Aircraft Engineering and Aerospace Technology

Aerodynamic parameter identification of hypersonic vehicle via Pigeon-inspired optimization

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Abstract

Purpose – The purpose of this paper is to propose a new approach for aerodynamic parameter identification of hypersonic vehicles, which is based on Pigeon-inspired optimization (PIO) algorithm, with the objective of overcoming the disadvantages of traditional methods based on gradient such as New Raphson method, especially in noisy environment.

Design/methodology/approach – The model of hypersonic vehicles and PIO algorithm is established for aerodynamic parameter identification. Using the idea, identification problem will be converted into the optimization problem.

Findings – A new swarm optimization method, PIO algorithm is applied in this identification process. Experimental results demonstrated the robustness and effectiveness of the proposed method: it can guarantee accurate identification results in noisy environment without fussy calculation of sensitivity.

Practical implications – The new method developed in this paper can be easily applied to solve complex optimization problems when some traditional method is failed, and can afford the accurate hypersonic parameter for control rate design of hypersonic vehicles.

Originality/value – In this paper, the authors converted this identification problem into the optimization problem using the new swarm optimization method – PIO. This new approach is proved to be reasonable through simulation.

Keywords Hypersonic vehicle, Aerodynamic parameter identification, Pigeon-inspired optimization (PIO)

Paper type Research paper

Introduction

Hypersonic vehicles flying with high Mach number usually greater than Mach 5 may play an important role for both commercial and military applications in the future. Compared with current traditional aircraft, hypersonic vehicles have a highly non-linear dynamics and input/output coupling, which also have a more board flight envelope. Owing to their complex hypersonic vehicle aerodynamic characteristics and the applications of air-breathing scramjet engine, hypersonic vehicles are more sensitive to the angle of attack (Armando, 2008; Wu, 2010). So how to design one guidance and control system becomes a great challenge.

As previously mentioned, one of the main challenges of hypersonic vehicles is to design the guidance and control systems with high degree of integration. In recent years, many advanced control methods are taken into consideration such as the robust nonlinear control (Marrison and Stengel, 1997; Qian and Stengel, 2000). Many design methods rely on the establishment of an accurate model of the kinetics and kinematics of hypersonic vehicles with more precise aerodynamic parameters. Therefore, aerodynamic parameter identification becomes more and more important.

Currently, there are some commonly used aerodynamic parameter estimation algorithms such as maximum likelihood method, estimation-before-modeling, extended Kalman filter and so on (Li and Duan, 2012). Among them, maximum likelihood method based on Newton–Raphson algorithm is widely used in aerodynamic parameter identification in engineering. However, when using Newton–Raphson algorithm, there exist some natural disadvantages insurmountable. They are sensitive to initialization of the parameters. Sometimes there are numerical computing difficulties on obtaining gradient information. For hypersonic vehicles, because of their significant characteristic such as high angle of attack, large Mach border, strong coupling and dramatic changes in aerodynamic characteristics, the limitation of algorithms based on gradient becomes more obvious. To overcome these disadvantages, intelligent optimization algorithm provides us a practical solution for this identification problem.

As for many engineering problem, they could be converted into optimization problem. Thus, intelligent optimization algorithms are good methods to be considered, and they show good performance for solving these problem. In recent years, several swarm intelligence algorithms appeared which provide

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Aircraft Engineering and Aerospace Technology: An International Journal
89/3 (2017) 425–433

[DOI 10.1108/AEAT-01-2015-0007]

This work was partially supported by National Natural Science Foundation of China under grant #61425008, #61333004 and #61273054, and Aeronautical Foundation of China under grant #2015ZA51013.

Received 11 January 2015
Revised 1 February 2016
Accepted 5 February 2016

us optimization approach to solve some problems we met, such as ant colony optimization (ACO) (Dorigo *et al.*, 1991, 2000), particle swarm optimization (PSO) (Kennedy and Eberhart, 1995), artificial bee colony algorithm (Karaboga *et al.*, 2005, 2007) and brain storm optimization (Shi, 2011). In 2014, Duan *et al.* (2014) firstly established Pigeon-inspired optimization (PIO), a new swarm intelligence algorithm. Some results show that the feasibility and the rapidness of this algorithm have been greatly improved compared with some other swarm intelligence algorithm such as PSO (Duan *et al.*, 2015; Zhang, 2015; Qiu *et al.*, 2015).

