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Pigeon-inspired optimization: a new swarm intelligence optimizer for air robot path planning

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Abstract

Purpose – The purpose of this paper is to present a novel swarm intelligence optimizer — pigeon-inspired optimization (PIO) — and describe how this algorithm was applied to solve air robot path planning problems.

Design/methodology/approach – The formulation of threat resources and objective function in air robot path planning is given. The mathematical model and detailed implementation process of PIO is presented. Comparative experiments with standard differential evolution (DE) algorithm are also conducted.

Findings – The feasibility, effectiveness and robustness of the proposed PIO algorithm are shown by a series of comparative experiments with standard DE algorithm. The computational results also show that the proposed PIO algorithm can effectively improve the convergence speed, and the superiority of global search is also verified in various cases.

Originality/value – In this paper, the authors first presented a PIO algorithm. In this newly presented algorithm, map and compass operator model is presented based on magnetic field and sun, while landmark operator model is designed based on landmarks. The authors also applied this newly proposed PIO algorithm for solving air robot path planning problems.

Keywords Evolutionary computation, Robotics

Paper type Research paper

1. Introduction

Population-based swarm intelligence algorithms have been widely accepted and successfully applied to solve many optimization problems. Unlike traditional single-point based algorithms such as hill-climbing algorithms, a population-based swarm intelligence algorithm consists of a set of points (population) which solve the problem through information sharing to cooperate and/or compete among themselves (Shi, 2011a, b). Exploration and exploitation is also the key issue for these meta-heuristic swarm intelligence algorithms. In recent years, there are a lot of population-based swarm intelligence algorithms existed, such as ant colony optimization, particle swarm optimization (Kennedy and Eberhart, 1995), artificial bee colony algorithm (Karaboga, 2005; Karaboga and Basturk, 2007), imperialist competitive algorithm (Esmaeil and Lucas, 2007) and brain strom optimization (Shi, 2011a, b). All the bio-inspired optimization algorithms are trying to simulate the natural ecosystem mechanisms, which have greatly improved the feasibility of the modern optimization techniques, and offered practical solutions for those

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complicated combinatorial optimization problems. Path planning is the problem of designing the path a vehicle is supposed to follow in such a way that a certain objective is maximized and a goal is reached (Ergezer and Leblebicioglu, 2013). Path planning is one of the most challenging issues of mission planning for air robots (Duan *et al.*, 2008, 2013; Duan *et al.*, 2010a, b), especially in complicated combating environments.

Pigeons are the most popular bird in the world, and they were once used to send the message by Egyptians, which also occurred in many military affairs. Homing pigeons can easily find their homes by using three homing tools: magnetic field, sun and landmarks. In this paper, we presented a new bio-inspired swarm intelligence optimizer – pigeon-inspired optimization (PIO). In this newly invented algorithm, map and compass operator model is presented based on magnetic field and sun, while landmark operator model is presented based on landmarks. We also applied this newly proposed PIO algorithm for solving air robot path planning problem.

The rest of the paper is organized as follows. Section 2 introduces the formulation of threat resources and objective function in air robot path planning. Section 3 describes natural pigeon behaviors and the inspirations from the natural ones. Section 4 presented the basic mathematical model of PIO and Section 5 specifies the detailed implementation procedure of PIO. Subsequently, a series of comparison experiments with the standard differential evolution (DE) are conducted, and the comparative results and analysis are given in Section 6. Our concluding remarks are contained in Section 7.

2. Problem Formulation

2.1 Threat sources in path planning

The threat sources modeling is the most important issue in air robot optimal path planning. There are two kinds of threat sources: artificial threats and natural threats. The artificial threats include the enemy's radar, missiles and artillery and so on. There are appropriate models of them under different circumstances. The traditional optimization algorithms generally use circle models to describe these threats, and the radius of the circle is the range of threat source, and the treat level can also be defined to calculate the threat cost. Mathematically, the problem of 3D path planning for air robot can be described as follows (Duan *et al.*, 2010a, b).

Given the starting point A and target point B, (A,B ∈), k threats set $\{T_1, T_2, \ldots, T_k\}$, and the parameters of air robot's maneuvering performance constraints (such as the restrictions of turning angle α, climbing/diving angle β and flying height h), our aim is to find a set of waypoints $\{W_0, W_1, \ldots, W_n, W_{n+1}\}$ with $W_0 = A$ and $W_{n+1} = B$ such that the resultant path is safe and flyable.

