the hunting process, grey wolves are able to identify the location of prey and surround them. When the grey wolf identifies the location of the prey, β, γ, led by α, guides the wolf pack to surround the prey. In the decision space of the optimization problem, the best solution (the location of the prey) is not known. Therefore, in order to simulate the hunting behavior of grey wolves, define α, β, γ to know more about the potential location of the prey. α, β, γ wolves that is, who saved the three optimal solutions obtained under the current and use the location of these three to judge the location of the prey, while forcing other grey wolf individuals including ω to update their location based on the location of the optimal grey wolf individuals to gradually approach the prey, and Equation in (9) defines the location updating.

$$\begin{cases} X_1 = X_\alpha - A_1 * D_\alpha \\ X_2 = X_\beta - A_2 * D_\beta \\ X_3 = X_\gamma - A_3 * D_\gamma \\ X(t+1) = \frac{X_1+X_2+X_3}{3} \end{cases} \tag{9}$$

When the grey wolf algorithm is caught in a local optimum in the search process and cannot jump out by its own search mechanism, this paper introduces the probabilistic sudden leap mechanism of the Simulated Annealing algorithm to overcome this defect. The earliest idea of the Simulated Annealing algorithm is a heuristic algorithm proposed by N. Metropolis in 1953 based on the annealing process in thermodynamic systems. The Simulated Annealing algorithm starts from some higher initial temperature, and the continuous decrease of the temperature parameter, combined with a certain probability of sudden leap in the whole solution space to randomly find the global optimal solution of the objective function, so it can be able to probabilistically jump out when the feasible solution of the algorithm falls into the local optimum, and the probability of getting the optimal solution will be greatly increased and eventually converge to the global optimum because of the introduction of more random factors. This is done by performing a small perturbation on the current optimal solution to generate a new solution, judging whether this new solution meets the output conditions according to the Metropolis criterion, and continuously iterating until the maximum number of iterations is reached.

Since the unique new solution acceptance criterion of Simulated Annealing algorithm allows convergence to avoid falling into local extremes, it makes up for the deficiency of the Grey Wolf Optimization algorithm that tends to fall into local optima, making the introduction of this mechanism desirably.

The workflow of the Improved GWO algorithm is as follows.

- Step 1: Define obstacles, starting point, and end point according to the environment model.
- Step 2: Initialize the values of relevant parameters of the Grey Wolf Optimization algorithm as well as the Simulated Annealing algorithm, such as population size, maximum number of iterations, initial temperature, etc.
- Step 3: Obtain the location of wolf α according to the convergence process of the Grey Wolf Optimization algorithm, i.e., the path feasible solution, record and output to the mechanism of the Simulated Annealing algorithm, consider the solution as the current optimal solution and carry out the Simulated Annealing convergence process.
- Step 4: Reach the maximum convergence number to output the final path optimal solution.

The overall workflow of the algorithm is shown in Fig. 7.

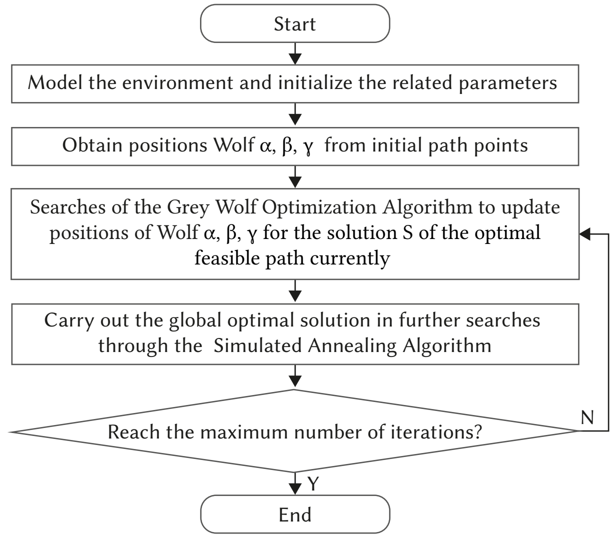


Fig. 7. Flow chart of the Improved GWO algorithm.

After considering the problem of how to adjust to achieve the optimal solution for the path points and to speed up the convergence, it is also necessary to add obstacle avoidance constraints to the designed combinatorial algorithm, which constrains so that all path points so that the overall path does not pass through obstacle regions on the linkage. Therefore, the path planning problem of UAV is considered as a constrained optimization problem with the main objective function of optimizing so that the overall path sum is minimized and the constraint condition of avoiding all obstacle regions. The overall search steps of the designed algorithm are as follows in Table I.

