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Pigeon inspired optimization approach to model prediction control for unmanned air vehicles

Rui Dou Haibin Duan

# Pigeon inspired optimization approach to model prediction control for unmanned air vehicles

*Rui Dou and Haibin Duan*
School of Automation Science and Electrical Engineering, Beijing University of Aeronautics and Astronautics (BUAA), Beijing, China

**Abstract**
**Purpose** – The purpose of this paper is to propose a novel concept of model prediction control (MPC) parameter optimization method, which is based on pigeon-inspired optimization (PIO) algorithm, with the objective of optimizing the unmanned air vehicles (UAVs) controller design progress.
**Design/methodology/approach** – The PIO algorithm is proposed for parameter optimization in MPC, which provides a new method to get the optimal parameter.
**Findings** – The PIO algorithm is a new swarm optimization method, which consists of two operators, so it can be better adapted for the optimal problems. The comparative consequences results with the particle swarm optimization (PSO) demonstrate the effectiveness of the PIO algorithm, and the superiority for global search is also verified in various cases.
**Practical implications** – PIO algorithm can be easily applied to practice and help the parameter optimization of the MPC.
**Originality/value** – In this paper, we first present the concept of using the PIO algorithm for parameter optimization in MPC so as to achieve the global best optimization. By using the PIO algorithm, the choice of the parameter could be easier and more effective. The authors also applied the algorithm to the designing of the MPC controller to optimize the response of the pitch rate of UAV.

**Keywords** Model prediction control (MPC), Pigeon inspired optimization (PIO), Unmanned air vehicles (UAVs)

**Paper type** Research paper



## Introduction

In recent years, the Unmanned Air Vehicles (UAVs) have gained more and more attention from different countries, and have been applied to more and more cases. As the aircraft can be controlled autonomously with high maneuver, the requirements for the control system of the UAV have become increasingly higher. In this paper, we applied the model prediction control (MPC) theory into use in designing the control system of the UAV.

MPC is an optimization-based control method originating in process of industry in the early 1970s. Now, the MPC theory has been applied into use in different fields, such as industry, medical, aerospace and so on. As a new form of control, the control action is obtained by solving online problem. At each sampling instant, the current state of plant is used as the initial state and a finite horizon open-loop optimal control is implemented. The optimization yields an optimal control sequence, and the first control variable in this sequence is applied to the plant. As its prediction capability allows solving optimal control problems online, the error between the predicted output and the desired reference is minimized over a future horizon, possibly subjected to constraints on the manipulated inputs and outputs. Because MPC is based on the finite horizon, MPC can solve the problem with constraints in input and state variables.

At the same time, the choice of the prediction horizon, the control horizon and the weight of inputs and outputs could have significant influence on the output of the control systems. It is necessary to propose an effective method to acquire the optimal parameters.

In recent years, a lot of population-based swarm intelligence algorithms were put forward, such as ant colony optimization (ACO)(Colorni *et al.*, 1991, Bonabeau *et al.*, 2000), particle swarm optimization (PSO)(Eberhart and Kennedy, 1995), artificial bee colony (ABC) algorithm (Karaboga *et al.*, 2005; Karaboga and Basturk, 2007), imperialist competitive algorithm(Esmaeil *et al.*, 2007) and brain storm optimization (BSO) (Shi, 2011). All the algorithms are trying to offer the practical solution for optimization problems.

A new bio-inspired optimization algorithm, namely, pigeon-inspired optimization (PIO) algorithm, was first proposed by Duan and Qiao (2014). According to the elements for pigeons to find the destination, the algorithm

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consists of two operators. Map and compass operator is based on magnetic field and sun, while the landmark operator is based on the landmark. The feasibility and rapidness of the algorithm have been greatly improved.

The remainder of the text is organized as follows. The next section introduces the principle of the MPC. Section 3 proposes the formulation of the problem. Section 4 describes the basic mathematical model of PIO. Section 5 presents the implementation procedure of the PIO algorithm for MPC parameter optimization problem. Subsequently, a series of comparative experiments are conducted, and the results and the analysis are given in Section 6.