In this paper, an aerodynamic parameters identification method based on PIO algorithm is established to overcome these disadvantages mentioned previously. Firstly, we will focus on aerodynamics parameter identification of hypersonic vehicles using this new bio-inspired algorithm, from which we convert the identification problem into the optimization problem. The goal is to get the parameters of the analytic fitting form of aerodynamic parameters which are the functions of flight status. The preliminary experiments have been conducted to demonstrate the effectiveness of this solution framework.

The rest of this paper is organized as follows: The commonly model of hypersonic is established in the next section. In Section 3, the primary mathematic formulation of PIO algorithm is introduced. Section 4 presents the implementation procedure for aerodynamic parameter identification of hypersonic vehicles. Experimental results demonstrated the feasibility and robustness of the proposed method in Section 5.

Hypersonic aircraft model

In this section, the typical model of hypersonic vehicles is established firstly, and the attitude dynamics equations are developed.

Owing to various countries maintain secrecy about hypersonic aircraft technology, confessed reference material is not available (Xu *et al.*, 2015; Zong *et al.*, 2015). In this work, we use aerodynamic parameters and body shape data of the Winged-cone model provided by National Aeronautics and Space Administration, Langley Research Centre (Shaughnessy, 1990). Aerodynamic Preliminary Analysis System estimated aerodynamic increment coefficients as functions of angle of attack, Mach number and aerodynamic surface deflection. Their work inspired us to take a similar form to get aerodynamic parameters based on data from wind tunnel simulation.

Parameters freezing method has been used in our identification process for the reason that we just pay attention to attitude motion of the hypersonic vehicle in this question (Li and Duan, 2012). Freezing the following flight status: flight speed $V = 3140 ft/s$, altitude $h = 40,000 ft$ and Track tilt angle $\gamma = 0°$.

The six status attitude kinetic equations of the hypersonic vehicle are as follows (Hu, 2010; Li and Duan, 2012):

$$\dot{\alpha} = q - \tan\beta(p\cos\alpha + r\sin\alpha) + \frac{1}{mV\cos\beta}(-L + mg\cos\gamma\cos\mu) \quad (1)$$

$$\dot{\beta} = -r\cos\alpha + p\sin\alpha + \frac{1}{mV}(Y\cos\beta + mg\cos\gamma\sin\mu) \quad (2)$$

$$\dot{\mu} = \sec\beta(p\cos\alpha + r\sin\alpha) + \frac{L}{mV}(\tan\gamma\sin\mu + \tan\beta) + \frac{g}{V}\cos\gamma\cos\mu\tan\beta + \frac{Y}{mV}\tan\gamma\cos\mu\cos\beta \quad (3)$$

$$\dot{p} = (c_1 r + c_2 p)q + c_3 M_x + c_4 M_z \quad (4)$$

$$\dot{q} = c_5 pr - c_6(p^2 - r^2) + c_7 M_y \quad (5)$$

$$\dot{r} = (c_8 p - c_2 r)q + c_4 M_x + c_9 M_z \quad (6)$$

where we define the state vector $x = [\alpha\ \beta\ \mu\ p\ q\ r]^T$.

In the above equations, inertia parameters are defined as follows:
$\sum = I_x I_z - I_{xz}^2$, $c_1 = (I_y - I_z)I_z - I_{xz}^2/\sum$, $c_2 = (I_x - I_y + I_z)I_{xz}/\sum$, $c_3 = I_z/\sum$, $c_4 = I_{xz}/\sum$, $c_5 = I_z - I_x/I_y$, $c_6 = I_{xz}/I_y$, $c_7 = 1/I_y$, $c_8 = I_x(I_x - I_y) + I_{xz}^2/\sum$, $c_9 = I_x/\sum$. L is the lift force, D is the drag force, Y is the slide force. M_x,M_y, M_z are external torque around the body axis.

The output equation is as follows:

$$y = Cx = [\alpha\quad\beta\quad\mu\quad p\quad q\quad r]^T \quad (7)$$

where $C = diag\{1, 1, 1, 1, 1, 1\}$. Obviously, it is an all-states output.

The measure equation is as follows:

$$z(t) = y(t) + v(t) \quad (8)$$

where$v(t)$ is measurement noise which are assumed to be characterized by a zero-mean white Gaussian noise (Li and Duan, 2012). T'his class of noise is commonly used and simulated in engineering.