TABLE I. The Improved GWO Algorithm

Algorithm: Improved GWO Algorithm

Input: *pop*, *Max_iteration*, *n*, *lb*, *ub*, *T*

Output: $X = \{X(1), X(2), X(3), ..., X(n)\}$, $Y = \{Y(1), Y(2), Y(3), ..., Y(n)\}$

pos$_{\alpha,\beta,\gamma}$ ← zeros$_{1,n}$;
val$_{\alpha,\beta,\gamma}$ ← inf;
$X(1)$ ← 1;
$Y(1)$ ← val;
While 1 < Max_iteration **do**
  for $j = lb; j \le ub$ **do**
    compute val$_{\alpha,\beta,\gamma}$ (j, n) $(n \in (lb, ub))$;
    Y(j) ← Min(val$_{\alpha,\beta,\gamma}$ (j, n));
    While $0 < T$ **do**
      compute $Y_t + 1(j)(j, t)$;
      a ← $2(1 - t^2/T^2)$;
      $\Delta y \leftarrow Y_{t+1} - Y_t$;
      if $Y_{t+1} \le Y_t$ **then**
        replace $Y_t(j)$ with Y_{t+1};
      else
        if *exp*(-Δy/T ≤ *random* [0,1]) **then**
          $T = 0.99 * T$;
      t++;
  for $i = lb; i \le ub$ **do**
    for $k = 1; k \le n$ **do**
      compute pos$_{\alpha,\beta,\gamma}$ (i, k);
      $r_{1,2,3,4,5,6}$ ← random[0,1];
      compute $X_{1,2,3}$ (pos$_{\alpha,\beta,\gamma}$, a, r_m, $X(i)$)$m \in (1,6)$;
      $X(i) \leftarrow (X_1 + X_2 + X_3))/3$;
Return *X*,*Y*

III. Feasibility Analysis For Improvement

On account of the simple structure and easy implementation of the population intelligence optimization algorithm, it has been applied to solve various complex optimization planning problems. With the continuous development of heuristic search, the Grey Wolf Optimization algorithm has been widely used in various scheduling problems and path planning because of its high performance in problem solving optimization since its introduction.

Theoretically, in the UAV path planning problem, because the algorithm imitates the strict social hierarchy of grey wolves, it can follow the three best positioned wolves like a wolf pack hunting, and can search the best UAV path point quickly and accurately, and in the parameter selection by a linear decreasing convergence factor and two random weight parameters make the algorithm in local optimization and The algorithm maintains a good balance between local optimization and global optimization. However, in terms of the limitations of the algorithm, if the individual wolf with the highest rank is selected as the local optimum instead of the global optimum, the strict wolf-closing hierarchy will make the algorithm fall into a local optimum that cannot be jumped out, and the search mechanism of the algorithm by virtue of the distance between the wolf and the target will lead to the slow convergence of the grey wolf algorithm at the later period. Thus, there is some space for improvement in the optimization problem of UAV path planning.

Considering the deficiency of slow convergence rate in the late period of the algorithm search, the convergence factor parameter in the Grey Wolf Optimization algorithm is adjusted. The convergence mode of the factor is changed from linear decreasing to exponential decreasing. For another difficulty, the algorithm could fall into local optimum when iteratively searching the solution space of the path points. This paper designs a method to introduce the mechanism of Simulated Annealing algorithm into the Grey Wolf Optimization algorithm. The property of probabilistic leap out of the local optimum of Simulated Annealing algorithm is utilized to improve the performance of Grey Wolf Optimization algorithm search with a view to achieving a better optimization search effect.

IV. Experimental Results and Discussion

A. Performance Indicators

In this paper, we focus on the path planning of crop pest monitoring by UAV in a farmland environment, which is a constrained combinatorial optimization problem, so the performance index is compared with the optimal path length L_{total} that is successfully completed by the algorithm under different precision simulation environments. The total path length is an important indicator to reflect the best result of the proposed algorithm in the current precision of the map environment. As Equation in (10) is shown below.

$$L_{total} = \sum_{i=1}^{r} L_i \tag{10}$$

From the perspective of the constrained optimization problem, the problem exists multiple feasible paths under the premise of avoiding collision obstacles, so the search for the optimal path becomes necessary for path planning, while setting the obstacle collision index, as Equation in (11) is shown below. The experimental phase of this paper is designed to compare the search results with some other heuristic algorithms, according to the established indicators used to judge the superiority of the algorithm to meet the shortest path and has avoided all obstacles on the path, and made a comparison of the final experimental results.

