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Multiple UCAVs Target Assignment via Bloch Quantum-Behaved Pigeon-Inspired Optimization

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Abstract: In this paper, an improved air-to-air multiple Uninhabited Combat Aerial Vehicles (UCAVs) target assignment model is established and an integrated advantage function with three affecting factors, which are angle, velocity and combat capability, is proposed. Then, Bloch Quantum-Behaved Pigeon-Inspired Optimization (BQPIO) algorithm is designed and applied to optimize the integrated advantage function and solve the multiple UCAVs target assignment problem, which combines the quantum chromosome mechanism with the basic Pigeon-Inspired Optimization (PIO). The detailed procedure is also given. Comparative results with basic PIO and Particle Swarm Optimization (PSO) verified the feasibility and effectiveness of our proposed approach.

Key Words: Uninhabited Combat Aerial Vehicles (UCAVs), Pigeon-Inspired Optimization (PIO), Bloch sphere, Target assignment

1 Introduction

With the rapid development of aviation science and technology and the demand of low casualties in modern warfare, Uninhabited Combat Aerial Vehicles (UCAVs) are becoming more and more popular in many countries. As a single UCAV has the disadvantages of low combat effectiveness and limited abilities, in real situation, usually, multiple UCAVs are used to execute a few tasks together. Thus the multiple UCAVs target assignment problem has become a hot topic in aviation science field.

Recently, many researches focus on the multiple UCAVs target assignment from different aspects. Random strategy, unit greedy strategy and team optimal strategy are applied to analyze the problem [11]. For the team optimal strategy, Gravitational Search Algorithm (GSA), Particle Swarm Optimization (PSO), Differential Evolutionary (DE) and genetic algorithms (GA) have obtained outstanding optimal results. [1]-[3][8]-[10]. Although these optimization algorithms obtain remarkable result, take PSO as an example, there is large room for improvement in the convergence speed and the global searching ability [12]. The Pigeon-Inspired Optimization (PIO) algorithm is a novel swarm intelligence algorithm, which was firstly proposed by Duan in 2014 [4]. Compared with the basic PSO, PIO possesses faster convergence speed and the ability of avoiding the local optimal solution. PSO has been modified in many different ways [13] [14]. As for PIO, Li modified PIO by adding the simulated annealing mechanism [16]. Sun has combined the Prey-Predator strategy with PIO to avoid premature solutions [17]. Hao use a modified PIO in the multiple UAV mission assignment while the evaluation function is not satisfactory enough [18]. In this paper, to obtain a much better solution, an improved PIO, which is called as Bloch Quantum-Behaved Pigeon-Inspired Optimization (BQPIO), is used as a foundation and brought in [5].

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The rest of the paper is organized as follows. Section 2 presents the problem formulation process, including fundamental assumptions, scenario description and, the most important part, establishing the advantage calculating function. Subsequently, the basic principle of PIO is introduced in Section 3. Then in Section 4, our proposed BQPIO is discussed in detail. The result of multiple UCAVs mission assignment and the comparative results are given in Section 5. Our concluding remarks are contained in Section 6.

2 Problem Formulation

2.1 Fundamental Assumptions

In this paper, four fundamental assumptions have to be satisfied.

1. All the UCAVs have the identical ability to accomplish all the targets. In other words, the internal differences of UCAVs can be ignored [1].
2. Each UCAV can't be allocated to another mission until it accomplished the current one.
3. The priorities of all targets are identical, which means the task execution sequence will be ignored.
4. No-fly zones, obstructive terrains and unexpected threats are not exist [15].

2.2 Scenario Description

There exist m blue UCAVs, denoted as $U=\{U_1,U_2,U_3,...U_m\}$ and n red targets UCAVs, denoted as $T=\{T_1,T_2,T_3,...T_n\}$. Considering the real situation, assume the number of targets is larger than that of our UCAVs and both our UCAVs and the targets UCAVs are flying in fixed formations. U_i represents i-th our UCAV, T_j denotes j-th target. The combat pose of a pair of UCAVs is shown in Fig.1. V_i and V_j denote the velocities of U_i and T_j. α_i

and α_j are the angles between the velocity vectors and the line segment U_iT_j.