2.2 The performance evaluation function

Suppose that the terrain of the environments and the information of threat regions are known, and the starting points and targets are also known. The cost function of air robot flight path can be defined as follows (Zhu and Duan, 2014; Duan *et al.*, 2010a, b; Duan and Li, 2014):

$$F = w_1 f(l) + w_2 f(h) + w_3 f(c) \tag{1}$$

where w_1, w_2 and w_3 are weight coefficients, which have relations to length, height and threat cost separately, and $w_1 + w_2 + w_3 = 1$.

For the given path, the length cost can be defined as:

$$f(l) = \sum_{i=1}^{n} l_i^2 \tag{2}$$

where l_i is the length of the i-th path segment.

The height cost $f(h)$ can be defined as:

$$f(h) = \sum_{i=1}^{n} h_i \tag{3}$$

where h_i is the average altitude above the sea level of the i-th route segment.

In order to simplify the calculations, more efficient approximation to the exact solution is adopted. In this work, threat cost of each edge connecting two discrete points was calculated at five points along it, as is shown in Figure 1.

Suppose the air robot fly in path $L_{i,j}$, we can divide the path $L_{i,j}$ into five sections in this case, and the threat cost $f_{\min}$ can be calculated by:

$$f_{\min} = \begin{cases} 0 & R_{ij} > R_j \\ \frac{L_{ij}}{5} \sum_{k=1}^{N_t} t_k \left(\frac{1}{d_{0.1,k}^4} + \frac{1}{d_{0.3,k}^4} + \frac{1}{d_{0.5,k}^4} + \frac{1}{d_{0.7,k}^4} + \frac{1}{d_{0.9,k}^4} \right) & R_{ij} \leqslant R_j \end{cases} \tag{4}$$

where L_{ij} is the length of $L_{i,j}$, t_k is the k-th threat level, R_j is the radius of the j-th threat, N_t is the number of the threat, R_{ij} denotes the average distance between the i-th path segment and the j-th threat, $d_{0.1,k}$ is the length of the 1/10 point and the k-th threat center. By controlling the threat cost defined here, the survival probability of air robot can be increased accordingly.

3. Natural pigeon behavior

The word "pigeon" is derived from the Latin word "pipio," meaning "young cheeping bird." Pigeon is a type of very common and popular bird. The wild pigeon is found in coastal areas, and the feral pigeon is found almost exclusively in areas of human habitation. Pigeons were once widely used in the military because of their homing behavior (see Figure 2).

During First World War and Second World War, pigeons especially contributed to the Australian, French, German, American and UK forces. Pigeons have the special homing ability that they are thought to use a combination of the sun, the Earth's magnetic field and landmarks to find their way around. Guilford argues that pigeons probably use different navigational tools during different parts of their journey

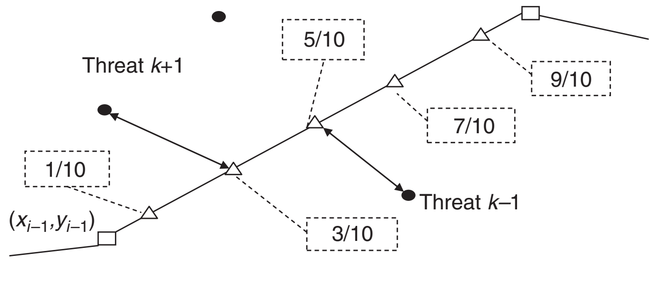


Figure 1.
Computation of threat cost of air robot

Figure 2. Homing behavior of pigeons

(Guilford *et al.*, 2004). Guilford and his colleagues developed a mathematical model that predicts when pigeons will swap from one technique to another. When pigeons start their journey, they may rely more on compass-like tools. While in the middle of their journey, they could switch to using landmarks when they need to reassess their route and make corrections.

