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Paper

Three-dimensional path planning of UAV based on improved PSO

Lixia Deng[*a)] Non-member, Huanyu Chen[*] Non-member
Haiying Liu[*] Non-member, Xiaoyiqun Zhang[*] Non-member

The traditional particle swarm optimization algorithm is fast and efficient, but it is easy to fall into a local optimum. An improved PSO algorithm is proposed and applied in 3D path planning of UAV to solve the problem. Improvement methods are described as follows: combining PSO algorithm with genetic algorithm (GA), setting dynamic inertia weight, adding sigmoid function to improve the crossover and mutation probability of genetic algorithm, and changing the selection method. Simulation results show that the route results solved by the improved PSO algorithm are better, which is 10% higher than that of PSO, and 58.3% better than that of GA.

Keywords: Particle Swarm Algorithm, UAV, 3D Path Planning, Genetic Algorithm

1. Introduction

At present, as robots enter our lives, boring, repetitive work is transformed into more unmanned and intelligent work using machines instead. Among them, the development of UAV-related technology has brought great convenience to our lives, such as the use of UAV for plant protection operations, logistics and distribution. Due to the short flight duration of UAV, path planning is one of the key issues in the automatic control of UAVs.

Path planning algorithms suitable for UAVs can be divided into two categories, one is the global path planning algorithm in the continuous domain, and the other is the local path planning algorithm in the continuous domain [(1)]. Three-dimensional path planning belongs to global path planning, which can be optimized by using traditional algorithms or swarm intelligence. Qiang Bian and others [(2)] used greedy search, adaptive processing of search direction and other methods to improve the A* algorithm for path planning.Wang Yihu and others [(3)] introduced the chemotaxis and migration operations of the bacterial foraging algorithm (BFO) into the PSO algorithm, which effectively improved some of the defects of the PSO algorithm and improved its search ability.Wang Zhihui and others [(4)] proposed the moth to flame algorithm, which introduced a dynamic adjustment strategy, and constantly generated new individuals to avoid falling into local optimum and enhance population diversity.Sun and others [(5)] proposed a high-performance bacterial foraging-genetic-particle swarm hybrid algorithm to improve the computing speed and the availability of the method.Kong [(6)] introduced the artificial potential field method and added random pheromones to improve the ant colony algorithm to improve the problem of slow convergence and the tendency to fall into local optima.Xie and Kong [(7)] proposed a high-performance bacterial foraging-genetic-particle swarm hybrid algorithm to address the shortcomings of the particle swarm algorithm, improving the computational speed and capability of the algorithm and further enhancing the usability of the method.Pan [(8)] designed a step-based A* algorithm that not only guarantees path planning but also optimises search time.Particle swarm optimization algorithm is easy to fall into local optimization in the later stage, so Fu and Hu [(9)] mixed particle swarm optimization with longicorn beetle beard algorithm (BAS) to obtain the more reasonable path and the higher search-efficiency.Chengyang Lu and others [(10)]introduced the A* idea on the basis of RRT, which enables RRT to be targeted in the search and improves the path quality.Manh Duong Phung and Quang Phuc Ha [(11)] proposed a particle swarm optimization algorithm based on spherical vector (SPSO), which transforms the path planning problem into an optimization problem with UAV feasibility and safe operation requirements and constraints. Through the corresponding relationship between the particle position and the UAV speed, turning angle and pitch angle, the SPSO algorithm is used to find the optimal path. B. Abhishek [(12)] et al. proposed a particle swarm optimization algorithm based on harmony search algorithm, which performs exploratory search and utilization search at the same time. In order to solve the problem of UAV path planning under unknown threats, Jong-Jin Shin and Hyochoong Bang [(13)] proposed an improved particle swarm optimization algorithm consisting of preprocessing steps, multi-swarm PSO algorithm and post-processing steps.