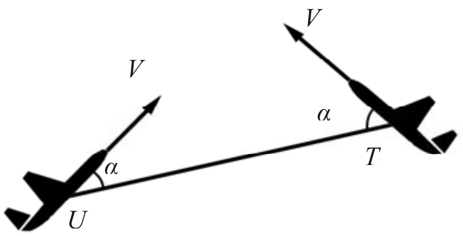

Fig. 1 Combat pose

2.3 The Advantage Function of Angle

A simple model of multiple UCAVs target assignment has been indicated in last paragraph. The angle between our UCAV and the target will decide which side has more advantage. So the advantage function of angle can be expressed as

$$f_{ij}^{a}=\begin{cases}1 & ,0^\circ \le \alpha_i \le 90^\circ, 90^\circ < \alpha_j \le 180^\circ \\ (\alpha_j-\alpha_i)/180^\circ & ,0^\circ \le \alpha_i \le 90^\circ, 0^\circ < \alpha_j \le 90^\circ \\ -1 & ,90^\circ \le \alpha_i \le 180^\circ, 0^\circ < \alpha_j \le 90^\circ \end{cases} \tag{1}$$

where $0^\circ \le \alpha_i \le 90^\circ, 0^\circ < \alpha_j \le 90^\circ$. If f_{ij}^{a} is positive, it means that our UCAV has a better position against the target, otherwise the target is dominant.

2.4 The Advantage Function of Velocity

The relative flight speeds of UCAVs is an important parameter to make a strategic decision. According to the model in this paper, a speed advantage function can be established as follows.

$$f_{ij}^{v}=\begin{cases}1 & ,V_i-V_j>1km/s \\ V_i-V_j & ,|V_i-V_j|\le 1km/s \\ -1 & ,V_i-V_j<-1km/s \end{cases} \tag{2}$$

where V_i and V_j denote the velocities of U_i and T_j. The sign symbol of f_{ij}^{v} will decide whether our UCAVs take the initiative. If f_{ij}^{v} is positive, our UCAVs will have more advantage.

2.5 The Advantage Function of Combat Capacity

In the air-to-air battle, the combat capacity is determined by the maximum range of the UCAV missiles. Therefore, the advantage function of combat capacity can be expressed as

$$f_{ij}^{c}=\begin{cases}1 & ,R_{mi}-D_{ij}>5km \\ (R_{mi}-D_{ij})/5 & ,R_{mi}-D_{ij}\le 5km \\ -1 & ,R_{mi}-D_{ij}<0km \end{cases} \tag{3}$$

where R_{mi} is the maximum attack range of the i-th blue UCAV and D_{ij} is the distance between the i-th blue UCAV and the j-th red target. If f_{ij}^{c} is positive, it indicates that our UCAV has advantage. Otherwise, our UCAV has disadvantage.

2.6 The Integrated Advantage Function

According to the three advantage functions above, an integrated advantage function can be established as

$$f_{ij}=k_a f_{ij}^{a}+k_v f_{ij}^{v}+k_c f_{ij}^{c} \tag{4}$$

where k_a, k_v and k_c are the weight factors. Each weight factor can make a slight adjustment based on the real situation including the environment, UCAVs' weapon condition and experience. If, for instance, our UCAVs' weapon systems are extremely advanced, our UCAVs can complete tasks within a short range. So the maximum transmission range will be an insignificant factor and k_c will be supposed to turn down. But the weight factors must always satisfy one basic rule which is $k_a+k_v+k_c=1$.

3 Pigeon-inspired Optimization

Pigeon-inspired optimization is one of the new bio-inspired optimization proposed in the last few years. Inspired by the method pigeons rely on to find their way home, map and compass operator and landmark operator are brought in the optimal algorithm.