According to aerodynamics knowledge, we can obtain these forces and moments as follows:

$$L = C_L Q S_w,\quad Y = C_Y Q S_w,\ D = C_D Q S_w \quad (9)$$

$$M_x = C_l Q S_w b \quad M_y = C_m Q S_w C_A + x_{cg}(D\sin\alpha + L\cos\alpha) \quad M_z = C_m Q S_w b + x_{cg} Y \quad (10)$$

where Q is the dynamic pressure and can be computed by $Q = 1/2\rho V^2$.

The aerodynamic increment coefficients are all functions of Mach number and the angle of attack (Wang *et al.*, 2015). Keshmiri *et al.* (2005) fitted each aerodynamic derivative as fifth-order polynomials about angle of attack and Mach number according to the aerodynamic data provided by NASA Langley research center. In this work, we adopt a similar approach to give out the polynomial result of the lift coefficient as an example. A similar process can be used to deal with other aerodynamic parameters.

The lift coefficient C_L is given as follows:

$$C_L = C_{L\alpha} + C_{L_{\delta_e}} + C_{L_{\delta_a}} + C_{L_{\delta_c}} \quad (11)$$

where $C_{L\alpha}$ is the basic vehicle lift increment coefficient; and $C_{L_{\delta_e}}$, $C_{L_{\delta_a}}$ and $C_{L_{\delta_c}}$ are the increment coefficients for the right elevon, the left elevon and the canard, respectively. As previously mentioned,$C_{L\alpha}$,$C_{L_{\delta_a}}$,$C_{L_{\delta e}}$ and $C_{L_{\delta c}}$ are regarded as polynomials of angle of attack, Mach number and surface deflection. Because Mach number has been frozen, we choose the coefficients of α in the fitting polynomials as the identification vector (Li and Duan, 2012).

By analyzing the aerodynamic data, we choose fitting forms as follows (Keshmiri *et al.*, 2005; Li and Duan, 2012):

$$\begin{aligned} C_{L\alpha} = {} & -8.19 \times 10^{-2} + M(4.70 \times 10^{-2}) \\ & + \alpha\zeta_1 - \alpha M\zeta_2 - M^2 \cdot 9.19 \times 10^{-3} - \alpha^2\zeta_3 \\ & + (\alpha M)^2\zeta_4 + M^3 \times 7.74 \times 10^{-4} + \alpha^3\zeta_5 \\ & - M^4 \cdot 2.93 \times 10^{-5} - \alpha^4\zeta_6 \\ & + M^5 \cdot 4.12 \times 10^{-7} + \alpha^5\zeta_7 \end{aligned} \tag{12}$$

$$\begin{aligned} C_{L_{\delta_a}} = {} & -1.45 \times 10^{-5} + \alpha\zeta_8 + M \cdot 7.10 \times 10^{-6} \\ & - \delta_a\zeta_9 + \alpha\delta_a\zeta_{10} + \alpha M\zeta_{11} + M\delta_a\zeta_{12} - \alpha M\delta_a\zeta_{13} \end{aligned} \tag{13}$$

$$\begin{aligned} C_{L_{\delta_e}} = {} & -1.45 \times 10^{-5} + \alpha\zeta_8 + M \cdot 7.10 \times 10^{-6} - \delta_e\zeta_9 \\ & + \alpha\delta_e\zeta_{10} + \alpha M\zeta_{11} + M\delta_e\zeta_{12} - \alpha M\delta_e\zeta_{13} \end{aligned} \tag{14}$$

$\zeta = [\zeta_1\ \zeta_2[\ldots]\zeta_{13}]$ is the vector we would identify. In addition, the coefficient $C_{L_{\delta c}}$ has less contribution to the aerodynamic force and moment, so we can ignore it in our study.

Mathematic model of Pigeon-inspired optimization algorithm

The bird flocks in the nature always give us many inspirations for better improvement of the human being (Qiu *et al.*, 2015). PIO algorithm inspired by the behavior of pigeons consists of two basic operators:

1 the map and compass operator based on sun; and
2 magnetic field and the landmark operator based on landmarks (Duan and Qiao, 2014).