Investigation of pigeons' ability to detect different magnetic fields demonstrates that the pigeons' impressive homing skills almost depend on tiny magnetic particles in their beaks. Specifically, there are iron crystals in pigeons' beaks, which can give birds a nose for north. Studies show that the species seem to have a system in which signals from magnetite particles are carried from the nose to the brain by the trigeminal nerve (Mora *et al.*, 2004). Evidence that the sun is also involved in pigeon navigation has been interpreted, either partly or entirely, in terms of the pigeon's ability to distinguish differences in altitude between the Sun at the home base and at the point of release (Whiten, 1972). Recent researches on pigeon behavior also show that the pigeon can follow some landmarks, such as main roads, railways and rivers rather than head for their destination directly.

Inspired by the above homing behaviors of pigeons, a novel bio-inspired swarm intelligence optimizer has been proposed in this paper, which is named PIO.

4. Mathematical model of PIO

In order to idealize some of the homing characteristics of pigeons, two operators are designed by using some rules:

(1) *Map and compass operator*: pigeons can sense the earth field by using magnetoreception to shape the map in their brains. They regard the altitude of the sun as compass to adjust the direction. As they fly to their destination, they rely less on sun and magnetic particles.

(2) *Landmark operator*: when the pigeons fly close to their destination, they will rely on landmarks neighboring them. If they are familiar with the landmarks, they will fly straight to the destination. If they are far from the destination and unfamiliar to the landmarks, they will follow the pigeons who are familiar with the landmarks.

4.1 Map and compass operator

In the PIO model, virtual pigeons are used naturally. In this map and compass operator, the rules are defined with the position X_i and the velocity V_i of pigeon i, and the positions and velocities in a D-dimension search space are updated in each iteration. The new position X_i and velocity V_i of pigeon i at the t-th iteration can be calculated with the following equations:

$$V_i(t) = V_i(t-1) \cdot e^{-Rt} + rand \cdot (X_g - X_i(t-1)) \quad (5)$$

$$X_i(t) = X_i(t-1) + V_i(t) \quad (6)$$

where R is the map and compass factor, *rand* is a random number, and X_g is the current global best position, and which can be obtained by comparing all the positions among all the pigeons. Figure 2 shows the map and compass operator model of PIO.

As shown in Figure 3, the best positions of all pigeons are guaranteed by using map and compass. By comparing all the flied positions, it is obvious that the right-centered pigeon's position is the best one. Each pigeon can adjust its flying direction by following this specific pigeon according to Equation (5), which is expressed by the thick arrows. The thin arrows are its former flying direction, which has relation to $V_i(t-1) \cdot e^{-Rt}$ in Equation (5). The vector sum of these two arrows is its next flying direction.

4.2 Landmark operator

In the landmark operator, half of the number of pigeons is decreased by N_p in every generation. However, the pigeons are still far from the destination, and they are unfamiliar with the landmarks. Let $X_c(t)$ be the center of some pigeon's position at the t-th iteration, and suppose every pigeon can fly straight to the destination. The position updation rule for pigeon i at the t-th iteration can be given by:

$$N_P(t) = \frac{N_P(t-1)}{2} \quad (7)$$

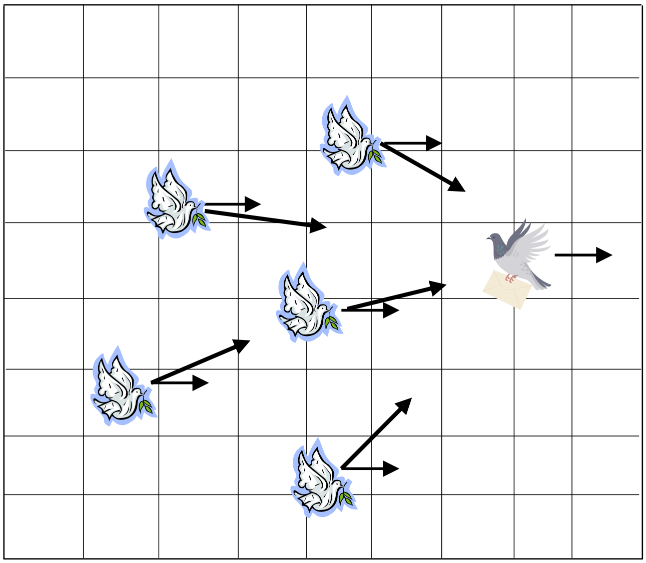


Figure 3.
Map and compass operator model of PIO

$$X_c(t) = \frac{\sum X_i(t) \cdot fitness(X_i(t))}{N_P \sum fitness(X_i(t))} \tag{8}$$

