A path planning method for UAVs based on multi-objective pigeon-inspired optimisation and differential evolution

Bingda Tong and Lin Chen

School of Automation Science and Electrical Engineering,
Beihang University,
No. 37 Xueyuan Road, Haidian District, Beijing, 100083, China
Email: tongbingda@buaa.edu.cn
Email: bulinchen@buaa.edu.cn

Haibin Duan*

School of Automation Science and Electrical Engineering,
Beihang University,
No. 37 Xueyuan Road, Haidian District, Beijing, 100083, China
and
Peng Cheng Laboratory,
No. 2, Xingke 1st Street, Nanshan District, Shenzhen, 518000, China
Email: hbduan@buaa.edu.cn
*Corresponding author

Abstract: Inspired by the behaviour of pigeon flocks, an improved method of path planning and autonomous formation for unmanned aerial vehicles based on the pigeon-inspired optimisation and differential evolution is proposed in this paper. Firstly, the mathematical model for UAV path planning is devised as a multi-objective optimisation with three indices, i.e., the length of a path, the sinuosity of a path, and the risk of a path. Then, the method integrated by pigeon-inspired optimisation and mutation strategies of differential evolution is developed to optimise feasible paths. Besides, Pareto dominance is applied to select the global best position of a pigeon. Finally, a series of simulation results compared with standard particle swarm optimisation algorithm and standard differential evolution algorithm show the effectiveness of our method.

Keywords: path planning; unmanned aerial vehicle; UAV; pigeon-inspired optimisation; differential evolution.

Reference to this paper should be made as follows: Tong, B., Chen, L. and Duan, H. (2021) 'A path planning method for UAVs based on multi-objective pigeon-inspired optimisation and differential evolution', *Int. J. Bio-Inspired Computation*, Vol. 17, No. 2, pp.105–112.

Biographical notes: Bingda Tong received his BS degree in College of Automation Engineering, Nanjing University of Aeronautics and Astronautics in 2019. He is pursuing his PhD degree in the Bio-inspired Autonomous Flight Systems Research Group, School of Automation Science and Electrical Engineering, Beihang University. His research interests include bio-inspired computation and unmanned aircraft systems control.

Lin Chen received her BS and MS degrees from Sichuan University in 2015 and 2018, respectively. She is currently pursuing her PhD degree in Guidance, Navigation and Control of Aerial Vehicles at School of Automation Science and Electrical Engineering, Beihang University. Her current research interests include navigation, control and decision of unmanned aerial vehicles, and bio-inspired computation.

Haibin Duan is a Full Professor in the School of Automation Science and Electrical Engineering, Beihang University. He is the Vice Director of State Key Laboratory of Virtual Reality Technology and Systems, and is also the Head of the Bio-inspired Autonomous Flight Systems (BAFS) Research Group. He received his National Science Fund for Distinguished Young Scholars of China. He is also enrolled in the Scientific and Technological Innovation Leading Talent of 'Ten Thousand Plan'-National High Level Talents Special Support Plan, Top-Notch Young Talents Program of China, Program for New Century Excellent Talents in University of China, and Beijing NOVA Program. He has authored or co-authored more than 70 publications and three monographs. He is a senior member of the IEEE. His current research interests are bio-inspired computing, biological computer vision, and multi-UAV autonomous formation control.

1 Introduction

Unmanned aerial vehicle (UAV) plays an important role in some high-risk missions because of its small size, easy of use, low cost, low environment requirements, and strong survivability, etc. UAV path planning refers to finding the optimal or suboptimal collision-free path with some certain performance indices for a UAV from the departure point to the terminal point under certain constraints, which can be formulated as a typical constrained optimisation problem.

Population-based optimisation algorithms have been applied to solve path planning problems. Unlike traditional single-point base algorithms that may easily get trapped into local optimal and unsuitable for dynamic or nonlinear problems, the population-based optimisation algorithms can overcome these disadvantages and have more efficiency in solving path planning problems. Genetic algorithm (GA) is a search heuristic inspired by the process of natural selection which belongs to evolutionary algorithms (EA). GA based on mutation, crossover and selection. Hu and Yang (2004) proposed a knowledge-based GA for path planning of a mobile robot, which uses problem-specific GAs for robot path planning instead of the standard GAs. Ant colony optimisation (ACO) is a metaheuristic which takes inspiration from the foraging behaviour of ant species. ACO based on autocatalysis, i.e., the exploitation of positive feedback, can be used by ants to find the shortest path between a food source and their nest. Brand et al. (2010) investigated the application of ACO to robot path planning in a dynamic environment. Particle swarm optimisation (PSO) is an evolutionary computation technique developed by Kennedy and Eberhart in 1995. The method is inspired by social behaviour of bird flocking or fish schooling. Qin et al. (2004) presented an advanced PSO algorithm for mobile robot path planning. Roberge et al. (2013) used GA and PSO to cope with real-time UAV path planning problems. Cui et al. (2020) proposed a hybrid multi-objective particle swarm optimisation (HMOPSO) algorithm for multi-objective optimisation by combining particle swarm search with local search.