Under the operation of the two operators, it can achieve good performance with the global best position of all pigeons. The process of the basic PIO algorithm can be described as follows: each pigeon is regarded as a search individual which is randomly initialized with the initial velocity $V_{i1} = [V_{i1}\ V_{i2}[\ldots]V_{iD}]$ and initial position $X_i = [X_{i1}X_{i2}[\ldots]X_{iD}]$, where i means the index of pigeon and D is the dimension of the problem to be solved. The velocity of each pigeon used to update their positions in each iteration which reflects the swarm intelligence. The global best position of pigeons in one PIO process is the final result we want to obtain. In this study, the position of pigeons means the parameter: $\zeta = [\zeta_1\ \zeta_2\ [\ldots]\zeta_{13}]$ which is defined before to be identified. Subsequently, the fitness value of pigeons reflects the difference between the identification parameter and true parameter.

In the PIO algorithm, the map and compass operator and the landmark operator are introduced to simulate the homing characteristics of pigeons. By using the map and compass operator in the initial search period, the best position of all the pigeons can be available; thus, each pigeon adjusts itself following the best position (Li and Duan, 2014). In the map and compass operator, the information of the pigeons can be updated according to the following formulation:

$$V_i(t) = V_i(t-1) \cdot e^{-Rt} + rand \cdot (X_g - X_i(t-1)) \tag{15}$$

$$X_i(t) = X_i(t-1) + V_i(t) \tag{16}$$

where R is the map and compass operator, *rand* is a random number with the range $[0, 1]$ and the X_g is the best position of all the pigeons. During the landmark operator, the number of pigeons is halved in every generation. These pigeons are strange with the landmark, and they fall behind in the trip to destination. We take in $X_c(t)$ as the center of some positions partial area. The updating law can be developed as follows:

$$X_c(t) = \frac{\sum_{N_p} X_i(t) \cdot fitness(X_i(t))}{\sum_{N_p} fitness(X_i(t))} \tag{17}$$

$$X_i(t) = X_i(t-1) + rand \cdot (X_c(t) - X_i(t-1)) \tag{18}$$

where N_p is the number of the pigeon.

Procedure of aerodynamic parameter identification using Pigeon-inspired optimization algorithm

To apply PIO algorithm, the identification problem should be converted into the optimization problem firstly. The goal of the parameter identification is to find the parameter vector becomes to find the best parameter vector which minimizes the chosen objective function. So the key work is to choose an objective function which can demonstrate the error between the identification parameters and true parameters. The natural idea is to compare the respond of models with identification parameters and true parameters.

To incentive the motion mode of the hypersonic vehicle sufficiently, the typical 3-2-1-1 input is usually used in the identification process. In this study, the 3-2-1-1 input is used.

As illustrated, predetermined surface inputs are applied to the aircraft model and the responses are recorded as measurement data. The same inputs go for the system with the parameters to be identified by PIO algorithm and we get the estimated responses. The quadratic cost function can be defined as follows to determine the differences between the measure responses and estimated responses which we want to minimize:

$$\mathcal{J}(\zeta) = \sum_{i=1}^{N} \sum_{j=1}^{m} \{[y(i,j) - z(i,j)]w_i\}^2 \tag{19}$$

where N is the number of measured data points, m is the dimension of the observation vector and w_i is the weight value. So far, the aerodynamic parameter identification has been converted into the optimization problem. Thus, the PIO algorithm, as an optimization algorithm, can be used to solve this parameter identification problem. The whole framework of the solutions is shown in Figure 1.

The procedure of our PIO algorithm approach to identify the aerodynamic parameter can be explained as follows:

- *Step 1*: Data pre-processing. Obtain the outputs by take in the typical 3-2-1-1 inputs to the true model of the selected aircraft. Then add the white noise to the outputs as the real measurement flight data.
- *Step 2*: Set the algorithm parameters of PIO. The parameters include the dimension of the solvation space D, the number of pigeons N_p, the map and compass operator R, the iteration number of two operators N_{c1}, N_{c2}, the initial iteration counter $N = 1$ and so on.