3.1 Map and Compass Operator

In nature, map and compass help pigeons locate their position and determine the direction. Analogously, the map and compass operator assists the virtual pigeons ascertain their positions and velocities in each iteration. After initializing the number of pigeons N, the maximum number of iteration t_{1max}, and the map and compass factor R, the evolution rules are given as [4]

$$v_i(t)=v_i(t-1)\cdot e^{-Rt}+rand\cdot\left(x_g-x_i(t-1)\right) \tag{5}$$

$$x_i(t)=x_i(t-1)+v_i(t) \tag{6}$$

where x_g is the current global best position, $v_i(t)$ is the velocity of the i-th virtual pigeon in the t-th ($0<t\le t_{1\max}$) iteration, $x_i(t)$ is the position of the i-th virtual pigeon in the t-th ($0<t\le t_{1\max}$) iteration and $rand$ is a number picked randomly between 0 and 1.

3.2 Landmark Operator

When pigeons realize that they are near enough to their destination, they will use landmarks as guidance to complete the rest journey instead of map and compass. The landmark operator is a reflection from nature into the algorithm.

Let the maximum iteration time of this operator be $t_{2\max}$, the center of a group of virtual pigeons be x_c, the fitness value calculating function be $F(x)$. In each iteration, sort x_i by calculating all the $F(x_i)$ to find x_c and then cut the pigeon number to a half. Those virtual pigeons which are far away from the destination are supposed to follow those nearer ones. The evolution equation expresses as [4]

$$N(t) = N(t-1)/2 \tag{7}$$

$$x_i(t) = x_i(t-1) + rand \cdot (x_c(t) - x_i(t-1)) \tag{8}$$

where $1 < t < t_{2\max}$.

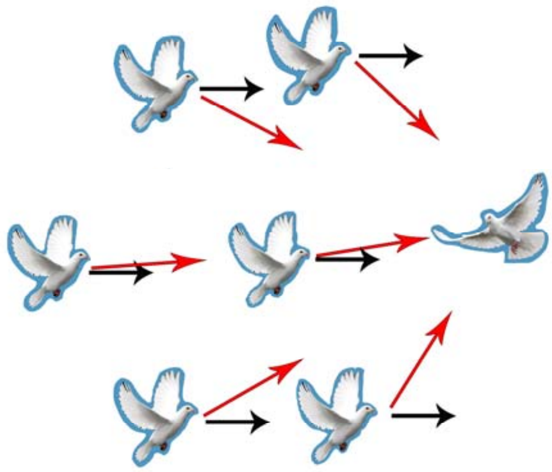

Fig. 2 The landmark section illustration

4 Bloch Quantum-behaved Pigeon-inspired Optimization

In order to improve the optimization efficiency and to avoid trapping into a locally optimal solution, Bloch Sphere encoding mechanism is added to the basic PIO. Every virtual pigeon will be added quantum behavior.

4.1 Quantum Chromosome

In quantum evolutionary theory, the positions of all the particles are supposed to be encoded by the probability amplitudes of qubits. The quantum rotation gates lead to the movements of particles and then achieve range searching. To increase the diversity of particles, quantum non-gate are used to mutate the particles. Each qubit contains two probability amplitudes, so one particle corresponds two positions in the space, therefore the convergence speed is improved [7]. Assume an n quantum bits quantum chromosome, it express as

$$C = \left[\begin{array}{c|c|c|c} \alpha_1 & \alpha_2 & \alpha_3 & \cdots & \alpha_n \\ \beta_1 & \beta_2 & \beta_3 & & \beta_n \end{array} \right] \tag{9}$$

where $i = 1, 2, 3 \ldots n$, $|\alpha_i|^2$ represents the possibility that the quantum bit will be found in the '0' state. Otherwise, $|\beta_i|^2$ represents the possibility that the quantum bit will be found in '1' state. The quantum bit chromosome is the linear superposition of all possible solutions. Then we compare $|\alpha_i|^2$ with a random number between 0 and 1. If the $|\alpha_i|^2$ is larger, i-th quantum bit of the classical quantum chromosome is 0. On the contrary, if the random number is larger, i-th bit will be 1. The traditional mutation operation is completely random with no directions, and the convergence speed is average. But the quantum rotation gate leads the quantum mutation and the quantum mutation can be regarded as a mutation operator. Fig.3 shows the rotation gate for quantum bit chromosome in polar plot [5]. The updating rule for $[\alpha_i, \beta_i]^T$ can be expressed as