The paper designs a hybrid particle swarm optimization algorithm to solve the 3-dimensional path planning problem of UAV. Build a 3D environment model, and constructing a fitness function based on obstacles and path lengths. At the same time, the inertia weights of the particle swarm algorithm are improved. The selection operation of Genetic Algorithm (GA) is introduced, and the crossover and mutation probability models are improved. Finally, the proposed algorithm is simulated by MATLAB to verify the effectiveness.

a) Correspondence to: AmandaDeng084@126.com
* School of Information and Automation Engineering,Qilu University of Technology(shandong Academy of Sciences), Jinan 250353, China. This work is sponsored by Natural Science Foundation of Shandong Province (ZR2018QF005)

2. Model Establishment

2.1 Environmental Model The 3D path planning of the UAV needs to obtain information from the terrain model, and the actual situation should be considered when modeling the terrain. By considering obstacles, environment and other factors, the established terrain model [14] is described as follows.

$$Z_1(x,y) = \sin(y+a) + b\cdot\sin(x) + c\cdot\cos(d\cdot\sqrt{x^2+y^2} + e\cdot\cos(y) + f\cdot\sin(g\cdot\sqrt{x^2+y^2}) \tag{1}$$

where x and y are the horizontal and vertical coordinates, and Z_i are the corresponding height values. a, b, c, d, e, f, and g are constants used to control the height distribution of the map. For a mountain in 3D environment, it can be represented by the following model.

$$z(x,y) = \sum_{i=1}^{n} h_i \exp\left[-\left(\frac{x-x_i}{x_{si}}\right)^2 - \left(\frac{y-y_i}{y_{si}}\right)^2\right] \tag{2}$$

where n represents the total number of mountain peaks,(x_i, y_i) represents the center coordinate of the i-th peak, and h_i is the parameter that controls the height. x_{si} and y_{si} are the attenuations of the i-th peak along the x-axis and y-axis which can be used to control the slope, respectively.

2.2 Path Smoothing Algorithm Based on Cubic B-Spline Curve In order to prevent frequent angle adjustment during the flight, ensure the safety of the UAV, and reduce the sailing time, a cubic B-spline curve is introduced [15]. In a given $m+n+1$ plane or space vertex $P_i(i = 0, 1, \ldots, m+n)$, it is called a parametric curve segment of degree n:

$$P_{k,n}(t) = \sum_{i=0}^{n} P_{i+k} G_{i,n}(t) t \in [0,1] \tag{3}$$

where $P_{k,n}(t)$ is the n-th degree B curve segment of the k-th segment, and these curve segments are called n-th degree B-spline curves. $G_{i,n}(t)$ is the basis function which is defined based on Eq. (4).

$$G_{i.n}(t) = \frac{1}{n!}\sum_{j=0}^{n-i}(-1)^j C_{n+1}^j (t+n-i-j)^n \quad t\in[0,1] i = 0,1,...n \tag{4}$$

In order to ensure the smoothness of the path and consider the difficulty, let $n = 3$, and a cubic B-spline curve is used to smooth the path.

3. Improve Particle Swarm Optimization

3.1 Particle Swarm Optimization Particle Swarm Optimization (PSO) is an evolutionary computational technique proposed by Dr. Eberhart and Dr. Kennedy [16] by simulating the foraging behavior of birds. A mass-less particle is designed to simulate a bird in a flock, and the particle has only two properties: velocity and position. The velocity represents the speed of movement and the position represents the direction of movement. Each particle individually searches for the optimal solution, which is recorded as the current individual extremum, and shares the individual extremum with the other particles in the whole particle swarm. For the optimal solution, all particles in the particle swarm adjust their speed and position according to the current individual extreme value. They find the current global optimal solution shared by the entire particle swarm. The basic idea of particle swarm optimization algorithm is to find the optimal solution through cooperation and information sharing among individuals in the swarm. The particle swarm optimization algorithm is described as Eqs. (5) and (6).

$$v_{i,j}(t+1) = wv_{ij}(t) + c_1 r_1(t)\left[pbest_i - x_{ij}(t)\right] + c_2 r_2(t)\left[gbest_i - x_{ij}(t)\right] \tag{5}$$

$$x_{ij}(t+1) = x_{ij}(t) + v_{ij}(t+1) \tag{6}$$

where w is the inertia weight, indicating the degree of trust in the current velocity direction. c_1, c_2 respresent the learning factor (or acceleration constant). r_1, r_2 respresent a random value between 0 and 1, adding randomness to the search.