Pigeon-inspired optimisation (PIO) (Duan and Qiao, 2014) is a new bio-inspired swarm intelligence optimiser especially for air robot path planning. Inspired by natural pigeons' behaviour, the algorithm presents a map and compass operator model based on magnetic field and sun, landmark operator model based on landmarks.

Further improvements and discussions of PIO path planning are as follows. Zhang and Duan (2017) proposed a novel Predator-prey pigeon-inspired optimisation (PPPIO) to solve the three-dimensional path planning problem of UAVs in a dynamic environment. Li and Deng (2018) proposed a new algorithm for independent navigation of UAV path planning based on pigeon-inspired optimisation and quantum entanglement theory. Cui et al. (2019) establish an external archive to store the best solution that is continuously generated during the evolution of the population. Qiu and Duan (2018) modified multi-objective pigeon-inspired optimisation (MPIO) based on the hierarchical learning behaviour in pigeon flocks.

Despite good performance of PIO, it still has deficiencies in solving multi-objective problems. For example, it uses a single objective function or multiplying multiple objective functions with different weight coefficients. The latter is a single objective method and has some inescapable problems. Therefore, in this paper, an improved method is proposed by integrating mutation strategies of differential evolution into the PIO algorithm and applying Pareto dominance to deal with the UAV path planning problem.

The rest of the paper is organised as follows. Section 2 gives a mathematical model of UAV path planning. In Section 3, a brief review of the principle of basic PIO is presented. Section 4 concerns the proposed method based on multi-objective PIO and DE. Comparative simulation validations are elaborated in Section 5. Finally, our conclusions and future perspectives are drawn in Section 6.

2 Mathematical model of UAV path planning

To achieve the goal of UAV path planning, the environment of the flying airspace should be expressed and stored first to make the UAV understand the surrounding environments. The method is proposed by Sun et al. (2005) and improved to three-dimensional model in this paper.

Figure 1 UAV flying airspace model

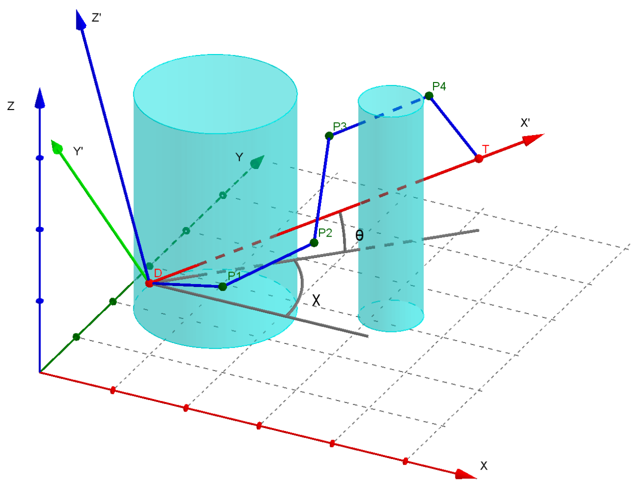


Figure 1 describes the global coordinate system *O-XYZ*, and the cylinders, defined as *m*, are a series of dangerous areas, such as enemy radar detection areas. UAV must keep clear of these areas, otherwise it will be shot down by anti-aircraft weapons. *D* and *T* are the departure point and the terminal point of a UAV. *O'-X'Y'Z'* is a local coordinate system which is set *D* as the origin, the line between *D* and *T* as *X'* axis and the *Y'* axis and *Z'* axis accord with the Cartesian coordinate system. The corresponding transformation equation between the global coordinate system and the local coordinate system is as follows:

$$\begin{pmatrix} x' \\ y' \\ z' \end{pmatrix} = \begin{bmatrix} \cos\theta\cos\chi & \sin\theta & -\cos\theta\sin\chi \\ -\sin\theta\cos\chi & \cos\theta & \sin\theta\sin \\ \sin\chi & 0 & \cos\chi \end{bmatrix} \left[\begin{pmatrix} x \\ y \\ z \end{pmatrix} - \begin{pmatrix} x_D \\ y_D \\ z_D \end{pmatrix} \right] \quad (1)$$

where θ is the inclination angle and χ is the deflection angle from the X axis to the line DT. (x', y', z') is the coordinate in the local coordinate system, (x, y, z) is the coordinate in the global coordinate system, (x_D, y_D, z_D) is the departure point D in the global system.

At first, the flying path DT is split into $n+1$ segments. The path can be defined as

$$P = (D, P_1, P_2, \ldots, P_n, T) \quad (2)$$

Furthermore, denote the departure point D and the terminal point T as P_0 and P_{n+1}, and then the path can be defined as

$$P = (P_0, P_1, \ldots, P_n, P_{n+1}) \quad (3)$$

If the UAV expects to arrive at the terminal point T safely, it must not enter the dangerous areas in the flying airspace. Times which the UAV enters these areas will be calculated to determine whether the path is feasible. If the flying path segment (Pi, P_{i+1}) of the UAV intersects the border of the dangerous area j, the attribute value, defined as ET_{ij}, is one. Otherwise, the attribute value is zero. Then the sum of the times of a path P is

$$ET(P) = \sum_{i=0}^{n} \sum_{j=1}^{m} ET_{ij} \quad (4)$$

The UAV path planning is to find the optimal or suboptimal collision-free path with some certain performance indices. In this paper, three performance indices, i.e., the length of a path, the sinuosity of a path, and the risk of a path are concerned.