**Figure 1** The optimization of input sequence

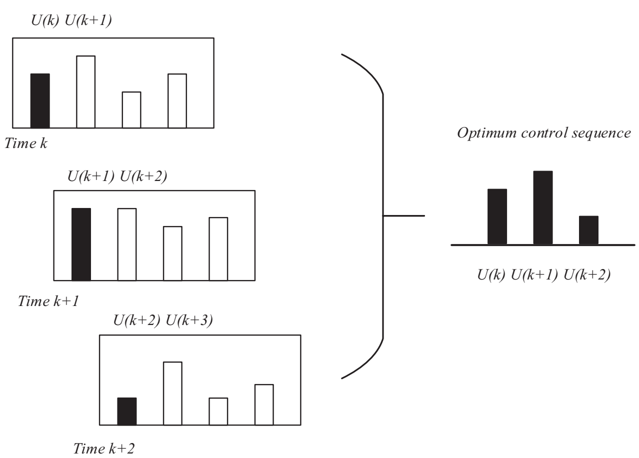
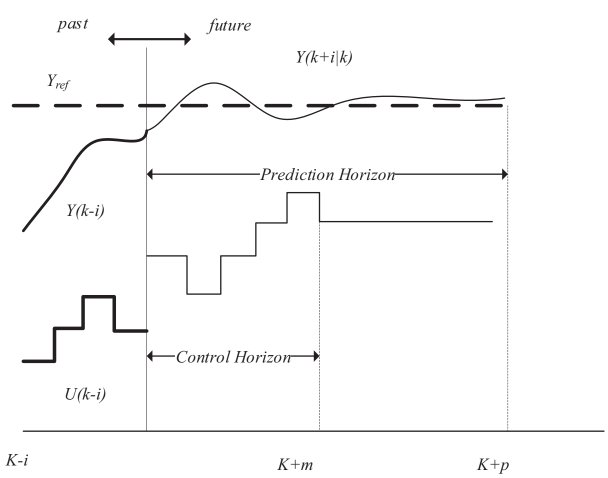



**Figure 2** The process of MPC




## Principle of MPC

MPC consists of three parts: Inner model, feedback correction and receding optimization. Receding optimization is the most important part of MPC, which is quite different from the common control ideas. The whole process could be divided into several intervals called receding horizon. In each interval, MPC optimizes the new input sequence based on the current available information, as shown in Figure 1.

Based on the current state at time $k$, MPC controller computes the next predicted sequence of $p$ predictive time horizons, and the states in the predictive time horizon, namely, $y(k+1|k)$, $y(k+2|k)$, . . . , $y(k+p|k)$, can be