$$X_i(t) = X_i(t-1) + rand \cdot (X_c(t) - X_i(t-1)) \tag{9}$$

where *fitness* ( ) is the quality of the pigeon individual. For the minimum optimization problems, we can choose $fitness(X_i(t)) = \frac{1}{f_{\min}(X_i(t))+\varepsilon}$. For maximum optimization problems, we can choose $fitness(X_i(t)) = f_{\max}(X_i(t))$. For each individual pigeon, the optimal position of the Nc-th iteration can be denoted with X_p, and $X_p = \min\ (X_{i1}, X_{i2}, \ldots, X_{iNc})$. Figure 4 shows the landmark operator model of PIO.

As shown in Figure 4, the center of all pigeons (the pigeon in the center of the circle) is their destination in each iteration. Half of all the pigeons (the pigeons out of the circle) that are far from their destination will follow the pigeons that are close to their destination, which also means that two pigeons may be at the same position. The pigeons that are close to their destination (the pigeons in the circle) will fly to their destination very quickly.

5. PIO implementation procedure

The detailed implementation procedure of PIO for air robot path planning can be described as follows.

Step 1: according to the environmental modeling in Section 2, initialize the terrain information and the threaten information including the coordinates of threat centers, threat radiuses and threat levels.

Step 2: initialize parameters of PIO algorithm, such as solution space dimension D, the population size N_p, map and compass factor R, the number of iteration Nc_1 max and Nc_2 max for two operators, and Nc_2 max $> Nc_1$ max.

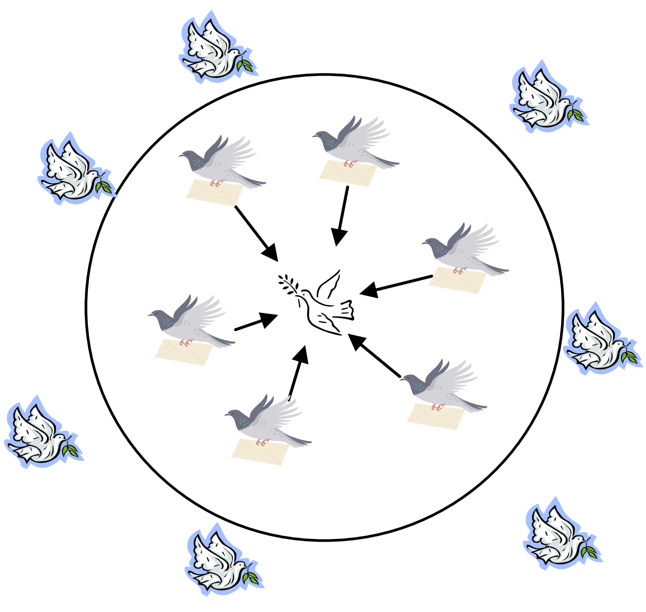


Figure 4.
Landmark operator model

Step 3: set each pigeon with a randomized velocity and path. Comparing the fitness of each pigeons, and find the current best path.

Step 4: operate map and compass operator. Firstly, we update the velocity and path of every pigeon by using Equations (5) and (6). Then we compare all the pigeons' fitness and find the new best path.

Step 5: if $Nc > Nc_{1\max}$, stop the map and compass operator and operate next operator. Otherwise, go to Step 4.

Step 6: rank all pigeons according their fitness values. Half of pigeons whose fitness are low will follow those pigeons with high fitness according to Equation (7). We then find the center of all pigeons according to Equation (8), and this center is the desirable destination. All pigeons will fly to the destination by adjusting their flying direction according to Equation (9). Next, store the best solution parameters and the best cost value.

Step 7: if $Nc > Nc_{2\max}$, stop the landmark operator, and output the results. If not, go to Step 6.