According to the flying airspace model, the length of a UAV's path is defined as $F_L(P)$:

$$F_L(P) = \sum_{i=0}^{n} D(P_i, P_{i+1}) \quad (5)$$

where $D(\cdot,\cdot)$ is the Euclidean distance between the point P_i and P_{i+1}.

When the UAV flies in the airspace, we hope the sinuosity of the path should be as low as possible. The sinuosity of a path is defined as follows:

$$F_S(P) = \min_{i=1,2,\ldots,n} \left(\alpha_0, (180^\circ - \alpha_i)\right) \quad (6)$$

where α_0 is the angle between the X' axis and (P_0,P_1), α_i is the intersection angle between the line (P_i,P_{i+1}) and (P_{i+1},P_{i+2}).

To evaluate the risk degree of a flying path, function $F_R(P)$ is defined as follows:

$$F_R(P) = \exp\left(-\xi \cdot D(P, d_j)\right) \quad (7)$$

where ξ is a parameter, $D(P,d_j)$ is the minimum distance between the path and the dangerous areas.

Integrate the functions (5), (6) and (7), the mathematical optimisation model of the UAV path planning can be described as the following multi-objective optimisation with a constraint:

$$\begin{aligned} &\min F(P) = \left(F_L(P), F_S(P), F_R(P)\right) \\ &s.t.\ ET(P) = 0 \end{aligned} \quad (8)$$

The length, sinuosity and risk degree of a path are dependent in some ways, which makes the algorithm difficult to get the best solutions at the same time. Therefore, it is necessary to find a Pareto set to keep balance among all objectives.

3 Brief review of basic PIO

Pigeons have the special homing ability by using three special navigation tools: the sun, the earth's magnetic field and the landmarks. As the pigeons gradually approach to their loft, the effect of the sun and magnetic field will decline progressively. The pigeons will use familiar landmark image messages to correct their route. Inspired by the pigeons' navigation behaviour, a bio-inspired swarm intelligence optimiser is proposed named PIO. In PIO, the position of each pigeon and the loft represent the potential solution and the optimal solution to an optimisation problem respectively. In other words, the behaviour of pigeon homing represents the convergence process of solutions to the global optimum. The map and compass operator is presented to imitate the navigation tool of the sun and the magnetic field on pigeons, while the landmark operator is raised to imitate the impact of familiar landmarks on the pigeon homing. PIO employs the two independent operators to optimise feasible solutions to optimise problems.

In the map and compass operator, the rules are denoted by the position X_i and the velocity V_i of pigeon i. The positions and velocities in a D-dimension search space are updated each iteration. The position X_i and the velocity V_i at the t^{th} iteration can be calculated in the following formulas:

$$\begin{cases} V_i(t) = V_i(t-1) \cdot e^{-Rt} + rand \cdot \left(X_g - X_i(t-1)\right) \\ X_i(t) = X_i(t-1) + V_i(t) \end{cases} \quad (9)$$

where R is the map and compass factor, rand is a random number within [0,1], and X_g is the current global best position.

In the landmark operator, half of the pigeons are decreased by N_p every iteration. $X_c(t)$ is defined as the centre of some pigeons' position at the t^{th} iteration. Each pigeon's position X_i can be can be calculated with the following equations:

$$\begin{cases} N_p(t) = \dfrac{N_p(t-1)}{2} \\ X_c(t) = \dfrac{\sum_{i=1}^{N_p} X_i(t) \cdot fitness\left(X_i(t)\right)}{\sum_{i=1}^{N_p} fitness\left(X_i(t)\right)} \\ X_i(t) = X_i(t-1) + rand \cdot \left(X_c(t) - X_i(t-1)\right) \end{cases} \tag{10}$$

where $fitness(\cdot)$ is the quality of each pigeon. For minimum optimisation problems,

$$fitness\left(X_i(t)\right) = \frac{1}{f_{\min}\left(X_i(t)\right) + \varepsilon}$$

where ε is a constant value.

Given the formulas (9) and (10), the basic PIO process generally follows the steps described in Table 1.

Table 1 Steps of basic PIO

Step 1	Initialise the airspace information and the dangerous areas information.
Step 2	Initialise PIO algorithm parameters, including space dimension D, population size Np, map and compass factor R, the number of N_{c1} and N_{c2} for two operators, etc.
Step 3	Set each pigeon with a randomised velocity and position. Then compare the fitness of each pigeon and find the global best position X_g.
Step 4	Operate map and compass operator. Update velocity and path of each pigeon using equation (9). Compare the fitness of each pigeon and find the new X_g.
Step 5	If the number of iterative times is greater than N_{c1}, stop the map and compass operator and operate the landmark operator. Otherwise go to Step 4.
Step 6	Rank all of the pigeons according to the fitness value. Half pigeons whose fitness values are low will follow the pigeons with higher fitness. According to equation (10), calculate X_c and update the position X_i.
Step 7	If the number of iterative times is greater than N_{c2}, stop the landmark operator. Otherwise, go to Step 6.