**Figure 4** Map and compass operator model

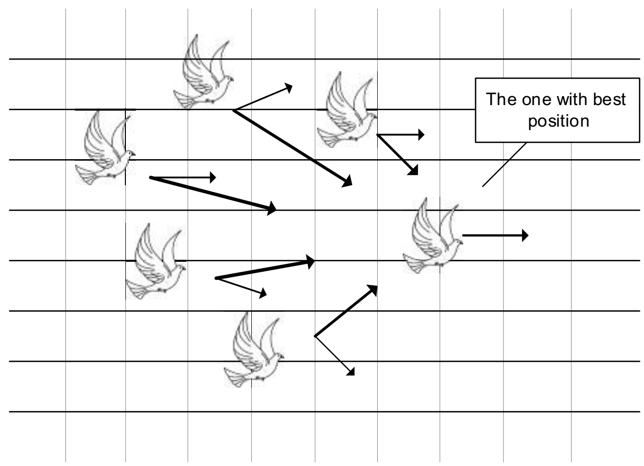



**Figure 5** Landmark operator model

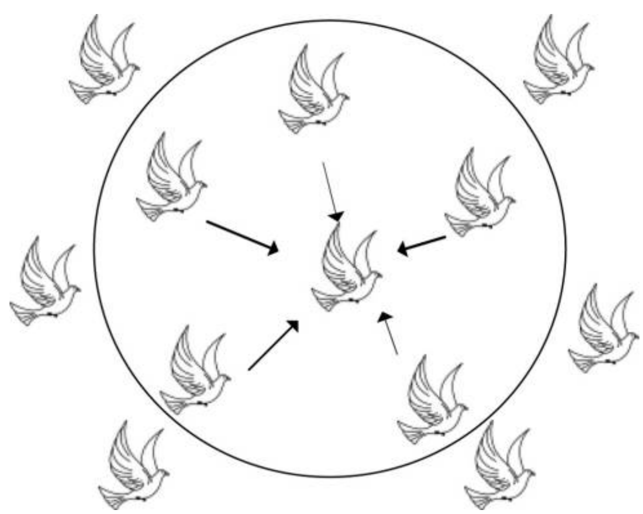


**Figure 3** The block diagram of the system

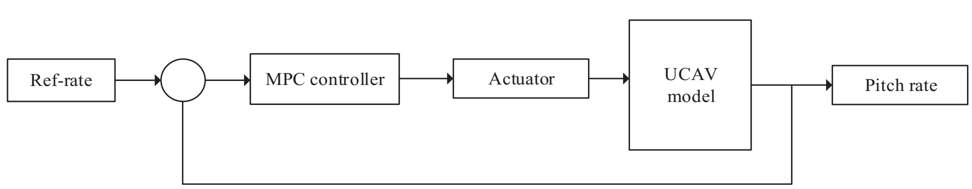


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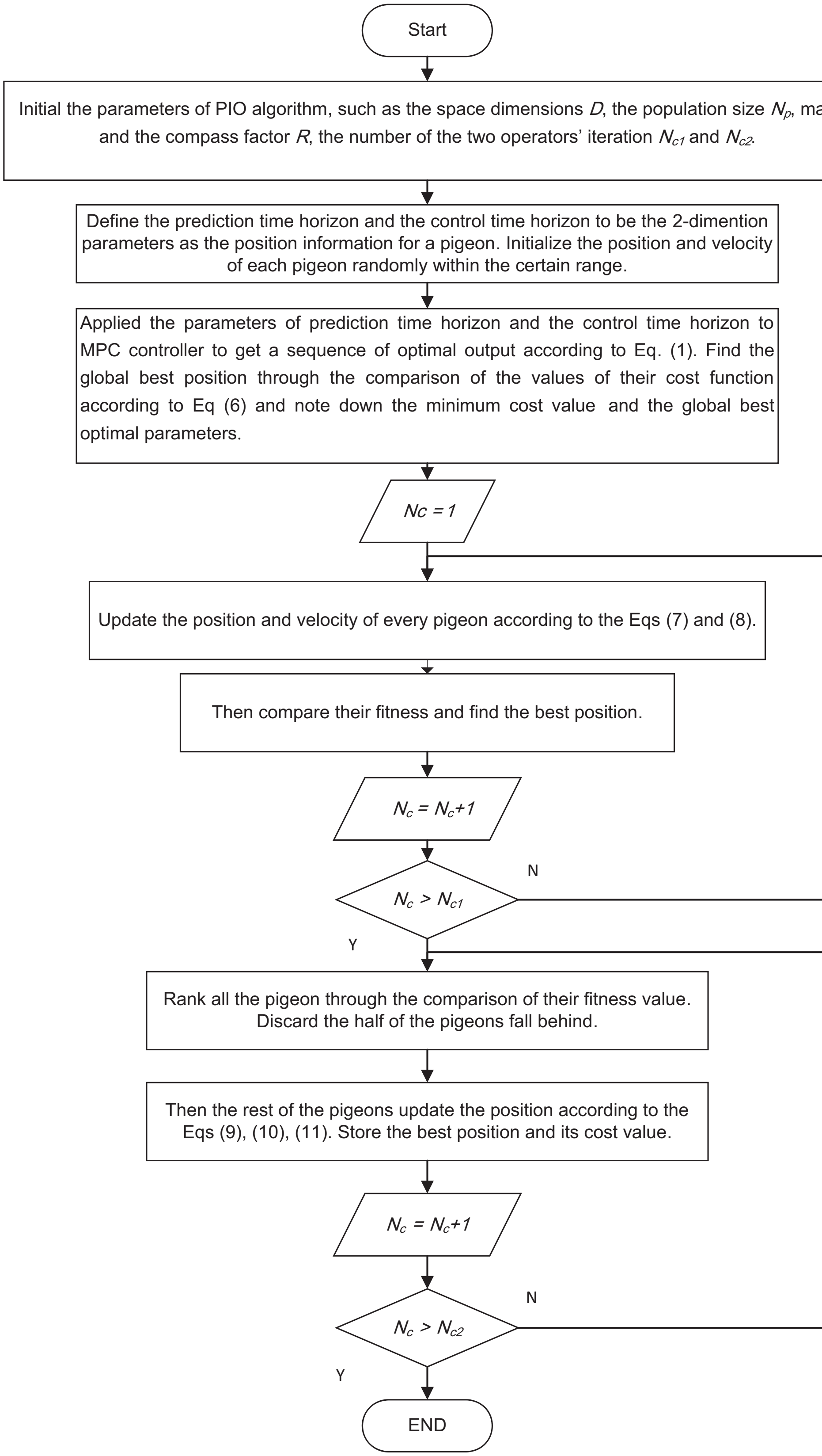
**Figure 6** Flow chart of PIO algorithm for MPC parameter optimization



obtained. The calculation of the fitness function at the $k$-th time is shown as:

$$\min J = \sum_{j=1}^{p} [y(k+j) - y_{ref}(k+j)]^2 + \sum_{j=1}^{m} w[\Delta u(k+j-1)]^2 \quad (1)$$

where $p$ is the predicted time, $m$ represents the control time, $w$ describes the input weight matrix, $y_{ref}$ equals the reference output value and $y(k+j)$ represents the output value at the $i$-th sampling time. By minimizing the fitness function, the optimal solution to the local optimization problem can be obtained. The preceding $m$ control actions, namely, the current and following $m$-1 time horizons are applied to the system successively. Subsequently, repeated sampling, predicting and optimization procedures are implemented. The process of MPC is described in Figure 2.

## Problem formulation

In this section, we will describe the detailed formulation of the problem. The state space model of the UAV could be described as:

$$\dot{x} = Ax + Bu \quad (2)$$

$$y = Cx + Du \quad (3)$$

where the state variable $x = (V/V_0, \alpha, \theta, q, h/V_0)^T$, the control input $u = (\delta_e, \delta_{LEF}, \delta_{PL}, \alpha_w)^T$ and the output $y=(h, nz/V0, \alpha, V, \theta, q)T$.