3.2 Fitness Function Design The quality of the path length is one of the important indicators to measure the success of the algorithm improvement. Due to the lack of battery capacity of the UAV, the flight distance is limited. The shorter the flight path, the less time and energy it takes.

Based on the cubic B-spline curve fitting path, the interpolation process is performed, and the interpolation is differentiated to obtain the fitness function:

$$fitness = \sqrt{(x_{i+1}-x_i)^2 + (y_{i+1}-y_i)^2 + (z_{i+1}-z_i)^2} \tag{7}$$

The obstacle risk factor f is introduced to avoid the collision between the UAV and the obstacle. The barrier coefficient formula is described as follows:

$$f = \begin{cases} 0 & L_{\min} > L_d \\ 1 & L_{\min} < L_d \end{cases} \tag{8}$$

Considering the real environment, UAV is not a particle, and it has its own size. So, setting $L_{\min}$ as the minimum distance close to the peak, and L_d as the safe distance. When $f = 1$, the minimum distance is less than the safe distance, and it is easy to cause danger, so the fitness function needs to be increased. At the same time, the fitness function is modified to Eq. (9).

$$fitness = kfitness \tag{9}$$

where k is the multiple of expansion, $k = 5$.

3.3 Set Dynamic Weights The inertia weight is an important control parameter in the particle swarm algorithm, and the size of the inertia weight indicates how much of the current velocity inheritance to the particle. If inertia weight is set larger, the global search ability is stronger, and if inertia weight is set smaller, the local search ability is stronger and the global search ability becomes weaker [17]. In this paper, a linearly decreasing inertia weight is designed. In the early stage of the algorithm, a larger inertia weight is used to ensure the global search ability. With the increasing of number of iterations, the inertia weight becomes smaller and the local search ability is enhanced. The formula is described as follows:

$$w = (w_{\max} - w_{\min}) \times \frac{(N - iter)}{N} + \frac{(w_{\max} - w_{\min})}{iter} \qquad (10)$$

where $w_{\max}$ is the maximum inertia weight, $w_{\min}$ is the minimum inertia weight, N is the maximum number of iteration, and *iter* is the current iteration number of the algorithm.

3.4 Select Operation Genetic algorithms (GA) are computational models of biological evolutionary processes that simulates the natural selection and genetics mechanisms of Darwinian biological evolution, and are a method for searching for optimal solutions by simulating natural evolutionary processes [18]. The main steps in this are selection, crossover, variation and fitness function design. Selection operation refers to the operation of selecting good individuals from a group and eliminating poor individuals. Based on the evaluation of fitness value, individuals with greater fitness are more likely to be selected and have a higher probability passing to the next generation.

In order to avoid the precocious situation, this paper adopts the mixed selection operator. First method uses the optimal fitness selection method to sort the fitness, selects the better fitness as the parent 1, and selects the proportion of the population as p. Second method uses the roulette method by selecting the probability $p_{\sec}$. The selected population is used as parent 2, and the population proportion is $1 - p$.

3.5 Improvement of Crossover and Mutation Probability Model The crossover operation is an operation to generate a new individual by replacing and recombining the partial structure of the selected parent individual, so that the search ability is improved. The mutation operation is to randomly change the values of some genes with a small mutation probability, which belongs to the auxiliary search operation, and the purpose is to maintain the diversity of the population. Generally, a random number *rand* is generated, and if $rand < P_m$, the operation is performed. Crossover probability and mutation probability have important influence on the selection of new population.

The crossover probability P_c controls the frequency of the crossover operation. A larger crossover probability can enhance the search ability, but it is easy to destroy the searching performance. If the probability is too low, it will easily lead to the degradation of the algorithm performance. The variation probability cannot be too large, otherwise the algorithm will tend to search randomly [19].

This paper introduces the sigmoid function to change the probability of crossover and mutation. To prevent the fixed crossover probability and mutation probability from destroying some individuals in the population as the iteration proceeds [20]. The formula is described as follows.

$$P_c = P_{cro} + \frac{1}{1 + e^{f_{ibest} - f_{iave}}} \qquad (11)$$

$$P_m = P_{mut} + \frac{1}{1 + e^{f_{ibest} - f_{iave}}} \qquad (12)$$

where $P_{cro} = 0.8$, $P_{mut} = 0.2$, f_{ibest} are the optimal values of fitness in the i-th generation population, and f_{iave} is the average fitness value in the i-th generation population.