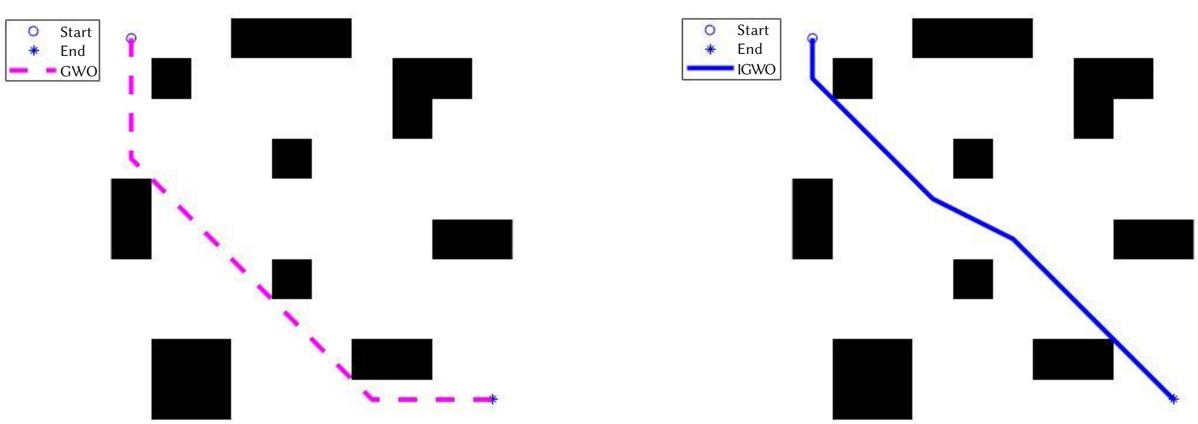
$$\frac{y_{ii}-y_i}{x_{ii}-x_i} * x_k + \zeta - y_k \neq 0 \tag{11}$$

After controlling the UAV to complete the overall crop pest monitoring target in farmland, the shorter the flight path, the less the battery usage and the lower the energy consumption, which also reduces the flight cost, while the realization of obstacle avoidance indicators greatly reduces the risk during the flight of the UAV.

The simulated experimental test environment is simulated on raster map models with precision of 15, 20, 25 and 30, and the path search planning of IGWO, GWO, SA and GA algorithms are performed to analyze the reliability of the designed algorithms by comparing the relevant indexes. First, the basic Grey Wolf Optimization algorithm, Simulated Annealing algorithm, and Genetic algorithm will be used to perform path search optimization after traversing each map to obtain the total path length index and collision obstacle situation, and then the Improved Grey Wolf Optimization algorithm will be used to conduct the experiments, and the relevant index data will also be recorded.

B. Experimental Analysis

The simulation experiments were conducted on a 3.8 GHz, 32 GB RAM computer with Matlab 2020a. A path planning of the GWO algorithm was firstly conducted on a simple map model when experimenting with the idea of the designed algorithm, and the GWO algorithm spent a total distance of 24 for the target path after planning the UAV flight path successfully, and then an improved GWO algorithm experiment was implemented, of which the results are shown in Fig. 8, and the total distance at this moment was reduced to 20 whose result was slightly improved. Meanwhile, the convergence rate which is shown in Fig. 9 is accelerated after the algorithm's improvement.



(a) The results of the GWO algorithm.

(b) The results of the improved GWO algorithm.

Fig. 8. Path planning results.