$$\begin{bmatrix} \alpha_i' \\ \beta_i' \end{bmatrix} = \begin{bmatrix} \cos\theta_i & \sin\theta_i \\ \sin\theta_i & \sin\theta_i \end{bmatrix} \begin{bmatrix} \alpha_i \\ \beta_i \end{bmatrix} \tag{10}$$

where θ_i is determined by quantum chromosome and classical chromosome.

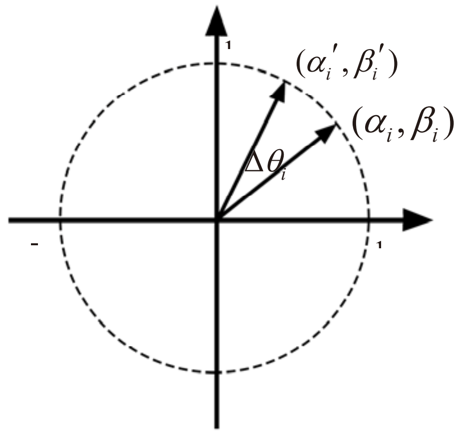

Fig. 3 The rotation gate for quantum bit chromosome

4.2 Bloch Quantum-behaved Pigeon-inspired Optimization

In Fig.4, A, a point, can be fixed by two angular coordinates, θ and φ in the situation of 3D Bloch sphere [5].

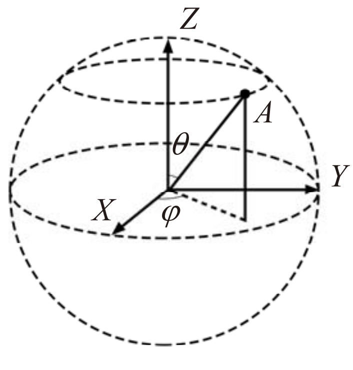

Fig. 4 Quantum bit bloch sphere

Each quantum bit has a single corresponding point in the Bloch Sphere, so the virtual pigeon positions can be corresponded in the Bloch Sphere coordinates. Then the virtual pigeon position, encoded by the quantum bit bloch sphere, can be described as follows:

$$P_i = \left| \begin{array}{c|c|c} \cos\varphi_{i1}\sin\theta_{i1} & \cdots & \cos\varphi_{id}\sin\theta_d \\ \sin\varphi_{i1}\sin\varphi_{i1} & \cdots & \sin\varphi_{id}\sin\varphi_{id} \\ \cos\theta_{i1} & \cdots & \cos\theta_{id} \end{array} \right| \tag{11}$$

where P_i represents the ith virtual pigeon among the swarm, $\varphi_{ij} = 2\pi \times rand$, $\theta_{ij} = \pi \times rand$. $rand$ is a random number between 0 and 1, $i = 1, 2, 3 \cdots N$ and $j = 1, 2, 3 \cdots d$ where N is the number of pigeons, d is the dimension of the space (the number of unknown numbers).

A 3D mutation operator is established to show the effect of quantum non-gate from Hilbert space's unit circle to the Bloch Sphere. The operator satisfy the following matrix equation:

$$\Phi\cdot\begin{bmatrix}\cos\varphi_{ij}(t)\sin\theta_{ij}(t)\\ \sin\varphi_{ij}(t)\sin\varphi_{ij}(t)\\ \cos\theta_{ij}(t)\end{bmatrix}=\begin{bmatrix}\cos(\frac{\pi}{2}-\varphi_{ij}(t))\sin(\frac{\pi}{2}-\theta_{ij}(t))\\ \sin(\frac{\pi}{2}-\varphi_{ij}(t))\sin(\frac{\pi}{2}-\theta_{ij}(t))\\ \cos(\frac{\pi}{2}-\theta_{ij}(t))\end{bmatrix} \tag{12}$$