Supposing the flight height is at the sea level, the airspeed is 69.96 m/s, and the angle of attack is 8.1°, we can obtain the state space model of the UAV:

$$A = \begin{bmatrix} -0.0705 & 0.0475 & -0.1403 & 0 & -0.0001 \\ -0.3110 & -0.3430 & 0 & 0.9913 & 0.0010 \\ 0 & 0 & 0 & 1 & 0 \\ 0.0218 & -1.166 & 0 & -0.2544 & 0 \\ 0 & -1 & 1 & 0 & 0 \end{bmatrix},$$

$$B = \begin{bmatrix} 0.0121 & 0.0025 & 0.2316 & 0.0475 \\ -0.0721 & 0.014 & -0.0338 & -0.343 \\ 0 & 0 & 0 & 0 \\ -1.815 & -0.079 & 0.0023 & -1.166 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

$$C = \begin{bmatrix} 0 & 0 & 0 & 0 & 69.96 \\ 0 & -1 & 1 & 0 & 0 \\ 0.311 & 0.343 & 0 & 0.0087 & -0.0010 \\ 0 & 1 & 0 & 0 & 0 \\ 69.96 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \end{bmatrix},$$

$$D = \begin{bmatrix} 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0.0721 & -0.014 & 0.0338 & 0.343 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix}$$

The transfer function of the actuator is:

$$G_0(s) = \frac{1325}{s^2 + 29.85s + 1325} \quad (4)$$

We can obtain the equivalent transfer function from the autopilot input to the pitch rate response:

$$G = \frac{2405s^4 + 882.7s^3 + 82.41s^2 + 0.265s}{s^7 + 30.52s^6 + 1346s^5 + 923.9s^4 + 1727s^3 + 125.9s^2 + 70.36s + 0.1325} \quad (5)$$

The block diagram of the whole system is shown in Figure 3.

Considering the actual condition of the actuator, we add an amplitude constraint to the input variable, which ranges from −40/57.3 to 40/57.3 rad. As the MPC can only calculate the local optimization result by each time interval, we proposed a fitness function so as to get the global optimization result as:

$$fitness = \sum_{i=1}^{n} 100 \cdot (y(i) - y_{ref})^2 \quad (6)$$

where $n = T/Ts$, $Ts$ represents the sampling period, $T$ denotes the sampling time, $n$ represents the whole sampling number, $y_{ref}$ equals the reference output value and $y(i)$ denotes the output value at the $i$-th sampling time.

Based on a certain set of parameters of prediction time horizon and control time horizon, MPC controller can get the optimal input sequence through the calculation of equation (1), but the parameters may not be the global best for the controller. The fitness function in equation (6) refers to the error between the reference output and the real output, which can provide the global optimal parameters for the controller with the minimal fitness function value. With the help of the PIO algorithm, we can obtain the global best prediction time horizon and the control time horizon for acquiring the global optimization for MPC system.

## Mathematical model of PIO

The PIO algorithm is a new swarm optimization method inspired from the behavior of pigeons. While the PSO

**Figure 7** Value of the fitness function in Case 1

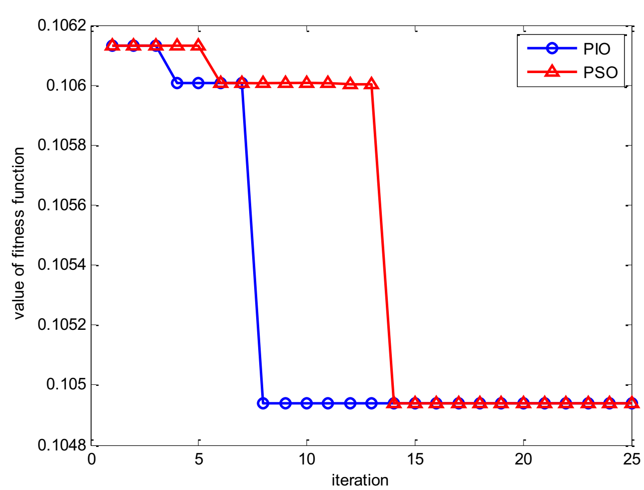
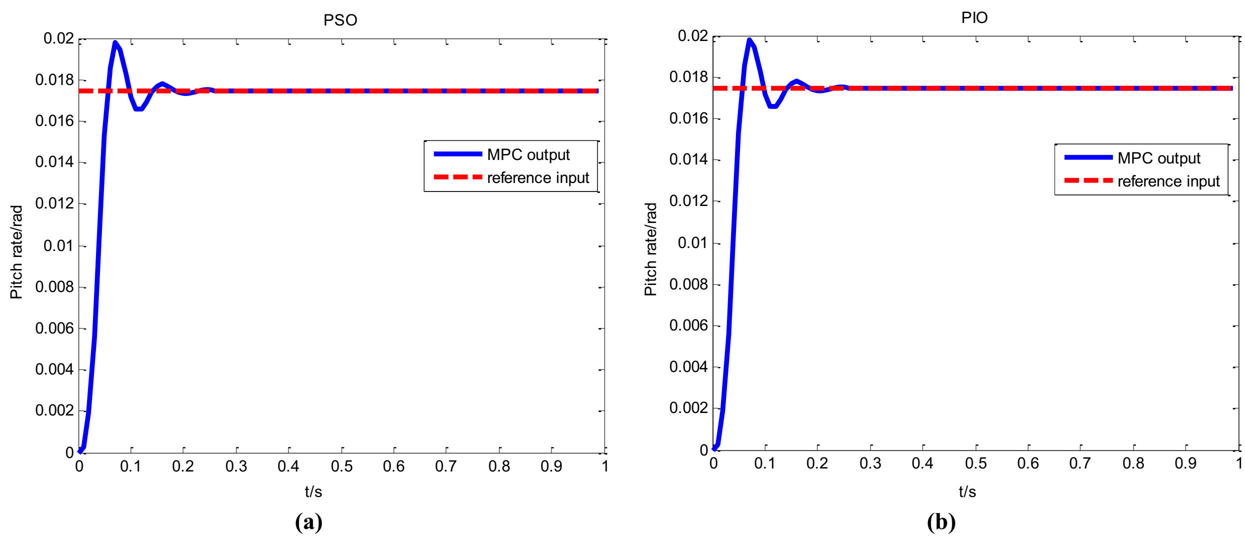