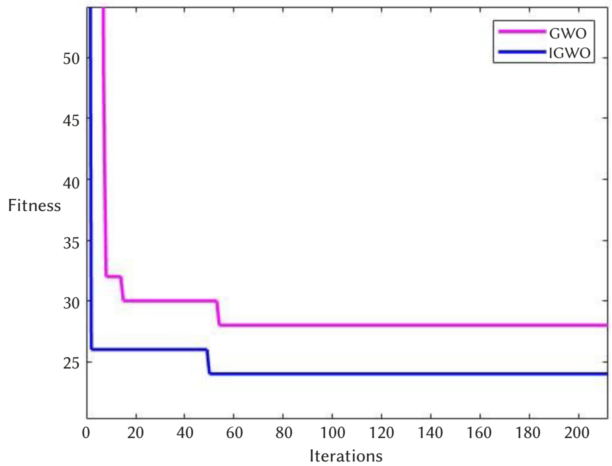
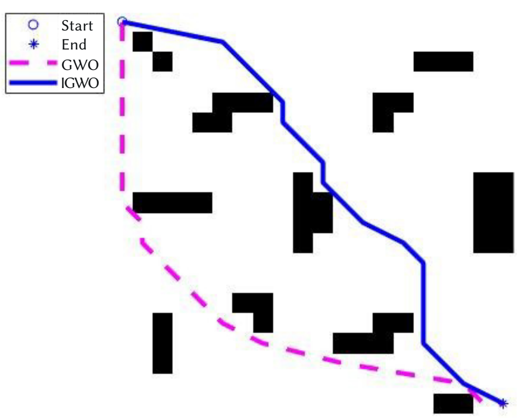
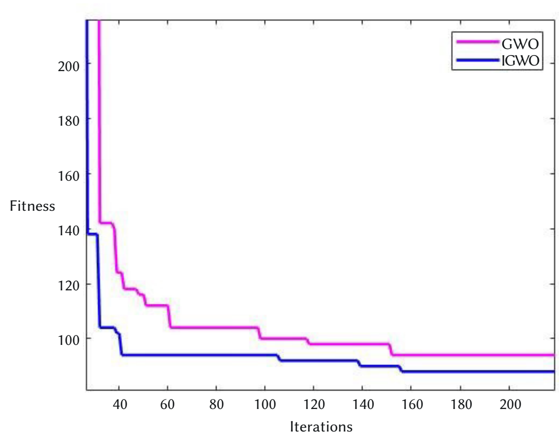


Fig. 9. Convergence curves of the algorithms..

In order to avoid the chance of the experiment, another comparison experiment was conducted on the map with higher precision between them, and the result is shown in Fig. 10, the experimental result of the improved algorithm is reduced from 82 to 48 in the total distance of the target path, whose effect is significant. Also the convergence rate is more stable that still higher than the original GWO algorithm.



(a) The results of the algorithms.



(b) Convergence curves of the algorithms.

Fig. 10. Path planning results in map with different precisions.

Based on this, by defining the start point and destination, the flight path of UAV is planned. More detailed and specific comparison experiments are conducted later on map models with precision of 15, 20, 25 and 30 respectively, as well as making a comparison of the convergence rate. Besides, the experiments of Simulated Annealing algorithm and Genetic algorithm were added to compare the path planning effect of the related methods to prove the superiority of the improved GWO algorithm. The experimental results of the four different methods for UAV path planning are shown in Fig. 11, and the convergence curve of each algorithm is shown in Fig. 12. The comparison data of each algorithm are shown in Table II, Table III, Table IV and Table V.

TABLE II. Comparison of the Results of Each Algorithm(Precision=15)

Algorithm	Total Paths	Whether to avoid obstacles
IGWO	22	Y
GWO	24	Y
SA	28	Y
GA	22	Y

TABLE III. Comparison of the Results of Each Algorithm(Precision=20)

Algorithm	Total Paths	Whether to avoid obstacles
IGWO	40	Y
GWO	48	Y
SA	48	Y
GA	42	Y

TABLE IV. Comparison of the Results of Each Algorithm(Precision=25)