The above steps can be summarized as pseudocode:

PIO algorithm
Input
N_P: number of individuals in pigeon swarm
D: dimension of the search space
R: the map and compass factor
Search range: the borders of the search space
$Nc_{1\max}$: the maximum number of generations that the map and compass operation is carried out
$Nc_{2\max}$: the maximum number of generations that the landmark operation is carried out.
Output
X_g: the global optima of the fitness function f
1. Initialization
Set initial values for $Nc_{1\max}$, $Nc_{2\max}$, N_P, D, R and the search range
Set initial path X_i and velocity V_i for each pigeon individual
Set $X_p = X_i$, $N_c = 1$
Calculate fitness values of different pigeon individuals
$X_g := \arg\min [f(X_p)]$
2. Map and compass operations
For Nc = 1 to $Nc_{1\max}$ do
for i = 1 to N_p do
while X_i is beyond the search range do
calculate V_i and X_i according to Equations (5) and (6)
end while
end for
evaluate X_i, and update X_p and X_g
end for
3. Landmark operations
For $Nc = Nc_{1\max} + 1$ to $Nc_{2\max}$ do
while X_p is beyond the search range do
rank all the available pigeon individuals according to their fitness values
$N_P = N_P/2$
keep half of the individuals with better fitness value, and abandon the other half
Xc = average value of the paths of the remaining pigeon individuals

calculate X_i according to Equation (9)
end while
evaluate X_i, and update X_p and X_g
end for
4. Output
X_g is output as the global optima of the fitness function f

The above programming steps of PIO algorithm can also be summarized as a flowchart (see Figure 5).

6. Comparative experiments

The PIO procedure can be implemented in various ways by setting up PIO algorithm's parameters differently. In order to investigate the feasibility and effectiveness of our proposed PIO algorithm, a series of experiments are conducted, and further comparative experimental results with the standard DE algorithm are also given.

Set the coordinates of the starting point as (0, 0, 30), and the target point as (65, 100, 30), while the initial parameters of PIO algorithm were set as: $N_P = 150$ (see Figures 6 and 8) and 300 (see Figures 7 and 9), $D = 20$, $R = 0.2$, $Nc_{1\max} = 150$,