4 Path planning method based on multi-objective PIO and DE

In the following section, a novel path planning method based on multi-objective pigeon-inspired optimisation and differential evolution (MOPIODE) is introduced to solve the problems in Section 2. To evaluate the quality of a path, Pareto dominance is used to select the global best position of a path. For the infeasible paths which blocked by the dangerous areas, the improved mutation operation of differential evolution is applied to improve the feasibility of these paths.

At first, generate initialisation pigeons randomly and set a feasible path for initial X_g. Then classify these pigeons by feasibility, i.e., whether $ET(P)=0$.

For those feasible paths, i.e., $ET(P) = 0$, $X_i(t)$ and $X_g(t)$ is defined as the position and global best position in the t^{th} iteration, respectively. The three objective functions, i.e., the length of a path, the sinuosity of a path and the risk of a path are used to construct multi-objective Pareto dominance to update the global best path. If $F(X_i(t+1)) \prec F(X_g(t))$ is satisfied, where $\prec$ represents Pareto dominance for feasible paths. If $X_i(t+1)$ and $X_g(t)$ do not dominate each other, keep the $X_g(t)$ unchanged. Then update each pigeon's position and velocity according to equation (9).

For the infeasible paths, i.e., the paths blocked by dangerous areas in the flying airspace, use the improved mutation operation to improve the feasibility and accelerate the search progress. In t^{th} iteration, select two infeasible paths randomly, denoted as $X_{R1}(t)$ and $X_{R2}(t)$, then apply the mutation operation. The equation for $X_i(t+1)$ of DE/rand/1 is as following:

$$X_i(t+1) = X_i(t) + F \cdot \left(X_{R1}(t) - X_{R2}(t)\right) \tag{11}$$

where F is the scaling factor to control the magnitude of the difference vector.

Table 2 Steps of path planning method

Step 1	Initialise the flying airspace and the dangerous areas, set the parameters including the space dimension D, the population size N_p, map and compass factor R, the number of N_{c1} and N_{c2} for two operators, the scaling factor F, etc.
Step 2	Initialise the pigeons randomly and select the global best position, then divide the pigeons into two sets, i.e., the feasible sets and the infeasible sets according to their feasibility.
Step 3	Update the position and velocity according to the map and compass operator, i.e., equation (9), in the feasible set's pigeons. Evaluate these paths' feasibility, if a path is infeasible, move it to the infeasible set. Then calculate each pigeon's fitness and select the global best position X_g.
Step 4	Update the position according to the improved mutation operation, i.e., the equation (11), in the infeasible set's pigeons. Evaluate these paths feasibility, if a path is feasible, move it to the feasible set.
Step 5	If the number of iterative times is greater than N_{c1}, go to Step 6, otherwise return to Step 4.
Step 6	Abandon the pigeons in the infeasible set. Stop the map and compass operator and apply the landmark operator.
Step 7	If the number of iterative times is greater than N_{c2}, stop the landmark operator and output the solution. Otherwise, go to Step 6.

If the number of iterative times is greater than N_{c1}, for the feasible pigeons, stop the map and compass operator and operate landmark operator. The infeasible pigeons will be abandoned because they will disturb the calculation of centre of the pigeons X_c.

The steps of the path planning method for UAV based on multi-objective pigeon-inspired optimisation and differential evolution are described in Table 2.

5 Comparative simulation results

To validate the proposed method in solving UAV path planning problems, the simulation experiments are conducted by MATLAB on a PC. The performances are compared with multi-objective particle swarm optimisation (MOPSO) algorithm and multi-objective differential evolution (MODE) algorithm.

Table 3 Flying airspace information

			$y(m)$	$z(m)$
D		5	5	25
T		95	95	25
	j	x_j	y_j	z_j
Dangerous area	1	20	20	10
	2	40	45	7
	3	75	65	8
	4	26	76	23
	5	82	35	12

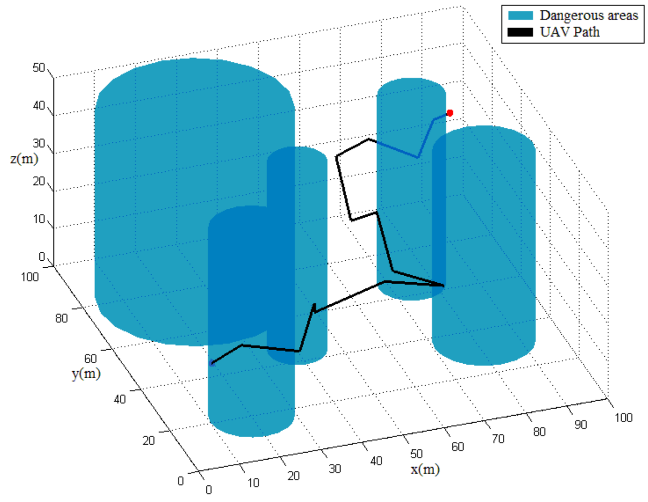
Table 4 Parameters of MOPIODE, MOPSO and MODE