In general, we define $N_p = 20 \sim 50$, $N_{c1} = 200 \sim 500$ and $N_{c2} = 20 \sim 50$. Obviously, larger N_p will contribute to a larger possibility to find the best solution of the problem, while it also means an increased computing complexity of the algorithm:

- *Step 3*: In this problem, the identification parameters are regard as the position information of the pigeon. Assign the initial position and velocity of each pigeon within the certain boundary. This boundary needs some prior information. Compute the cost function $\mathcal{J}(X_i)$ of each pigeon, namely, the fitness value according to equation (19), and find the global best position by looking for the minimum one. Record the global best position and the minimum fitness value.
- *Step 4*: Choose the operator. If the iteration counter satisfy $N < N_{c1}$, then operate the map and compass operator, update the position and velocity of each pigeon according to equations (15) and (16). Add iteration counter.$N = N + 1$. Otherwise, operate the landmark operator.
- *Step 5*: If the iteration counter satisfy $N < N_{c1}$, go to Step 4 to continue the map and compass operator. Else, change to the landmark operator and go to the following step.
- *Step 6*: Compare the fitness values of pigeons, and rank them in order. Half of pigeons are regard as the fall behind ones. These pigeons will be discarded. Update the individual according to equations (17) and (18) and record the global best position and the minimum fitness value in each iteration. Update the iteration counter.
- *Step 7*: Terminate this PIO process if the iteration counter number satisfy $N > N_{c2}$. Otherwise, go to Step 6 and continue.
- The procedure chart of combination of aerodynamic parameter identification and PIO algorithm is shown as follows (Figure 2).
- As a combination of hypersonic parameter identification and PIO algorithm, our proposed aerodynamic parameter identification method for hypersonic vehicles is demonstrated.

Simulation results

To demonstrate the robustness and feasibility of the biological approach in this work, a series of simulation are conducted under different noise condition. The experimental results with the PIO algorithm for parameter identification are shown as follows.

The simulation conditions set as follows: the initial state $X_0 = [000000]^T$, the input vector $[\delta_e \quad \delta_a \quad \delta_r]$ satisfies with

$$\delta_e = \delta_a = \begin{cases} \Delta & t \in (0, 3t_0) \\ -\Delta & t \in (3t_0, 5t_0) \\ \Delta & t \in (5t_0, 6t_0) \\ -\Delta & t \in (6t_0, 7t_0) \\ 0 & t \in (7t_0, t_{\max}) \end{cases} \delta_r = 0.$$

Case1: In this case, the measurement noise is weak with the signal-to-noise ratio (SNR) about 200db. The simulation results are given out as follows.

In the first case (see Figures 3-5), Figure 3 shows the cost function curves of PIO and PSO in the parameter identification process, and Figure 4 shows the angle of attack curves of prediction and measurement. The prediction curve is the response of the model with the identification aerodynamic parameters, while the measurement curve is the response of the model with the real aerodynamic parameters. Figure 5 shows the pitch rate curves of prediction and measurement. Table I shows the identification values compared to the reference value about the parameter to be identified. The results show that the prediction curve match with the measurement curve well which means the PIO algorithm for aerodynamic parameter identification is feasible