3.6 Constraint Condition In order to prevent the UAV from being dangerous during flight, constraints need to be set according to the actual situation. The altitude has a great influence on the UAV firstly. Flying at high altitude is susceptible to temperature and airflow, and flying at low altitudes is susceptible to disturbances from buildings and trees. Therefore, to fly at the appropriate altitude, which can be expressed as Eq. (13)

$$z_{\min} < z_j < z_{\max} \qquad (13)$$

Where z_j is the height position of the j-th time. $z_{\min}, z_{\max}$ represent the minimum and maximum heights. Meanwhile, the size of environment is set to 100×100×100m to prevent the UAV from flying out of the set environment.

3.7 Improved Algorithm Operation Flow The flow chart of the improved PSO algorithm is (1) Establishing a 3-dimensional scene according to Eq. (1) and Eq. (2), and setting the start point and end point.

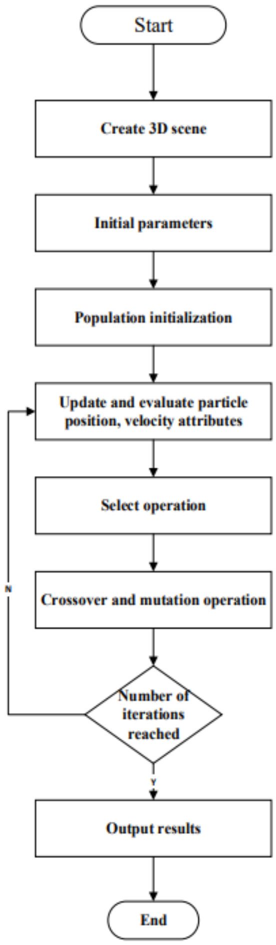

Fig. 1. Flow chart

(2) Parameters initialization. Setting the particle population size, maximum number of iterations, inertia weight, social weight and cognitive weight.

(3) Population initialization. Randomly generating particles and initializing the velocity, calculating the initial fitness and performing collision detection, and updating the individual optimum as well as the global optimum.

(4) Enter the main loop. Update velocity and position, perform velocity and position detection at the same time to avoid out-of-bounds; calculate fitness values and perform collision detection, update individual optimum and global optimum.

(5) Introduce genetic algorithm. A selection operation is carried out to select the best particle population, while crossover and mutation operations are carried out. The new generation of populations is used as the initial population for the next generation of cycles.

(6) End condition. Determine if the maximum number of iterations has been reached, and if so, exit the loop and output the result, otherwise return to step (4).

4. Experimental Simulation And Analysis

In order to verify the advantages of the proposed improved PSO algorithm, the traditional PSO algorithm and GA algorithm are selected as the control group, and the parameters such as the number of iterations remain unchanged. The above three algorithms are simulated and tested on MATLAB. Two sets of experiments are carried out and the experimental results are analyzed. The test environment is Windows10, 64-bit system, MATLAB R2020b simulation platform. Parameters in the algorithm are shown in Table 1:

In order to verify the superiority of the improved PSO algorithm in 3D path planning, the following two experiments are carried out respectively.

Table 1. ALGORITHM PARAMETERS

Quantity	Symbol	Numerical value
Spatial scope	/	100100100
Starting point	start	(1,1,1)
End point	goal	(86,73,25)
Total group Number	M	50
Number of iterations	N	100
Social weight	c1	2
Cognitive Weight	c2	2
Maximum Inertia weight	$w_{\max}$	0.9
Minimum Inertia weight	$w_{\max}$	0.4
Chromosome Length	k	3
Crossover Probability	p_{cro}	0.8
Mutation Probability	p_{mut}	0.2
Selection Probability	$p_{\sec}$	0.75

4.1 Comparative Analysis Under the Same Environment

Front view of 3D path planning results of the improved PSO algorithm, PSO, and GA algorithms are given in Figs. 2 4, and the adaptation curves of the three algorithms are shown in Fig. 5.