Algorithm	*Variable*	*Description*	*Value*
MOPIODE	N_p	Number of pigeons	50
	N_{c1}	Maximum iteration of map and compass operator	60
	N_{c2}	Maximum iteration of landmark operator	100
	V_U	Upper bound of velocities	2
	V_L	Lower bound of velocities	–2
	R	Map and compass factor	0.1
	F	Scaling factor	0.3
	ε	Constant in landmark operator	0.4
MOPSO	N	Number of particles	50
	N_c	Maximum iteration	100
	W	Inertia weight	0.8
	c_1	Personal attractor	0.5
	c_2	Global attractor	0.5
MODE	N	Number of populations	50
	N_c	Maximum iteration	100
	F	Scaling factor	0.5
	Cr_u	Upper bound of crossover probability	0.6
	cr_l	Lower bound of crossover probability	0.1

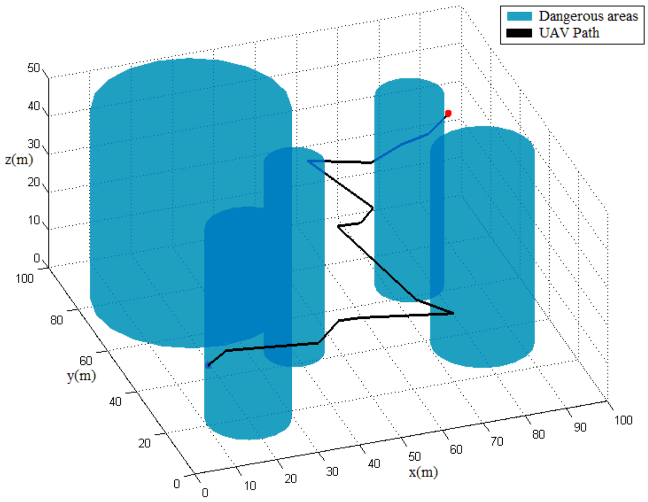
The coordinate of departure point D, terminal point T, and the dangerous areas' information are shown in Table 3. The number of path points, i.e., $n = 13$. The adjustable parameter α in formula $F_S(P)$ is set to 0.2. The simulation parameters are shown in Table 4.

Figure 2 descript the results of UAV path optimised by MOPIODE, MOPSO and MODE algorithms. Coordinates of these path points are shown in Table 5. Moreover, Figure 3 shows three evolution curves of the three algorithms.

Figure 2 Simulation results, (a) path optimised by MOPIODE (b) path optimised by MOPSO (c) path optimised by MODE (d) path optimised by MOPIODE in a top-down view (e) path optimised by MOPSO in a top-down view (f) path optimised by MODE in a top-down view (see online version for colours)



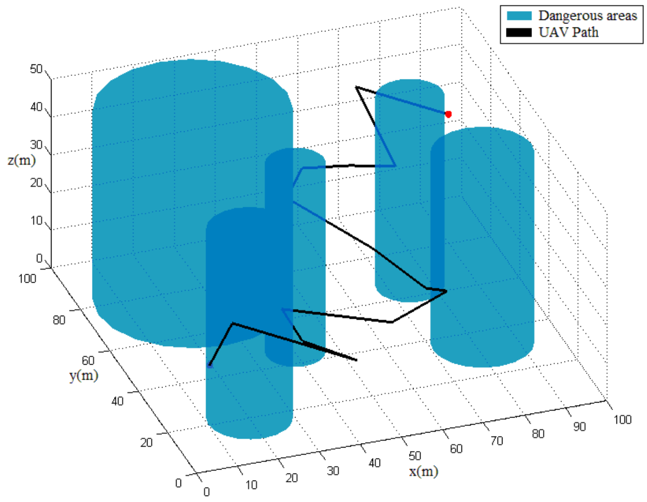
(a)



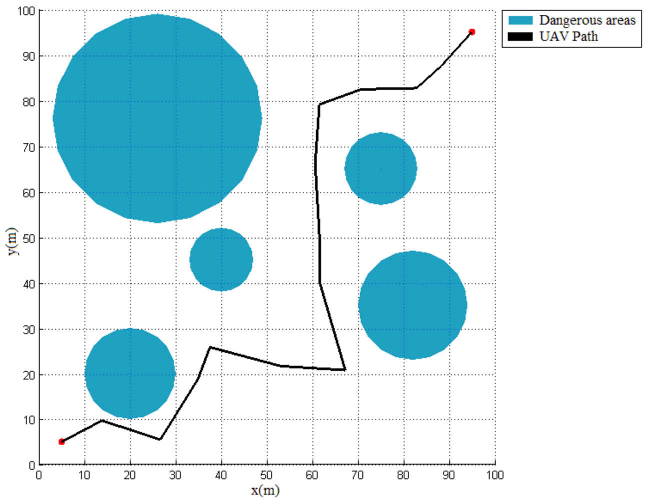
(b)