Derived from last equation, the 3D mutation operator Φ is

$$\Phi=\begin{bmatrix}0 & \cot\theta_{ij}(t) & 0\\ \cot\theta_{ij}(t) & 0 & 0\\ 0 & 0 & \tan\theta_{ij}(t)\end{bmatrix} \tag{13}$$

So the map and compass operator in PIO can be transformed as

If $u(t+1)\geq 0.5$,

$x_i(t+1)=$

$$P_bP_g(t+1)+\omega(t+1)\times\left|a_b(t+1)-x_i(t)\right|\times\ln\left(1/u(t+1)\right) \tag{14}$$

else $x_i(t+1)=$

$$P_bP_g(t+1)-\omega(t+1)\times\left|a_b(t+1)-x_i(t)\right|\times\ln\left(1/v(t+1)\right) \tag{15}$$

where P_b is the best position for one pigeon, P_g is the current best position for all the pigeons, $u(t+1)$ and $v(t+1)$ are random variables factors which are drawn with the same probability from [0,1], $P_bP_g(t+1)=u(t+1)\times P_b(t)+(1-u(t+1))\times P_g(t)$, ω is a constriction factor which is supposed to decrease from $\omega_{\max}$ to $\omega_{\min}$, $\omega(t)=\omega_{\max}-(\omega_{\max}-\omega_{\min})\times t/t_{1\max}$. $a_b(t)$ is the average fitness value of the optimal position of each pigeon at *t*-th iteration.

$$a_b(t+1)=\frac{1}{N}\sum_{i=1}^{N}P_i(t) \tag{15}$$

The landmark operator is same to the basic PIO.

4.3 The algorithm flow of BQPIO

Step 1: Initialize the parameters including N, D, $t_{1\max}$, $t_{2\max}$ and R.

Step 2: Initialize the position and the velocity of each virtual pigeon.

Step 3: Calculate the fitness value of each virtual pigeon and compare the individual best fitness values of all the pigeons to obtain the global best position.

Step 4: Operate the map and compass operator. Update the velocities and positions of every virtual pigeons according to equations (11)-(15), and update the global best position.

Step 5: If $t > t_{1\max}$, go to the next step else go back to step 4.

Step 6: Operate the landmark operator. Sort all the virtual pigeons by their fitness values, and take out a half of pigeons whose fitness values are lower. Then find out the center pigeon of the rest virtual pigeons and assume the position of the center pigeon is the destination. All the other pigeons are supposed to fly towards the destination by adjusting their directions.

Step 7: If $t > t_{2\max}$, output the result else go back to the step 6.

5 Experimental Results

In this section, the BQPIO is applied to the multiple UCAVs target assignment problem and PIO and PSO are brought in as contrasts. For the reason that PIO, PSO and BQPIO are used to solve continues problems while the multiple UCAVs target assignment problem is a discrete problem, we introduce a rank rule to solve the problem. The rank rule is that sort the coordinate in each dimension and assign the targets according to the coordinate rank.

The initial positions of our UCAVs and the targets are showed in Table 1 and 2, and Fig.5 presents the distribution diagram.

Table 1 The Coordinate of Our UCAV

Number of our UCAVs	Coordinates
1	(-15,0)
2	(-5,0)
3	(5,0)
4	(15,0)

Table 2 The Coordinate of Red Target UCAV

Number of Targets	Coordinates
1	(-20,60)
2	(-10,60)
3	(0,80)
4	(0,70)
5	(0,50)
6	(0,40)
7	(10,60)
8	(20,60)