**Figure 8** Response of pitch rate in Case 1




**Notes:** (a) Step response with PSO algorithm; (b) step response with PIO algorithm



algorithm requires the individual, the global best and the local best information of the particle, the basic PIO algorithm consists of two operators, namely, the map and compass operator and the landmark operator according to the behavior of pigeons, and it can achieve better performance with only the individual and global best position of pigeons under the conduction of these two operators.

According to the nature behavior of the homing pigeon, two operators are proposed.

### Map and compass operator

In this operator, the rules are defined with the position $X_i$ and the velocity $V_i$ of pigeon $i$, and the position and velocity in a $D$-dimension search space are updated in each iteration. The new position and velocity of pigeon $i$ at the $t$-th iteration can be calculated with the following equations:

$$V_i(t) = V_i(t-1) \cdot e^{-Rt} + rand \cdot (X_g - X_i(t-1)) \quad (7)$$

$$X_i(t) = X_i(t-1) + V_i(t) \quad (8)$$

where $R$ is the map and compass factor, $rand$ is a random number ranging from 0 to 1 and $X_g$ is the current global best position, which can be obtained by comparing all the positions of the pigeons. The operator model is shown in Figure 4.

As is shown in Figure 4, the pigeon on the right side of the figure is the one with the best position. The thin arrows are their previous flying directions, while the thick ones are the directions that they adjust according to the best one. The sum of the velocities is their current directions.

### Landmark operator

In this operator, half of the pigeons are decreased in every generation. To get to the destination quickly, the rest of the pigeons fly straight to the destination. Let the $X_c$ be the center position of the pigeons; the position updating rule for pigeon $i$ at the $t$-th iteration are given as follows:

$$N_p(t) = \frac{N_p(t-1)}{2} \quad (9)$$

$$X_c(t) = \frac{\sum X_i(t) \cdot fitness(X_i(t))}{N_p \cdot \sum fitness(X_i(t))} \quad (10)$$

$$X_i(t) = X_i(t-1) + rand \cdot (X_c(t) - X_i(t-1)) \quad (11)$$

**Table I** Results comparison of Case 1

| Optimization method | PIO | PSO |
|---|---|---|
| Minimum value | 0.1049 | 0.1049 |
| Optimal prediction horizon | 4 | 4 |
| Optimal control horizon | 1 | 1 |

**Figure 9** Value of the fitness function in Case 2

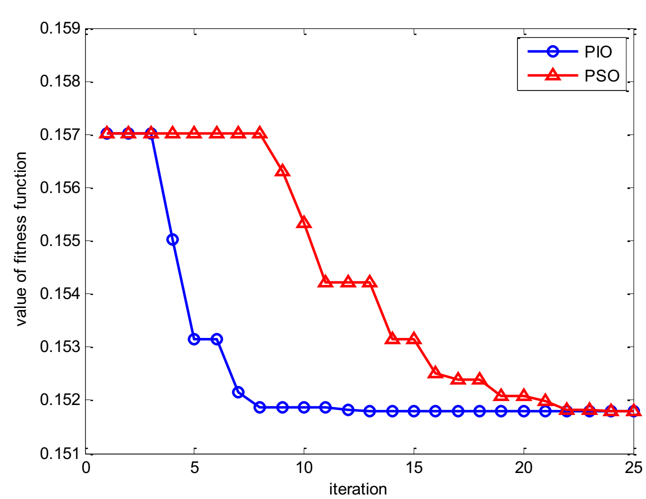
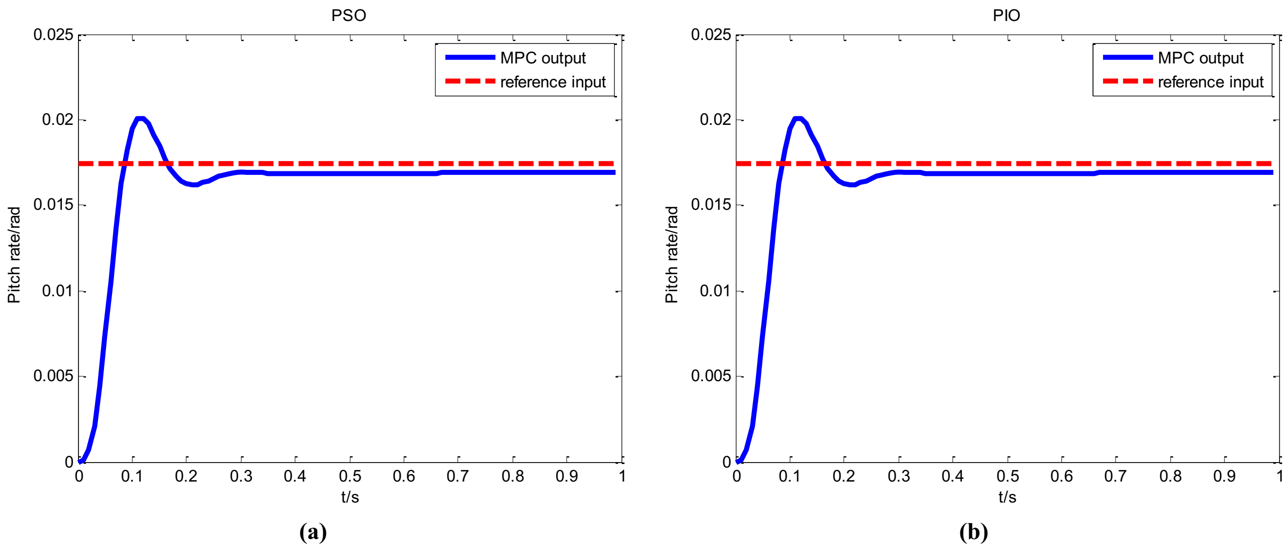