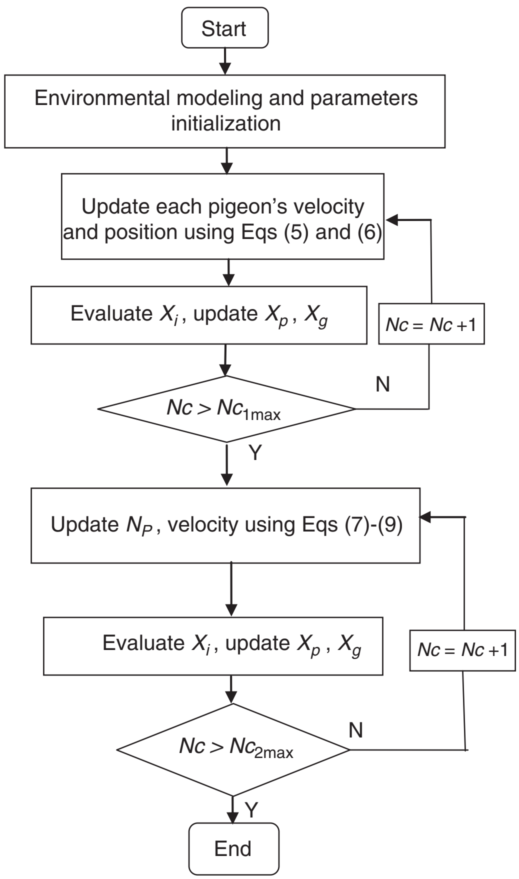


Figure 5.
The procedure of PIO

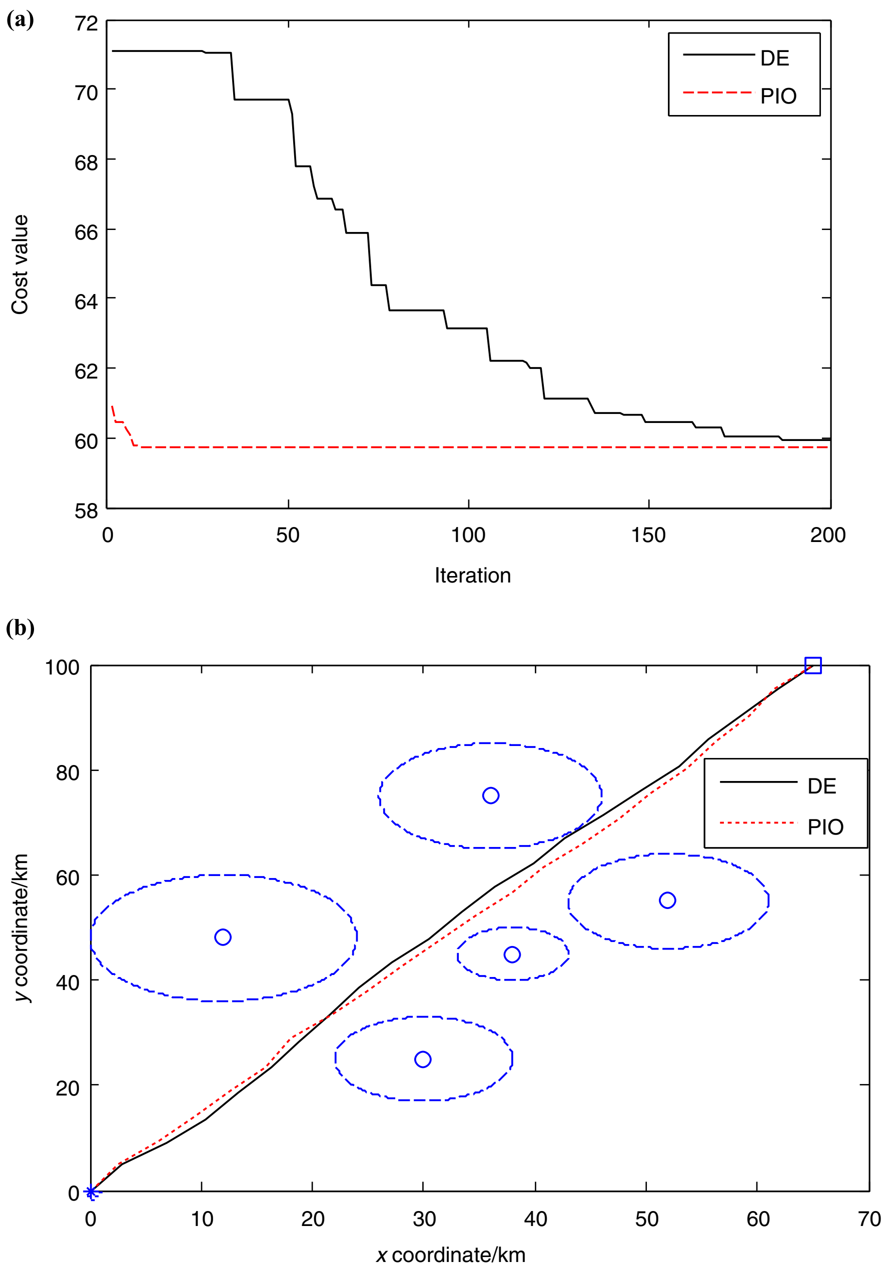
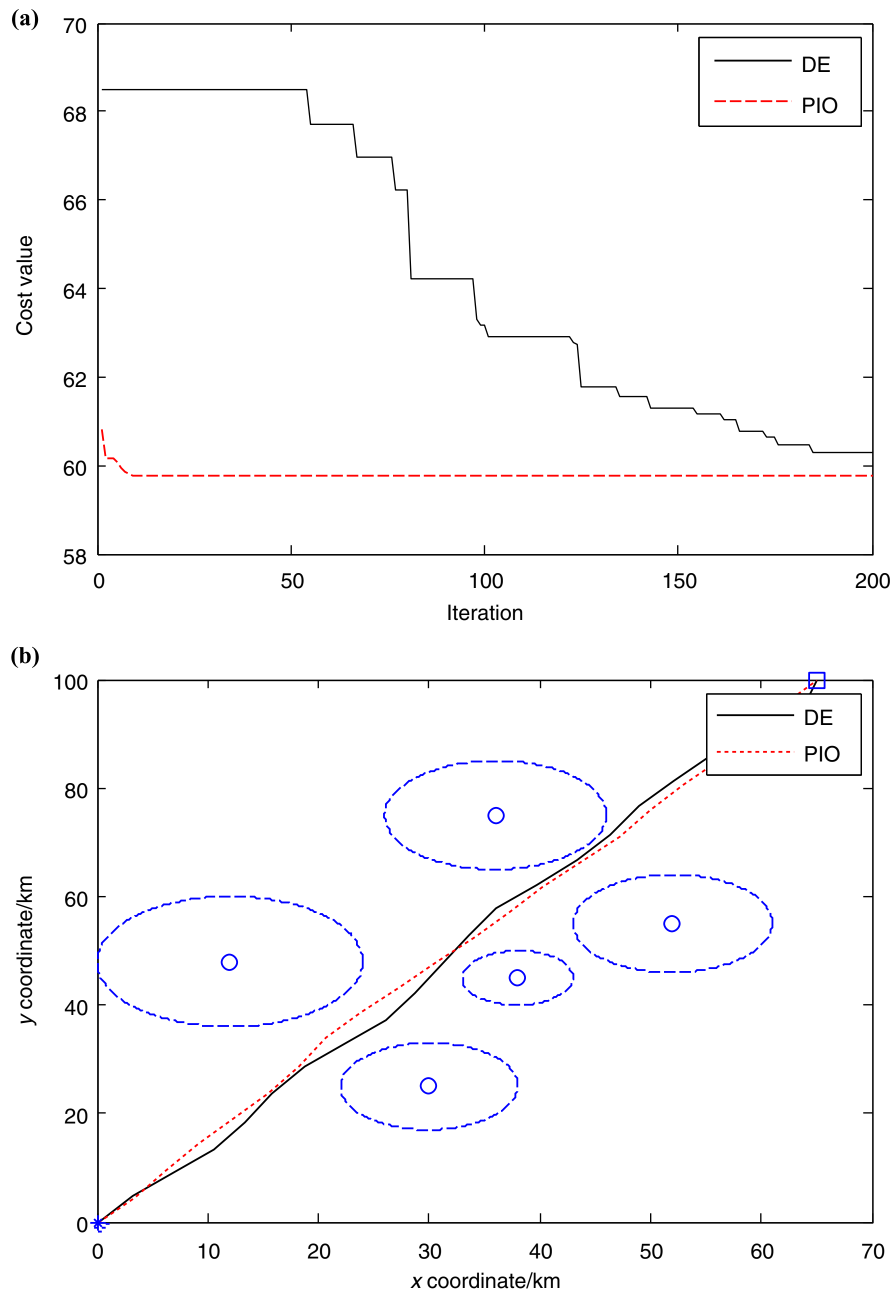