Figure 2 Simulation results, (a) path optimised by MOPIODE (b) path optimised by MOPSO (c) path optimised by MODE (d) path optimised by MOPIODE in a top-down view (e) path optimised by MOPSO in a top-down view (f) path optimised by MODE in a top-down view (continued) (see online version for colours)

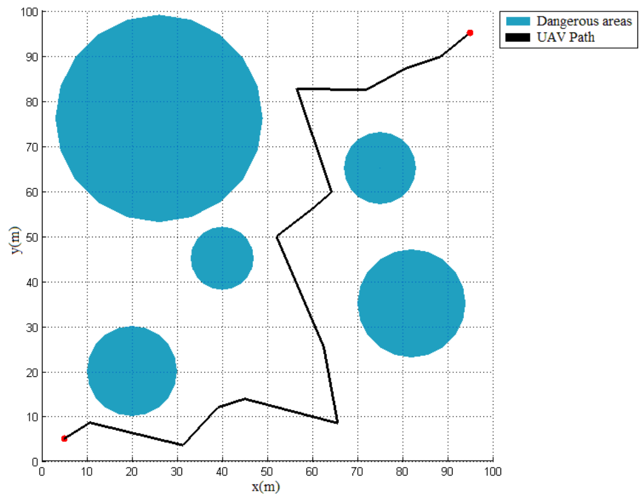
Figure 2 Simulation results, (a) path optimised by MOPIODE (b) path optimised by MOPSO (c) path optimised by MODE (d) path optimised by MOPIODE in a top-down view (e) path optimised by MOPSO in a top-down view (f) path optimised by MODE in a top-down view (continued) (see online version for colours)



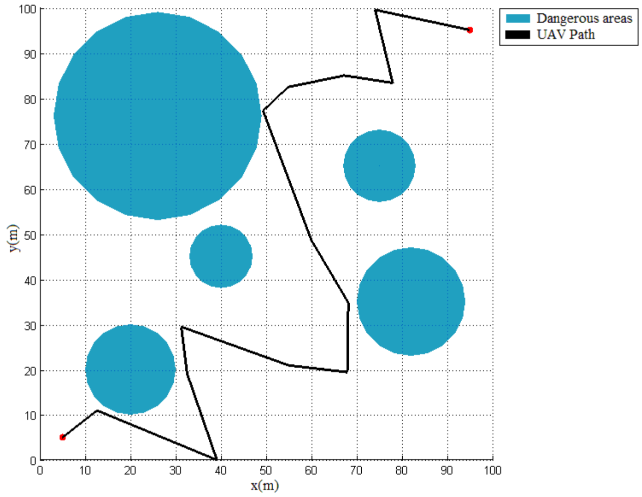
(c)



(d)



(e)



(f)

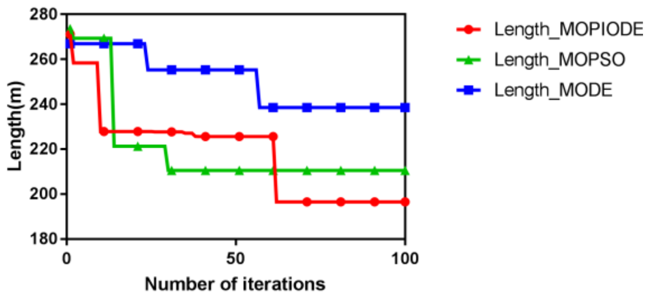
Table 5 Coordinates of path points

Algorithm	*Path i*	*x(m)*	*y(m)*	*z(m)*
MOPIODE	1	13.85	9.67	25.49
	2	26.64	5.48	23.69
	3	34.89	18.76	27.61
	4	37.52	25.77	20.91
	5	53.08	21.63	28.31
	6	67.21	20.73	24.98
	7	61.57	40.08	19.42
	8	61.51	50.93	29.17
	9	60.59	66.06	18.82
	10	61.52	79.05	28.65
	11	70.69	82.38	29.65
	12	82.84	82.65	22.22
	13	88.29	87.56	28.50
MOPSO	1	10.67	8.55	25.83
	2	31.30	3.54	26.59
	3	39.01	11.91	26.41
	4	45.02	13.82	24.99
	5	65.62	8.44	25.07
	6	62.53	25.37	20.12
	7	52.04	49.83	28.16
	8	60.01	55.96	24.12
	9	64.29	59.66	25.29
	10	56.53	82.62	26.70
	11	71.82	82.28	23.46
	12	80.72	87.09	23.82
	13	88.41	89.68	23.87