**Figure 10** Response of pitch rate in Case 2




**Notes:** (a) Step response with PSO algorithm; (b) step response with PIO algorithm

where $N_p$ is the number of the pigeons, while the *fitness* is the cost function of a pigeon. For minimum optimization, we can choose $f_{min}$ to be the destination function. The operator model is shown in Figure 5.

As is implied in the above figure, the pigeon in the center of the figure is the destination of the rest pigeons. The pigeons near the destination will fly towards the destination very quickly.

## Implementation procedure of PIO algorithm for MPC parameter optimization

To solve the optimization problem of the parameter optimization in MPC, the detailed implementation procedure of PIO is presented as follows:

- Step 1: Initialize the parameters in PIO algorithm, namely, the space dimension D, the population size Np, map and compass factor R, the iteration number of the two operators Nc1 and Nc2.
- Step 2: Define the prediction time horizon and the control time horizon to be the two-dimensional parameters as the position information for a pigeon. Initialize the position and velocity of each pigeon randomly within a certain range. Apply the parameters of prediction time horizon and the control time horizon to MPC controller to get a sequence of optimal output according to equation (1). Find the global best position through comparison of the values of cost function of the sequences according to equation (6), and note down the minimum cost value and the global best optimal parameters.
- Step 3: Operate the map and compass operator. Update the position and velocity of every pigeon according to equations (7) and (8). Then, compare their fitness and find the best position.Update the iteration number, let Nc = Nc + 1.
- Step 4: If Nc > Nc1, end the first operator and begin the landmark operator. Otherwise, go back to Step 3.
- Step 5: Rank all the pigeon according to their fitness value. Discard half of the pigeons which fall behind. Then, update the positions of the rest of the pigeons according to equations (9), (10) and (11). Store the best position and its cost value. Update the iteration number, let Nc = Nc + 1.
- Step 6: If Nc > Nc2, stop the optimization operator and output the results. Otherwise, go back to Step 5.
- The flow chart of the PIO is also illustrated in Figure 6.

**Table II** Results comparison in Case 2

| Optimization method | PIO | PSO |
|---|---|---|
| Minimum value | 0.1518 | 0.1518 |
| Optimal prediction horizon | 72 | 72 |
| Optimal control horizon | 3 | 3 |