Figure 1 Overview of the identification process

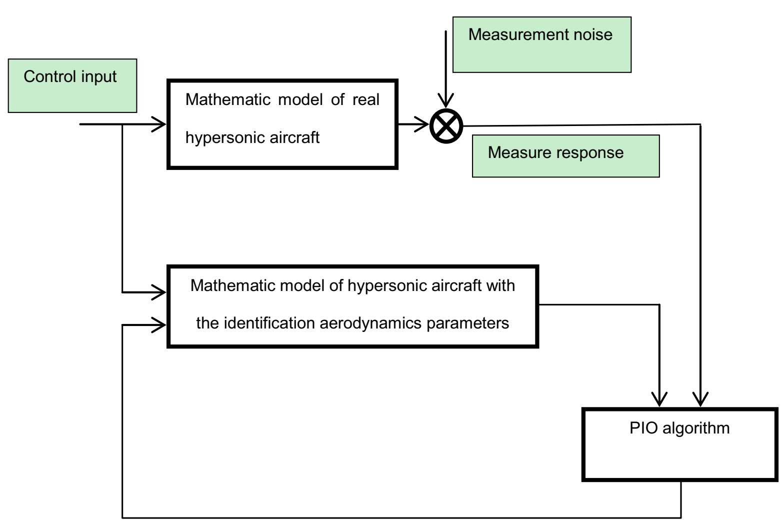
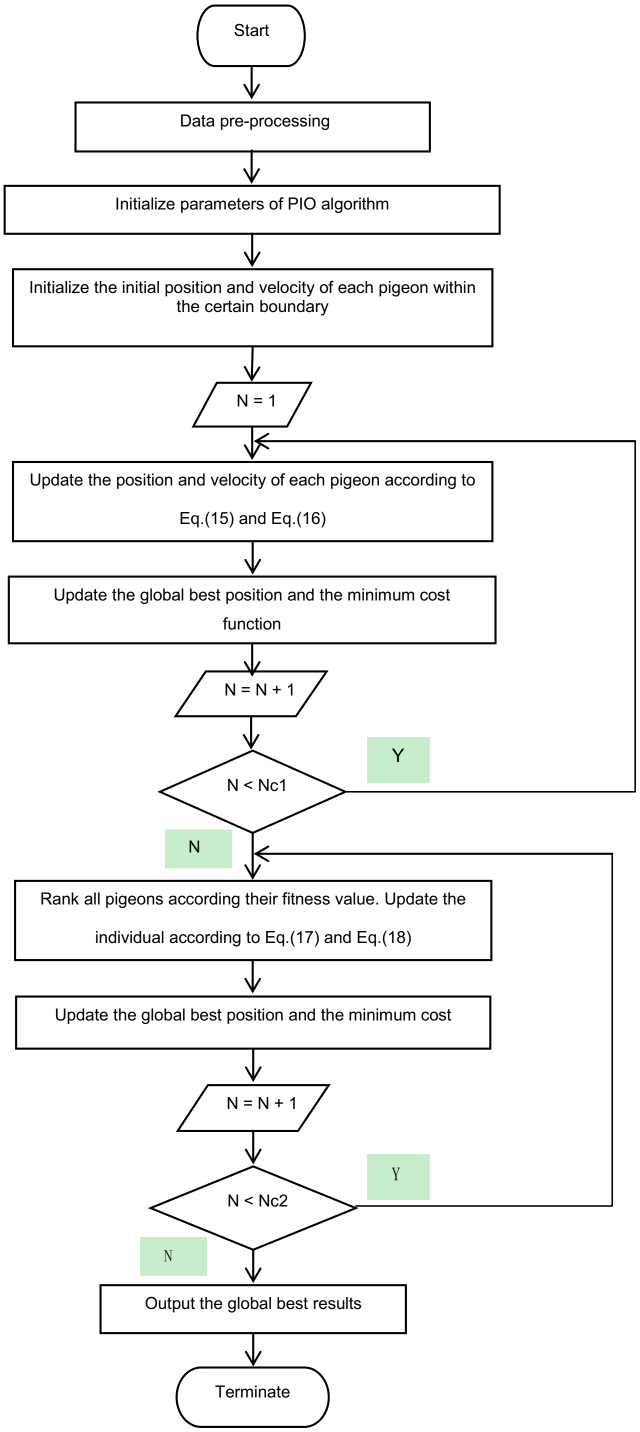


Figure 2 The procedure of the combinational method



and reasonable. The most of identification values have acceptable error compared to the true value, although some values have larger error. In this condition, PIO algorithm has a better performance than PSO algorithm.

Case 2: In this case, the SNR is 100db. We can get the parameter identification results and simulation results as follows.

Figure 6 gives out the cost function curves of PIO and PSO in the parameter identification process, Figures 7 and 8 show the angle of attack curve and the pitch rate curve of the prediction and measurement, respectively. Table II shows the identification values compared to the reference value. We can see the prediction curve match the measurement curve well. The identification value is acceptable enough to use.