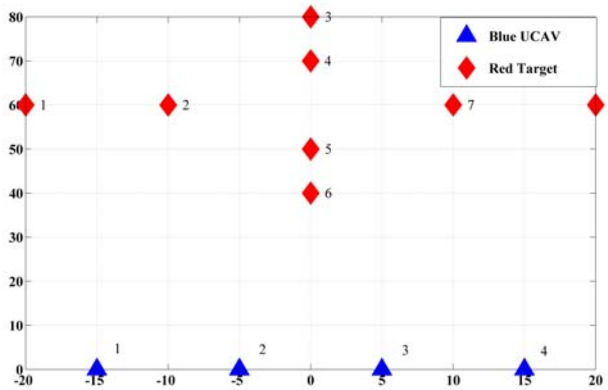

Fig. 5 The distribution diagram

Then initialize the maximum attack range $R_{mi}=100$, weight factor $k_a=0.5$ $k_v=0.4$ $k_c=0.1$ and the parameters of PIO, PSO and BQPIO. For PIO and BQPIO, the parameters are $R = 0.2$ $t_{1\max} = 150$ $t_{2\max} = 50$ $N = 30$ and $d = 8$. For PSO, N and d are the same to PIO and the rest parameters are $c_1 = c_2 = 1.4962$ and $t_{\max} = 200$.

In order to have a more intuitive comparison results, the convergence behaviors of these three algorithms are shown in Fig.6

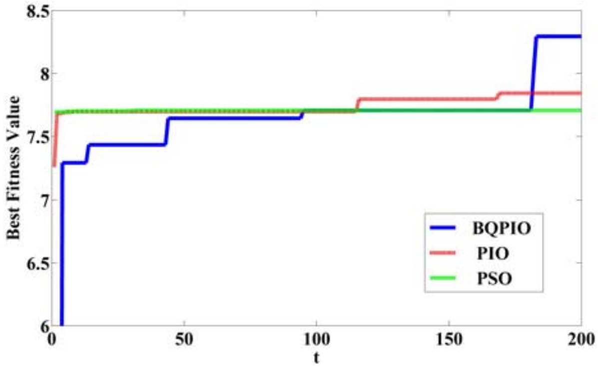

Fig. 6 Evolution curve comparison of BQPIO, PIO and PSO

As for the multiple UCAVs target assignment problem, the comparative results are given in Table 3 and Fig.7. The results verified the feasibility and effectiveness of our proposed approach.

Table 3 The match of our UCAVs and targets

Number of our UCAVs	Number of targets
1	1,2
2	4,5
3	3,6
4	7,8

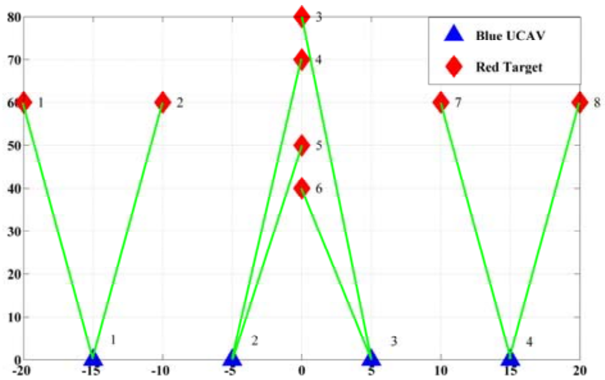

Fig. 7 The UCAV target matching results by using our BQPIO

6 Conclusion

In this paper, a BQPIO is proposed for solve the multiple UCAVs target assignment problems. In the mathematical model, an advantage calculation function is constructed, and our proposed BQPIO is applied to optimize the multiple UCAVs target assignment based on the advantage calculation function. We also compared our presented BQPIO with PSO and PIO in solving the multiple UCAVs target assignment problem. The comparative simulation result shows that our BQPIO is much more effective in solving multiple UCAVs target assignment problem than basic PIO and PSO algorithms.

Our future work will focus on the robustness of our BQPIO and other improvements in the landmark operator, we will also try to apply the BQPIO algorithm to solve other more complicated problems.