**Figure 11** Value of the fitness function in Case 3

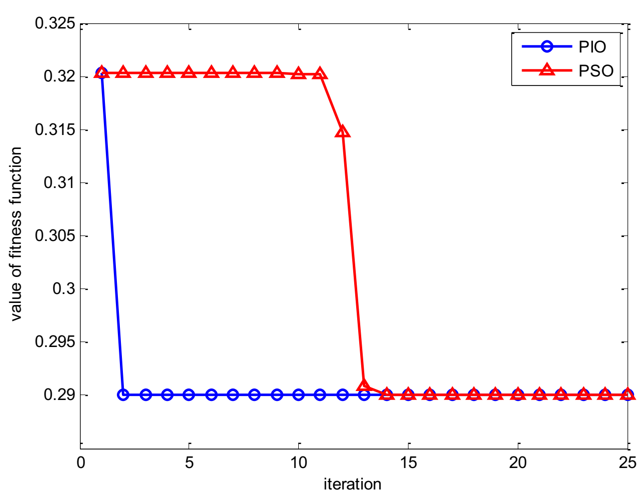


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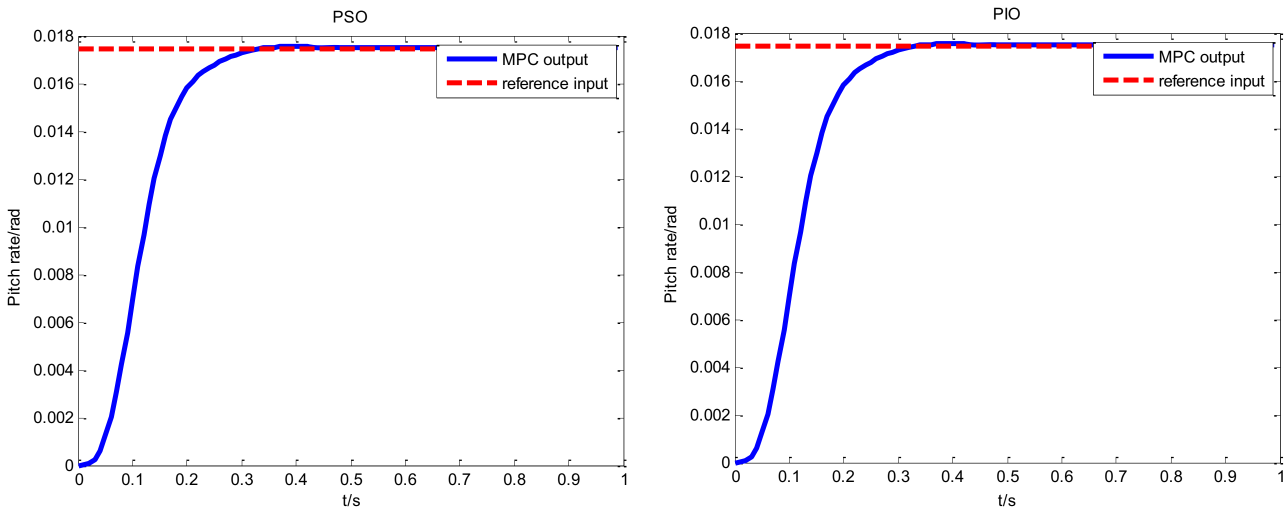
**Figure 12** Response of pitch rate in Case 3




**Notes:** (a) Step response with PSO algorithm; (b) step response with PIO algorithm

## Experiment results and analysis

A series of comparative experiments of PIO and PSO are conducted for verifying the feasibility and the effectiveness of our proposed PIO in solving MPC parameter optimization problem. As prediction time horizon and control time horizon are integers, the position of the pigeons in the algorithm needs to be rounded before the calculation of the fitness function.

The initial parameters of the PIO algorithm and the PSO algorithm are as follows:

- Population size: $N_p = 50$;
- Position range from 1 to 100;
- Velocity range from 1 to 5;
- Map and compass factor: $R = 0.02$;
- Inertia factor: $w = 1$;
- Self-confidence factor: $c_1 = 1.2$; and
- Swarm confidence factor: $c_2 = 1.2$;

### Case 1

In this case, the weight matrix $w = 0.01$, sampling period $T_s = 0.01$ s, $N_{cmax} = 25$, $N_{c1} = 15$, $N_{c2} = 25$, $y_{ref} = 1/57.3$ rad, and $t$ is the simulating time of the controller. The step response of the two algorithms and the value of the fitness function are shown in the following (Figures 7 and 8, Table I).

### Case 2

In this case, the weight matrix $w = 0.1$, sampling period $T_s = 0.01$ s, $N_{cmax} = 25$, $N_{c1} = 15$, $N_{c2} = 25$, $y_{ref} = 1/57.3$ rad, and $t$ is the simulating time of the controller. The step response of the two algorithms and the value of the fitness function are shown in the following (Figures 9 and 10, Table II).

### Case 3

In this case, the weight matrix $w = 1$, sampling period $T_s = 0.01$ s, $N_{cmax} = 25$, $N_{c1} = 15$, $N_{c2} = 25$, $y_{ref} = 1/57.3$ rad, and $t$ is the simulating time of the controller. The step response of the two algorithms and the value of the fitness function are shown in the following (Figures 11 and 12, Table III).

### Case 4

In this case, the weight matrix $w = 5$, sampling period $T_s = 0.01$ s, $N_{cmax} = 25$, $N_{c1} = 15$, $N_{c2} = 25$, $y_{ref} = 1/57.3$ rad, and $t$ is the simulating time of the controller. The step response of the two algorithms and the value of the fitness function are shown in the following (Figures 13 and 14, Table IV).

**Table III** Results comparison of Case 3

| Optimization method | PIO | PSO |
|---|---|---|
| Minimum value | 0.29 | 0.29 |
| Optimal prediction horizon | 17 | 17 |
| Optimal control horizon | 1 | 1 |