Figure 6.
Comparative path planning results of PIO and DE ($N_P = 150$) for Case 1

Notes: (a) Comparative evolutionary curves of PIO and DE ($N_p = 150$) for Case 1; (b) comparative path planning results of PIO and DE ($N_p = 150$) for Case 1



Notes: (a) Comparative evolutionary curves of PIO and DE (N_p=300) for Case 1; (b) comparative path planning results of PIO and DE (N_p=300) for Case 1

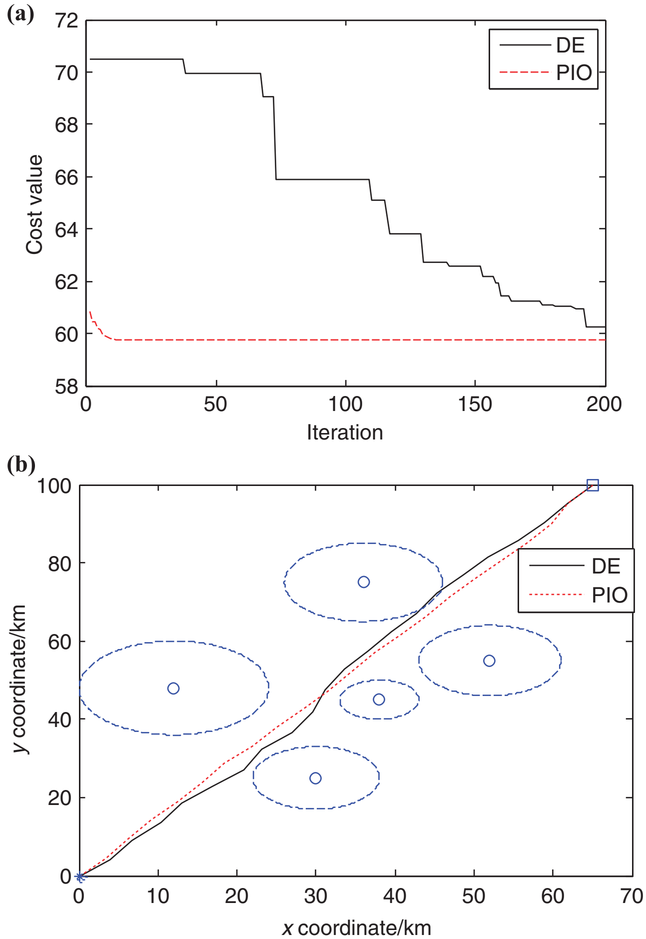
Figure 7.
Comparative path planning results of PIO and DE ($N_P = 300$) for Case 1