As shown in Fig. 2 Fig. 4, the abovethree algorithms can accomplish the path planning task in the 3D environment. However, in Fig. 4, due to the complex environment, the traditional GA algorithm is easy to fall into the "dead zone", and the generated paths are too complex and too long. Meanwhile, in Fig. 3, the traditional PSO has better path planning than GA and excellent global search capability. By comparing with Fig. 2, the improved PSO algorithm strengthens the local search ability at the later stage to avoid falling into local optimum, and the planned path length and smoothness are better than the traditional PSO algorithm.

In Fig. 5, according to the change of the fitness curve, the GA algorithm has fallen into the local optimum at about 20-th iteration and lacks the ability to jump out of the local optimum. PSO algorithm has fallen into the local optimum at the 9-th iteration. Although it is still searching for the optimum at the 115-th iteration, but the effect is no longer obvious. The improved PSO algorithm adds dynamic inertia weights with larger weights in the early iterations to ensure the global search ability of RI, and the fitness curve drops sharply. As the number of iterations increasing, the weights decrease. It can strengthen the local search ability and increase the convergence speed, and basically reach the optimum in 23-th generation. The selection, crossover and mutation operations in the genetic algorithm are introduced to improve the diversity of the population and enhance the search ability, and the local optimization search is still performed in the late iteration.

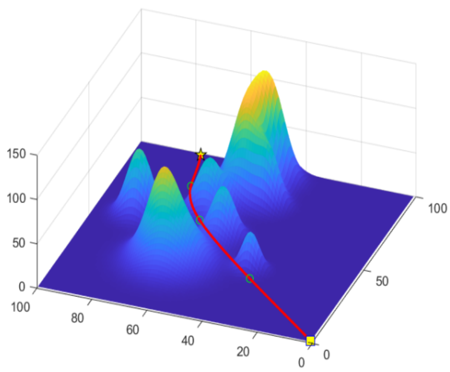

Fig. 2. Improve Algorithm

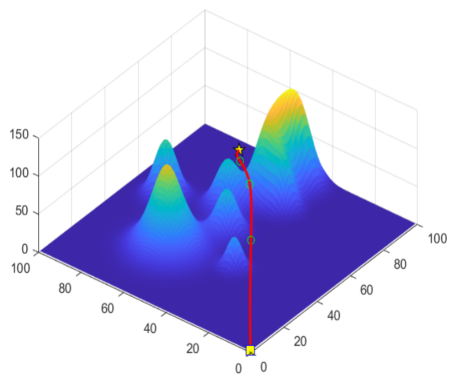

Fig. 3. PSO

4.2 Comparative Analysis In Random Environment

Establishing the restricted environment as a 3D random environment within 100×100×100m, setting the start point as (1,1,1) m and the end point as (100,100,50) m, generating 10 obstacles randomly, and iterating for 200 times. Three algorithms are tested for 10 simulations, and the simulation