References

[1] Y. Chen, H. Duan, Multiple UCAVs mission assignment based on modified gravitational search, *in Proceedings of the 11th IEEE International Conference on Control and Automation*, Taiwan, 2014: 540-545.

[2] H. Duan, Q. Luo, Y. Yu, Trophallaxis network control approach to formation flight of multiple unmanned aerial vehicles, *SCIENCE CHINA Technological Sciences*, 56(5): 1066-1074, 2013.

[3] L. Lin, Q. Sun, S. Wang et al, Research on PSO based multiple UCAVs real-time task assignment, *in Proceedings of the 25th Chinese Control and Decision Conference (CCDC)*, Liaoning, 2013: 1530-1536.

[4] H. Duan, P. Qiao, Pigeon-inspired optimization: A new swarm intelligence optimizer for air robot path planning, *International Journal of Intelligent Computing and Cybernetics*, 7(1): 24-37, 2014.

[5] H. Li, H. Duan, Bloch quantum-behaved pigeon-Inspired optimization for continuous optimization problem, *in Proceedings of 2014 IEEE Chinese Guidance, Navigation and Control Conference*, Yantai. 2014: 2634-2638

[6] D. Luo, H. Duan, S. Wu, M. Li, Research on air combat decision-making for cooperative multiple target attack using heuristic ant colony algorithm, *Acta Aeronautica et Astronautica Sinic*a, 27, 1166-1170, 2006.

[7] Y. Du, H. Duan, R. Liao, X. Li, Improved quantum particle swarm optimization by bloch sphere. *Lecture Notes in Artificial Intelligence*, 6145 (1): 135-143, 2010.

[8] G. Wang, M. Li, Z. Deng, et al. A new approach to solve the mission assignment problem for cooperative UCAVs using immune particle swarm optimizations, in *Proceedings of 10th World Congress on Intelligent Control and Automation*, Beijing, 2012: 549-554.

[9] Y. Fu, M. Ding, C. Zhou, et al. Route planning for unmanned aerial vehicle (UAV) on the sea using hybrid differential evolution and quantum-behaved particle swarm optimization, *IEEE Transactions on Systems Man and Cybernetics: Systems*, 43(6): 1451-1465,2013.

[10] D. Jing, C. Jian, S. Min, Cooperative task assignment for heterogeneous multi-UCAVs based on differential evolution algorithm, *IEEE Intelligent Computing and Intelligent Systems*, 2, 163-167, 2009.

[11] Galati D G, Simaan M A. Effectiveness of the nash strategies in competitive multi-team target assignment problems. *IEEE Transactions of Aerospace and Electronic Systems*, 43(1): 126-134, 2007.

[12] W. Chen, J. Zhang, Y. Lin, et al, Particle swarm optimization with an aging leader and challengers, *IEEE Trans. Evolutionary Computation*, 17(2):241-258, 2013.

[13] Higashi. N, Iba. H, Particle swarm optimization with Gaussian mutation, *in Proceeding of the IEEE Swarm Intelligence Symposium*, 72-79, 2003.

[14] Stacey. A., Jancic. M., and Grundy. I, Particle swarm optimization with mutation, *in Proceeding of IEEE Evolutionary Computation*, 2, 1425-1430, 2003.

[15] J. Du, F. Zhang, J. Yang, H. Wu, Cooperative task assignment for multiple UCAV using particle swarm optimization, *Control and Decision*, 27(11): 1751-1755, 2012.

[16] C. Li, H. Duan, Target detection approach for UAVs via improved pigeon-inspired optimization and edge potential function, *Aerospace Science and Technology*, 39: 352-360, 2014.
[17] H. Sun, H. Duan, PID controller design based on prey-predator pigeon-inspired optimization algorithm, *in Proceedings of IEEE International Conference on Mechatronics and Automation*, 2014, Tianjin, 1416-1421
[18] R. Hao, H. Duan, Multiple UAVs mission assignment based on modified pigeon-inspired optimization algorithm, *in Proceedings of IEEE Chinese Guidance, Navigation and Control Conference*, Yantai, 2014: 2692-2697.