$Nc_{2\max} = 200$. We also set $D = 20$. The comparative results with DE are shown in Figures 6 and 7.

From Figures 6-9, it is obvious that our proposed PIO algorithm can converge more quickly and more stable comparing with the standard DE algorithm, and the optimal path generated by using PIO is more smooth and satisfactory than the standard DE algorithm. With the increasing of pigeon number, the convergence performance is much better. Generally, the experimental results also show that our PIO algorithm is much better in stability and superiority over the standard DE algorithm.

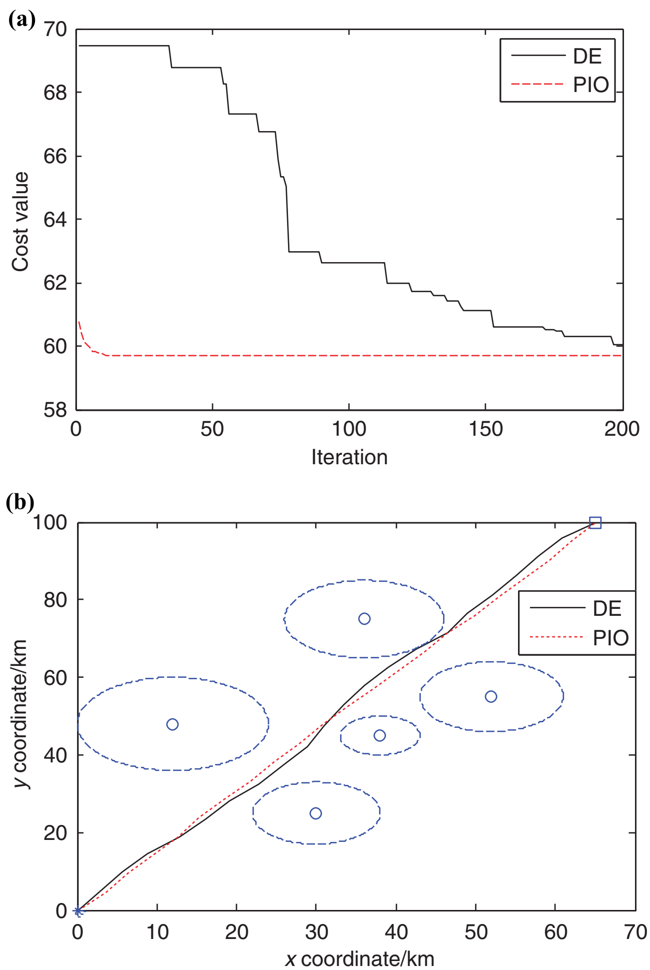
7. Conclusions

This paper presents a novel swarm intelligence optimizer, which is named PIO. We also applied this new algorithm for solving the air robot path planning problem.



Notes: (a) Comparative evolutionary curves of PIO and DE ($N_p = 150$) for Case 2; (b) comparative path planning results of PIO and DE ($N_p = 150$) for Case 2

Figure 8. Comparative path planning results of PIO and DE ($N_P = 150$) for Case 2



Notes: (a) Comparative evolutionary curves of PIO and DE (N_p=300) for Case 2; (b) comparative path planning results of PIO and DE (N_p=300) for Case 2

Figure 9. Comparative path planning results of PIO and DE ($N_P = 300$) for Case 2

Computational experiments are conducted to validate the performance of the proposed PIO algorithm. The comparative simulation results show that our proposed PIO algorithm is a feasible and effective algorithm for air robot path planning.

Our future work will apply this newly presented algorithm to solve other complicated optimization problems.

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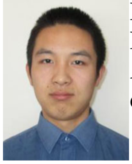

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