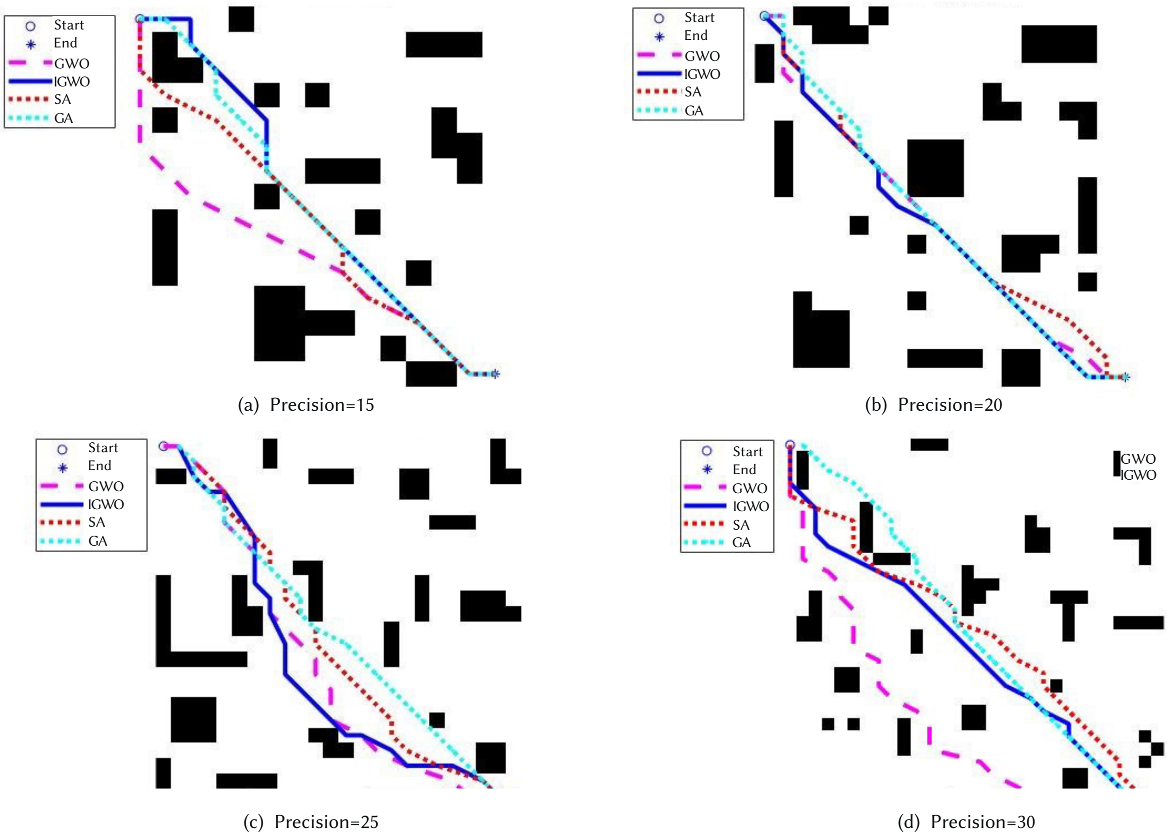
Algorithm	Total Paths	Whether to avoid obstacles
IGWO	50	Y
GWO	70	Y
SA	56	Y
GA	56	Y

TABLE V. Comparison of the Results of Each Algorithm(Precision=30)

Algorithm	Total Paths	Whether to avoid obstacles
IGWO	64	Y
GWO	106	Y
SA	112	Y
GA	66	Y

Fig. 11 visualizes the path planning results of the UAV for various methods on map models with different precisions. As shown in Table II, III, IV and V, the path planning effect demonstrated by the Improved Grey Wolf Optimization algorithm will be better than that of the simple heuristic algorithm. On maps with different precisions, several types of methods completely avoid obstacles in the map, but in terms of path length index, the designed combined algorithm can better match the specific map and related environment to achieve smaller total path distance and reduce UAV flight cost. The improved GWO algorithm improves the metrics of the basic GWO algorithm in path planning, reducing the total target distance consumption by 8.3%, 16.7%, 28.6%, and 39.6% on the map models with accuracies of 15, 20, 25 and 30 respectively, compared to the previous algorithm according to the total target path distance data from the tables.