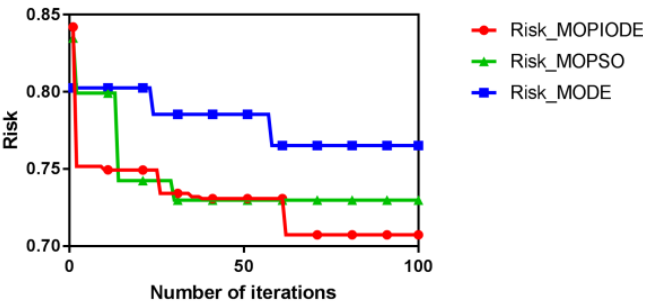
Table 5 Coordinates of path points (continued)

Algorithm	*Path i*	*x(m)*	*y(m)*	*z(m)*
MODE	1	12.61	10.95	31.36
	2	39.10	0.00	22.36
	3	32.53	19.04	18.34
	4	31.23	29.43	21.42
	5	54.97	20.91	17.99
	6	67.92	19.40	24.60
	7	68.14	34.73	16.98
	8	59.98	48.56	21.63
	9	49.29	77.17	21.40
	10	54.82	82.38	25.35
	11	67.23	84.94	22.28
	12	77.94	83.31	21.01
	13	74.07	99.45	33.87

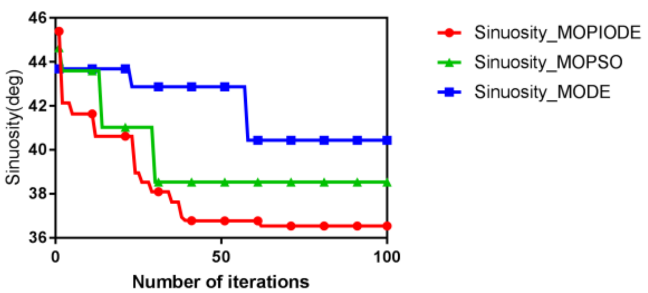
Figure 3 Evolution curves of three algorithms, (a) length of a UAV's path (b) sinuosity of a UAV's path (c) risk of a UAV's path (see online version for colours)



(a)



(b)



(c)

Figure 2 illustrates the detailed results of the UAV's path optimised by MOPIODE, MOPSO and MODE separately. Where Figures 3(d) to 3(f) describe these paths in a top-down view. It's obvious in Figures 3(a) to 3(c), the proposed path planning method outperformed the other two algorithms, in terms of the length, sinuosity and risk degree of the path. These prove that MOPIODE produces improvements in finding a short, smooth and safety path for UAV than PSO and DE algorithm.

6 Conclusions and future perspectives

This paper proposed a new path plan method by integrating PIO into DE algorithm, improving its ability to get out of dangerous areas. The performance of the proposed method was evaluated and compared with that of PSO and DE. Experimental results showed that MOPIODE outperforms generally the other two algorithms in solving the problem.

Our future work will focus on applications of the improved PIO algorithm to solve other complicated optimisation problems.

Acknowledgements

This work was partially supported by Science and Technology Innovation 2030-Key Project of 'New Generation Artificial Intelligence' under grant #2018AAA0102303, #2018AAA0102403, National Natural Science Foundation of China under grant #91948204, #91648205 and #U1913602, and Aeronautical Foundation of China under grant #20185851022.

References

Brand, M., Masuda, M., Wehner, N. and Yu, X.H. (2010) 'Ant colony optimization algorithm for robot path planning', *2010 International Conference on Computer Design and Applications*, Vol. 3, pp.436–440.

Cui, Z.H., Zhang, J.J., Wang, Y.C., Cao, Y., Cai, X.J., Zhang, W.S. and Chen, J.J. (2019) 'A pigeon-inspired optimization algorithm for many-objective optimization problems', *Science China Information Sciences*, Vol. 62, No. 7, pp.070212:1–070212:3.

Cui, Z.H., Zhang, J.J., Wu, D., Cai, X.J., Wang, H., Zhang, W.S. and Chen, J.J. (2020) 'Hybrid many-objective particle swarm optimization algorithm for green coal production problem', *Information Sciences*, Vol. 518, pp.256–271.

Davoodia, M., Panahib, F., Mohadesc, A. and Hashemi, S.N. (2015) 'Clear and smooth path planning', *Applied Soft Computing*, Vol. 32, pp.568–579.

Dorigo, M., Birattari, M. and Stutzle, T. (2006) 'Ant colony optimization', *IEEE Computational Intelligence Magazine*, Vol. 1, pp.28–39.

Duan, H.B. and Qiao, P.X. (2014) 'Pigeon-inspired optimization: a new swarm intelligence optimizer for air robot path planning', *International Journal of Intelligent Computing and Cybernetics*, Vol. 7, No. 1, pp.24–37.

Duan, H.B. and Qiu H.X. (2019) 'Advancements in pigeon-inspired optimization and its variants', *Science China Information Sciences*, Vol. 62, No. 7, p.070201.

Duan, H.B., Huo M.Z., Yang, Z.Y., Shi, Y.H. and Luo, Q.N. (2019a) 'Predator-prey pigeon-inspired optimization for UAV ALS longitudinal parameters tuning', *IEEE Transactions on Aerospace and Electronic Systems*, Vol. 55, No. 5, pp.2347–2358.