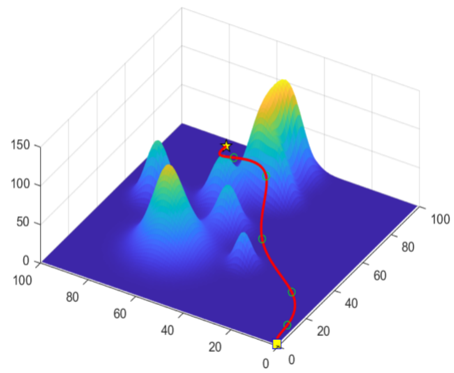

Fig. 4. GA

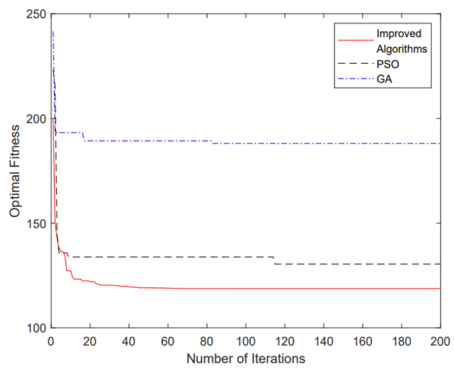

Fig. 5. Fitness value

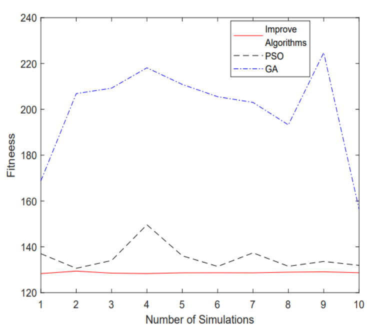

Fig. 6. 10 simulation results

results are shown in Fig. 6, and the agreed results are shown in Table 2. the average adaptation degree of the improved PSO algorithm is lower than that of PSO and GA algorithms, and it shows good merit-seeking ability. The improved algorithm has good stability by variance comparison. Although the improved algorithm has a longer running time than the PSO algorithm, by comparing the number of iterations and the time to reach the average fitness value through Table 2. It can be found that the improved algorithm can reach the average fitness in a shorter time with 14-th iteration and spending 14.48s. The traditional PSO algorithm requires 26-th iteration and spends 23.13s. While the GA algorithm requires 36-th iteration and consumes 57.76s. This proves that the improved algorithm is more stable and faster than the other two algorithms.

Table 2. SIMULATION RESULT STATISTICS

Algorithm	Average Fitness Value	Average Running Time/s	Fitness Value Variance	Average Number of Iterations to Reach Average Fitness Value	Time to Reach Average Fitness Value/s
Improve Algorithm	128.723	47.53	0.11	14	3.33
PSO	135.314	52.07	31.11	26	6.76
GA	199.675	78.96	460.86	36	14.21

5. Conclusions

In this paper, an improved PSO algorithm is proposed and applied for 3D path planning to overcome shortcomings of the traditional PSO algorithm, such as the tendency to fall into local optimality. The improvement method is: introducing dynamic inertia weights, and adding selection, crossover and mutation operations in genetic algorithm. Using the hybrid selection operation, the crossover and genetic probability model is improved to increase the population diversity, retain the global search capability of the particle swarm algorithm, and enhance the local search capability in the late iteration. The improved PSO algorithm is simulated and compared with PSO algorithm andGA algorithm by MATLAB. Results show that the improved PSO algorithm has better search ability and stability. Compared with the PSO and GA algorithms, the improved PSO algorithm generates shorter path lengths and better path smoothing, which improves the search volume and search efficiency of the UAV for path planning.

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Lixia Deng (Non-member) Lixia Deng received her bachelor's degree in Electrical Engineering and Automation from Shandong Jiaotong University, China, in 2011. She received her Ph.D. degree in the School of Control Science and Engineering, Shandong University, China, in 2016. She is a associate professor at Qilu University of Technology (Shandong Academy of Sciences). Her research interests mainly include multiple mobile robots coordination and pattern recognition.

Huanyu Chen (Non-member) received the B.S. degree in Control Technology and Instrument from the Qilu University of Technology (Shandong Academy of Sciences), Jinan, China, in 2020. he is currently pursuing the M.S. degree in Electronic and Information Engineering from Qilu University of Technology(Shandong Academy of Sciences), Jinan, China. His research interests are target detection, target tracking, especially target tracking.

Haiying Liu (Non-member) Haiying Liu received her Master degree and Ph.D. degrees from Shandong University, School of Control Science and Engineering in 2007 and 2012, respectively. She was a joint PhD. student from August 2009 to August 2011 in the Department of Electrical and Computer Engineering, University of Victoria, Canada. She conductedresearch as a postdoctoral fellow in the Department of Electrical and Computer Engineering, Dalhousie University, Canada from February 2015 to August 2016. She joined the School of Electrical Engineering and Au-tomation, Qilu University of Technology (Shandong Academy of Sciences) from 2013 and has been an associate Professor from 2017. Her currentresearch interests are mainly in the field of Pattern Recognition, DigitalImage Processing and Robot Vision, and stability analysis with applicationin mobile robots.

Xiaoyiqun Zhang (Non-member) received the B.S. degree in Electrical Engineering and Automation from the Qilu University of Technology (Shandong Academy of Sciences), Jinan, China, in 2019. he is currently pursuing the M.S. degree in Electronic and Information Engineering from Qilu University of Technology(Shandong Academy of Sciences), Jinan, China. His research interests are target detection, target tracking, especially target detection.