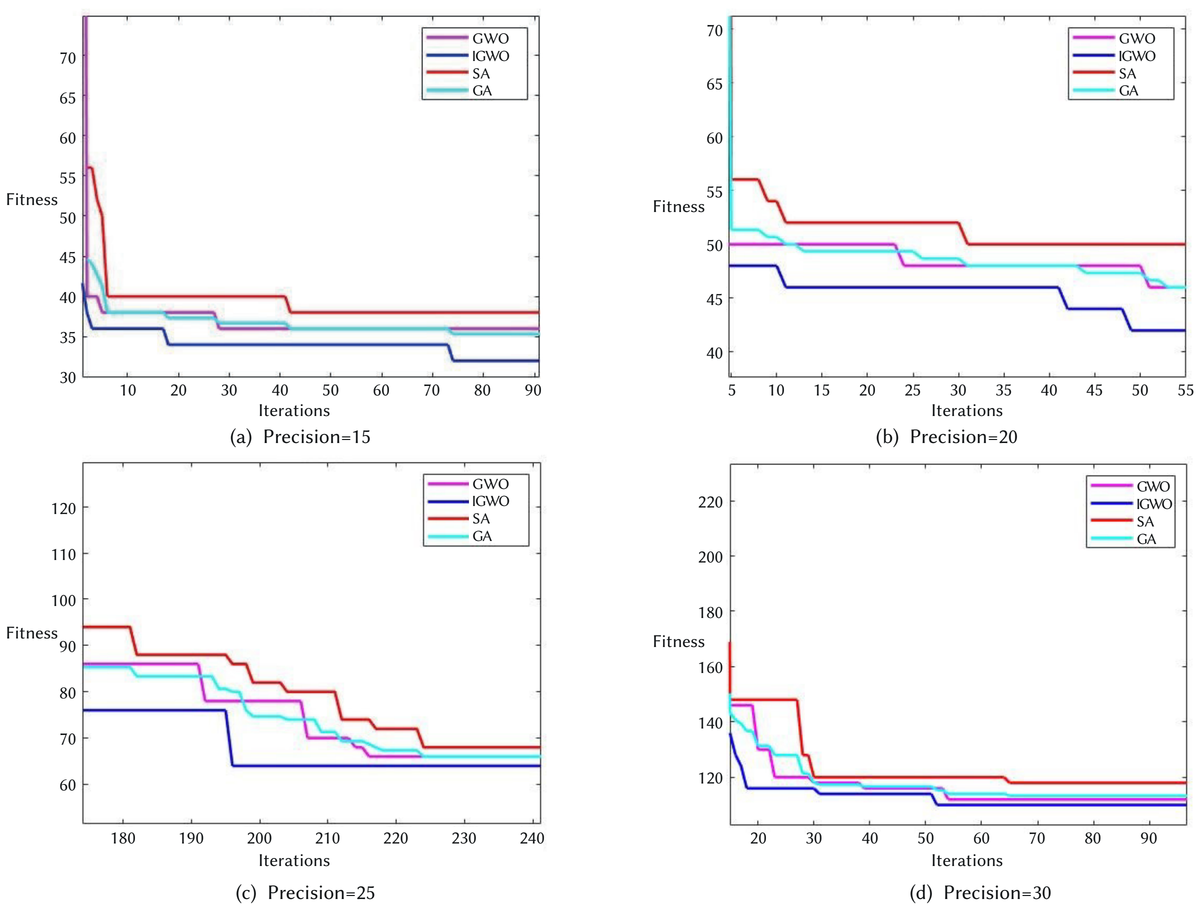
It can be known that swarm intelligence algorithms are always updated towards the current optimal result in the process of optimization, so the search result of UAV path is always the best target value in current stage, and finally the best path is obtained cumulatively. From the Fig. (a) and (b) in Fig.11, it is obvious that when there are many possibilities in the space, once the convergence ability of the algorithm is too strong, such as the GWO algorithm, it will lead to that in one stage, optimization falls into local optimum. If the algorithm does not have the ability to jump out of local optimum, it will lead to the overall poor flight path, trajectory deviation or even failure of the finally planned UAV. Therefore, an effective and reasonable adjustment is very important for the planning problem.



(a) Precision=15 (b) Precision=20

(c) Precision=25 (d) Precision=30

Fig. 11. Path planning results in map with different precisions.



(a) Precision=15 (b) Precision=20

(c) Precision=25 (d) Precision=30

Fig. 12. Convergence curves in map with different precisions.

Furthermore, the improvement of the exponential decay of the convergence factor of the GWO algorithm, shown in Fig. 12, accelerates the speed of the algorithm search convergence and improves the efficiency of path planning. The improved GWO algorithm is significantly better than the original GWO algorithm in terms of convergence rate, and also has greater superiority than some other swarm intelligence algorithms such as Simulated Annealing algorithm and Genetic Algorithm, no matter on which precision of map model. Compared with some other search algorithms, the algorithm is more suitable for UAV path point finding in the UAV path planning problem.

Thus it is experimentally verified that the introduction of the Simulated Annealing algorithm's probabilistic leap out of local optimum in the Grey Wolf Optimization algorithm can improve the performance of the basic Grey Wolf Optimization algorithm in path planning. Therefore, compared with other methods in the experiment, it can be seen that the improved method can not only maintain a high search rate, but also get better search results.

V. Conclusion

The work of this paper is to solve the path planning problem of UAVs for crop pest monitoring in agricultural fields. The improved Grey Wolf Optimization algorithm is used to perform optimal path planning while avoiding collisions between UAVs and obstacles during flight. It can be seen from the simulation experiments that the designed algorithm is more effective than some swarm intelligence methods. The adjustment of the convergence factor speeds up the convergence rate, and the property of probabilistic sudden leap of the Simulated Annealing algorithm introduced in the algorithm mechanism avoids to a certain extent the defect that the Grey Wolf Optimization algorithm falls into local optimum too early.