**Figure 13** Value of the fitness function in Case 4

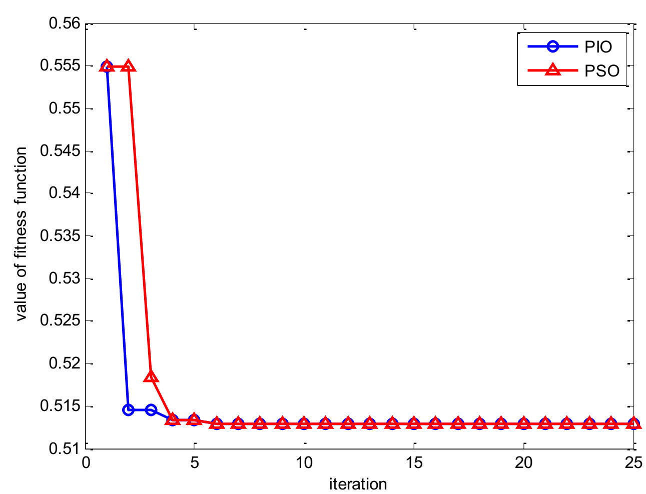


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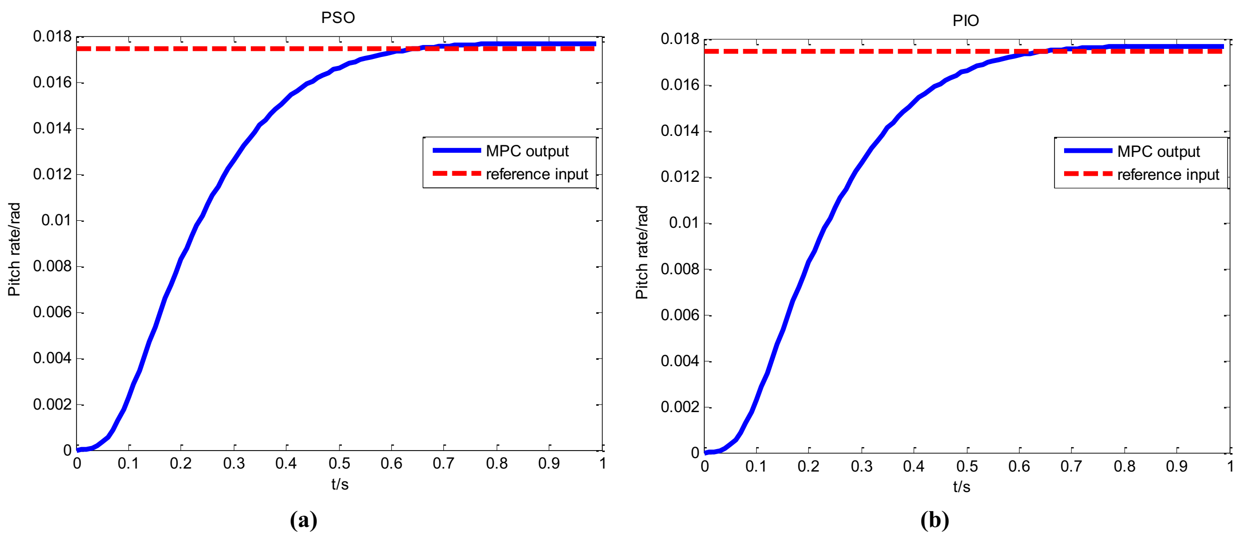
**Figure 14** Response of pitch rate in Case 4




**Notes:** (a) Step response with PSO algorithm; (b) step response with PIO algorithm

**Table IV** Results comparison of Case 4

| Optimization method | PIO | PSO |
|---|---|---|
| Minimum value | 0.513 | 0.513 |
| Optimal prediction horizon | 36 | 36 |
| Optimal control horizon | 1 | 1 |

## Conclusion

In this paper, a new method to optimize the parameters used in MPC controller based on PIO algorithm is proposed, which can reduce the burden of the parameter optimization in the design of a MPC controller.

Through a series of comparative experiments with PSO, the rapidity and efficiency of PIO is proved. It is obvious that with the increase in the weight of input, the response time of the pitch rate becomes much longer and the overshot become smaller. Though PIO and PSO can reach the same extent of convergence after several iterations, PIO can converge much faster than PSO.

In the future, we will further study the rapidity and efficiency of PIO and advance the method for parameter optimization in MPC.

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## About the authors

**Rui Dou** received his BSc degree in Automation Science and from Beihang University (formerly Beijing University of Aeronautics and Astronautics, BUAA) in 2014. He is currently a Master Candidate with the School of Automation Science and Electrical Engineering, Beihang University. He is a Member of Bio-inspired Autonomous Flight Systems (BAFS) Research Group of BUAA. His current research interest includes advanced flight control and bio-inspired computation.

**Haibin Duan** is currently a Full Professor of School of Automation Science and Electrical Engineering, Beihang University(formerly Beijing University of Aeronautics and Astronautics, BUAA), Beijing, China. He is the Head of Bio-inspired Autonomous Flight Systems (BAFS) Research Group of BUAA. He received the PhD degree from Nanjing University of Aeronautics and Astronautics (NUAA) in 2005. He was an Academic Visitor of National University of Singapore (NUS) in 2007 and a Senior Visiting Scholar of The University of Suwon (USW) of South Korea in 2011. He is currently an IEEE Senior Member. He has published 3 monographs and over 70 peer-reviewed papers in international journals. His current research interests include bio-inspired computation, advanced flight control and bio-inspired computer vision. Haibin Duan is the corresponding author and can be contacted at: hbduan@buaa.edu.cn