Duan, H.B., Tong, B.D., Wang, Y. and Wei, C. (2019b) 'Mixed game pigeon-inspired optimization for unmanned aircraft system swarm formation', *Advances in Swarm Intelligence*, Vol. 11655, pp.429–438.

Hadeel, A., Ahmad, S. and Khair, E.S. (2020) 'A feature selection algorithm for intrusion detection system based on pigeon inspired optimizer', *Expert Systems with Applications*, Vol. 148, No. 113249.

Hai, X.S., Wang, Z.L., Feng, Q., Ren, Y., Xu, B.H., Cui, J.J. and Duan H.B. (2019) 'Mobile robot ADRC with an automatic parameter tuning mechanism via modified pigeon-inspired optimization', *IEEE/ASME Transactions on Mechatronics*, Vol. 24, No. 6, pp.2616–2626.

Hu, Y.R. and Yang, S.X. (2004) 'A knowledge based genetic a1gorithm for path planning of a mobile robot', *Proc. of the 2004 IEEE International Conference on Robotics & Automation*, pp.4350–4355.

Jia, Z.X., Duan, H.B. and Shi, Y.H. (2016) 'Hybrid brain storm optimisation and simulated annealing algorithm for continuous optimization problems', *International Journal of Bio-Inspired Computation*, Vol. 8, No. 2, pp.109–121.

Kennedy, J. and Eberhart, R.C. (1995) 'Particle swarm optimization', *Proc. of IEEE International Conference on Neural Networks*, Vol. 4, pp.1942–1948.

Krüger, T.J., Davidović, T., Teodorović, D. and Šelmić, M. (2016) 'The bee colony optimization algorithm and its convergence', *International Journal of Bio-Inspired Computation*, Vol. 8, No. 5, pp.340–354.

Li, S.Q. and Deng Y.M. (2018) 'Quantum-entanglement pigeon-inspired optimization for unmanned aerial vehicle path planning', *Aircraft Engineering and Aerospace Technology*.

Qin, Y.Q., Sun, D.B., Li, N. and Cen, Q.G. (2004) 'Path planning for mobile robot using the particle swarm optimization with mutation operator', *Proc. of the Third International Conference on Machine Laming and Cybernetics*, Vol. 4, pp.2473–2478.

Qiu, H.X. and Duan, H.B. (2018) 'A multi-objective pigeon-inspired optimization approach to UAV distributed flocking among obstacles', *Information Sciences*.

Qiu, H.X. and Duan, H.B. (2020) 'A multi-objective pigeon-inspired optimization approach to UAV distributed flocking among obstacles', *Information Sciences*, Vol. 509, pp.515–529.

Roberge, V., Tarbouchi, M. and Labonté, G. (2013) 'Comparison of parallel genetic algorithm and particle swarm optimization for real-time UAV path planning', *IEEE Transactions on Industrial Informatics*, Vol. 9, No. 1, pp.132–141.

Sun, B., Chen, W.D. and Xi, Y.G. (2005) 'Particle swarm optimization based global path planning for mobile robots', *Control and Decision*, Vol. 20, No. 9, pp.1052–1060.

Xin, L. and Xian, N. (2017) 'Biological object recognition approach using space variant resolution and pigeon-inspired optimization for UAV', *Science China Technological Sciences*, Vol. 60, No. 3, pp.1577–1584.

Yigit, T., Unsal, O. and Deperlioglu, O. (2018) 'Using the metaheuristic methods for real-time optimisation of dynamic school bus routing problem and an application', *International Journal of Bio-Inspired Computation*, Vol. 11, No. 2, pp.123–133.

Zhang, B. and Duan, H.B. (2017) 'Three-dimensional path planning for uninhabited combat aerial vehicle based on predator-prey pigeon-inspired optimization in dynamic environment', *IEEE/ACM Transactions on Computational Biology and Bioinformatics*, Vol. 14, No. 1, pp.97–107.

Zhang, D.G., Xu, Y. and Yao, X.T. (2018a) 'An improved path planning algorithm for unmanned aerial vehicle based on RRT-Connect', *Proc. of the 37th Chinese Control Conference*, Vol. 3, pp.1418–1422.

Zhang, J.H., Zhang, Y. and Zhou, Y. (2018b) 'Path planning of mobile robot based on hybrid multi-objective bare bones particle swarm optimization with differential evolution', *IEEE Access*, Vol. 6, pp.44542–44555.

Zhang, Q.F. and Li, H. (2007) 'MOEA/D: a multiobjective evolutionary algorithm based on decomposition', *IEEE Transactions on Evolutionary Computation*, Vol. 11, No. 6, pp.712–731.

Zhang, X., Chen, J., Xin, B. and Fang, H. (2011) 'Online path planning for UAV using an improved differential evolution algorithm', *Proc. of the 18th World Congress the International Federation of Automatic Control*, Vol. 44, No. 1, pp.6349–6354.

Zhang, Y., Gong, D.W. and Zhang, J.H. (2012) 'Robot path planning in uncertain environment using multi-objective particle swarm optimization', *Neurocomputing*, Vol. 103, pp.172–185.