For the Grey Wolf Optimization algorithm to consider, due to its simplicity and efficiency, the algorithm has been successfully applied in many fields, in terms of the improvement of the Grey Wolf Optimization algorithm, in addition to the grey wolf population diversity can also be improved, better diversity can effectively improve the search efficiency of the algorithm and improve the planning performance; it can also improve its search mechanism, the Grey Wolf Optimization algorithm uses the adaptation value of A,C and a to balance the algorithm ability, easy to fall into local optimum, it can also consider introducing new search strategies to make up for the algorithm deficiency.

In the current context, the Grey Wolf Optimization algorithm can still be used in other fields and has broad application prospects.

Acknowledgment

We would like to thank the editors and reviewers in advance for their comments in helping us improve the quality of this paper. This work was supported by the National Natural Science Foundation of China under Grant 62072255.

References

[1] G. Tang, C. Tang, C. Claramunt, X. Hu and P. Zhou, "Geometric A-Star Algorithm: An Improved A-Star Algorithm for AGV Path Planning in a Port Environment," in IEEE Access, vol. 9, pp. 59196-59210, 2021, doi: 10.1109/ACCESS.2021.3070054.

[2] Y. Du, X. Zhang and Z. Nie, "A Real-Time Collision Avoidance Strategy in Dynamic Airspace Based on Dynamic Artificial Potential Field Algorithm," in IEEE Access, vol. 7, pp. 169469-169479, 2019, doi: 10.1109/ACCESS.2019.2953946.

[3] W. Huang, K. Sun, J. Qi and J. Ning, "Optimal Allocation of Dynamic Var Sources Using the Voronoi Diagram Method Integrating Linear Programing," in IEEE Transactions on Power Systems, vol. 32, no. 6, pp. 4644-4655, Nov. 2017, doi: 10.1109/TPWRS.2017.2681459.

[4] R. Zou and S. Bhattacharya, "On Optimal Pursuit Trajectories for Visibility-Based Target-Tracking Game," in IEEE Transactions on Robotics, vol. 35, no. 2, pp. 449-465, April 2019, doi: 10.1109/TRO.2018.2882747.

[5] L. Chen, Y. Shan, W. Tian, B. Li and D. Cao, "A Fast and Efficient Double-Tree RRT*-Like Sampling-Based Planner Applying on Mobile Robotic Systems," in IEEE/ASME Transactions on Mechatronics, vol. 23, no. 6, pp. 2568-2578, Dec. 2018, doi: 10.1109/TMECH.2018.2821767.

[6] D. Dev Misra, K. K. Sarma, U. Bhattacharjee, P. K. Goswami and N. Mastorakis, "Optimal Routing in the 5G Ultra Dense Small Cell Network using GA, PSO and Hybrid PSO-GA Evolutionary Algorithms," 2020 24th International Conference on Circuits, Systems, Communications and Computers (CSCC), 2020, pp. 39-44, doi: 10.1109/CSCC49995.2020.00016.

[7] R. M. C. Santiago, A. L. De Ocampo, A. T. Ubando, A. A. Bandala and E. P. Dadios, "Path planning for mobile robots using genetic algorithm and probabilistic roadmap," 2017 IEEE 9th International Conference on Humanoid, Nanotechnology, Information Technology, Communication and Control, Environment and Management (HNICEM), 2017, pp. 1-5, doi: 10.1109/HNICEM.2017.8269498.

[8] P. Hu, S. Chen, H. Huang, G. Zhang and L. Liu, "Improved Alpha-Guided Grey Wolf Optimizer," in IEEE Access, vol. 7, pp. 5421-5437, 2019, doi: 10.1109/ACCESS.2018.2889816.

[9] S. N. Ghorpade, M. Zennaro and B. S. Chaudhari, "GWO Model for Optimal Localization of IoT-Enabled Sensor Nodes in Smart Parking Systems," in IEEE Transactions on Intelligent Transportation Systems, vol. 22, no. 2, pp. 1217-1224, Feb. 2021, doi: 10.1109/TITS.2020.2964604.

[10] F. Ge, K. Li, W. Xu and Y. Wang, "Path Planning of UAV for Oilfield Inspection Based on Improved Grey Wolf Optimization Algorithm," 2019 Chinese Control and Decision Conference (CCDC), 2019, pp. 3666-3671, doi: 10.1109/CCDC.2019.8833455.

[11] L. Guo, Q. Xie, X. Huang and T. Chen, "Time difference of arrival passive location algorithm based on grey wolf optimization," 2017 3rd IEEE International Conference on Computer and Communications (ICCC), 2017, pp. 877-881, doi: 10.1109/CompComm.2017.8322669.

[12] Y. Gu and N. Liu, "An Adaptive Grey Wolf Algorithm Based on Population System and Bacterial Foraging Algorithm," 2020 IEEE International Conference on Artificial Intelligence and Computer Applications (ICAICA), 2020, pp. 744-748, doi: 10.1109/ICAICA50127.2020.9182707.

[13] S. Lee and S. B. Kim, "Parallel Simulated Annealing with a Greedy Algorithm for Bayesian Network Structure Learning," in IEEE Transactions on Knowledge and Data Engineering, vol. 32, no. 6, pp. 1157-1166, 1 June 2020, doi: 10.1109/TKDE.2019.2899096.

[14] R. Li and M. Chen, "Flight control law evaluation for UAV based on simulated annealing algorithm," Proceedings of the 32nd Chinese Control Conference, 2013, pp. 8697-8702.

[15] H. Daryanavard and A. Harifi, "UAV Path Planning for Data Gathering of IoT Nodes: Ant Colony or Simulated Annealing Optimization," 2019 3rd International Conference on Internet of Things and Applications (IoT), 2019, pp. 1-4, doi: 10.1109/IICITA.2019.8808834.

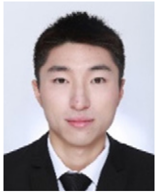
[16] J. Su et al., "Aerial Visual Perception in Smart Farming: Field Study of Wheat Yellow Rust Monitoring," in IEEE Transactions on Industrial Informatics, vol. 17, no. 3, pp. 2242-2249, March 2021, doi: 10.1109/TII.2020.2979237.

[17] Y. Mao, M. Chen, X. Wei and B. Chen, "Obstacle Recognition and Avoidance for UAVs Under Resource-Constrained Environments," in IEEE Access, vol. 8, pp. 169408-169422, 2020, doi: 10.1109/ACCESS.2020.3020632.

[18] B. Guo, H. Dai, Z. Li and W. Huang, "Efficient Planar Surface-Based 3D Mapping Method for Mobile Robots Using Stereo Vision," in IEEE Access, vol. 7, pp. 73593-73601, 2019, doi: 10.1109/ACCESS.2019.2920511.

[19] C. Picard and J. Schiffmann, "Realistic Constrained Multiobjective Optimization Benchmark Problems from Design," in IEEE Transactions on Evolutionary Computation, vol. 25, no. 2, pp. 234-246, April 2021, doi: 10.1109/TEVC.2020.3020046.

[20] Z. Li, V. Tam and L. K. Yeung, "An Adaptive Multi-Population Optimization Algorithm for Global Continuous Optimization," in IEEE Access, vol. 9, pp. 19960-19989, 2021, doi: 10.1109/ACCESS.2021.3054636.



Qun Ding

Qun Ding is currently working as a researcher for the Jiangsu Key Laboratory of Big Data Security & Intelligent Processing, Nanjing, China. His research interests include swarm intelligent optimization. He has won two provincial competition awards, and ranked the forefront of the municipal algorithm competition. He won several scholarships during university. He is going to pursue his master's degree major in Software Engineering in Nanjing University of Posts & Telecommunications, Nanjing, China.

Xiaolong Xu

Xiaolong Xu is currently a professor in the School of Computer Science, Nanjing University of Posts & Telecommunications, Nanjing, China. He is also working for the Jiangsu Key Laboratory of Big Data Security & Intelligent Processing. He received the B.E. in computer and its applications, M.E. in computer software and theories and Ph.D. degree in communications and information systems, in 1999, 2002 and 2008, respectively. He is a senior member of China Computer Federation. He teaches graduate courses and conducts research in areas of Artificial Intelligence, Cloud Computing, Big Data and Novel Network Computing Technologies. As the leader of project teams, he has successfully completed a number of high-level research projects, including the projects sponsored by the National Science Fund of China. He has published more than 100 Journal and conference papers as the first or corresponding author and 5 books. He is authorized 52 patents by the State Intellectual Property Office of China as the first inventor. He was rated as excellent young professor of Jiangsu Province in 2014, selected as the high-level creative talents of Jiangsu province in 2015, and won the title of outstanding expert in the area of computer science and technology.