Figure 3 SNR = 200db – cost function curve of PIO and PSO

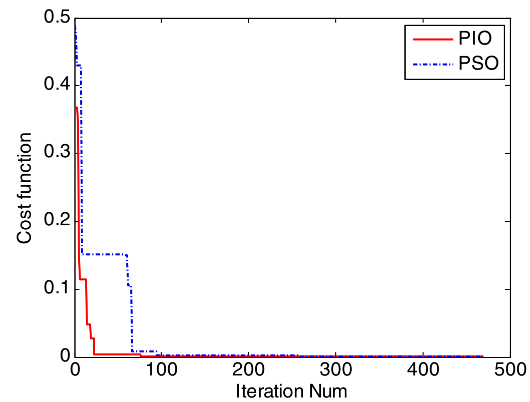


Figure 4 SNR = 200db – angle of attack curves of prediction and measurement

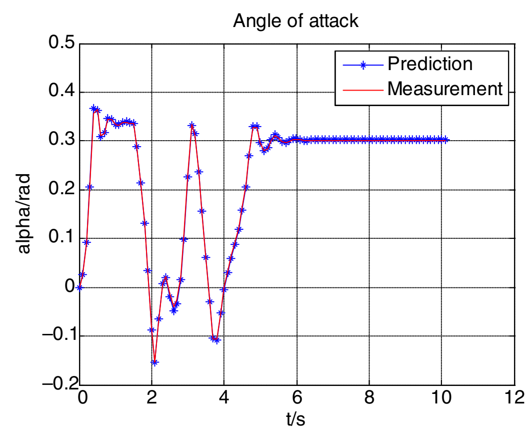


Figure 5 SNR = 200db – pitch rate curves of prediction and measurement

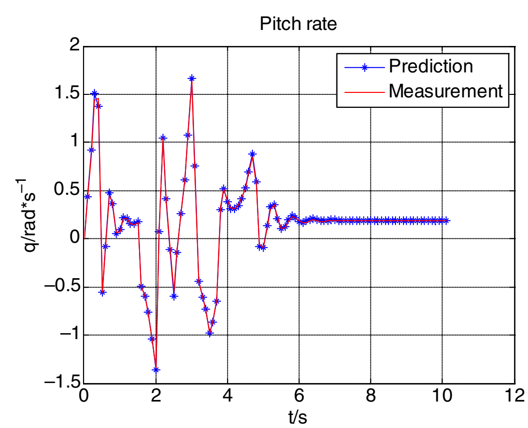


Table I SNR = 200db–identification value compared to the reference value

Parameter index	Reference value	Identification value (PIO)	Identification value (PSO)
1	1.86×10^{-2}	1.86×10^{-2}	1.92×10^{-2}
2	4.73×10^{-4}	4.02×10^{-4}	6.00×10^{-4}
3	1.52×10^{-4}	1.08×10^{-4}	2.00×10^{-4}
4	5.99×10^{-7}	5.42×10^{-7}	4.49×10^{-7}
5	4.08×10^{-6}	3.31×10^{-6}	5.95×10^{-6}
6	3.91×10^{-7}	4.25×10^{-7}	3.87×10^{-7}
7	1.30×10^{-8}	1.10×10^{-8}	2.00×10^{-8}
8	1.01×10^{-4}	6.70×10^{-5}	1.50×10^{-4}
9	4.14×10^{-4}	3.72×10^{-4}	3.60×10^{-4}
10	3.51×10^{-6}	3.21×10^{-6}	5.00×10^{-6}
11	4.70×10^{-6}	3.69×10^{-6}	6.00×10^{-6}
12	8.72×10^{-6}	7.38×10^{-6}	1.00×10^{-5}
13	1.70×10^{-7}	1.98×10^{-7}	2.22×10^{-7}

Figure 6 SNR = 100db – cost function curve of PIO and PSO

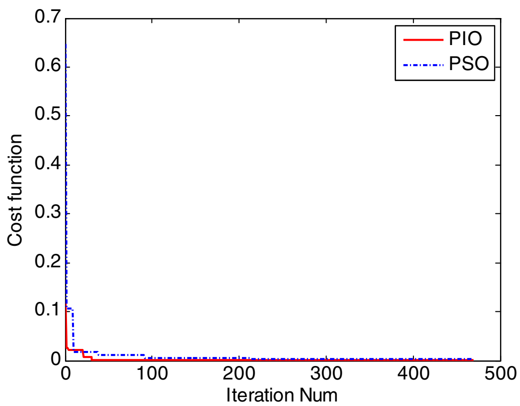
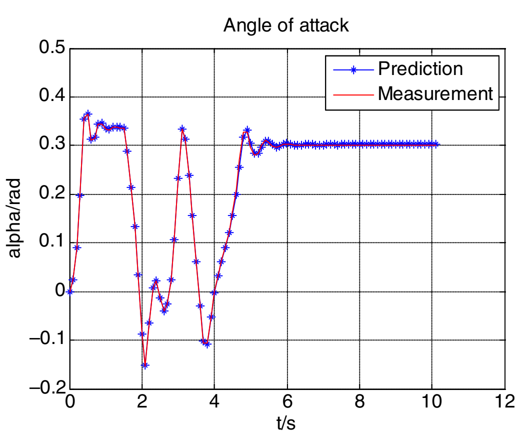


Figure 7 SNR = 100db – angle of attack curves of prediction and measurement



From the simulation results, we can learn that the parameter identification process can be completed well, although the measurement noise is stronger.

Case 3: In this case, the SNR is 60db. The identification results are showed as follows.

Figure 8 SNR = 100db – pitch rate curves of prediction and measurement

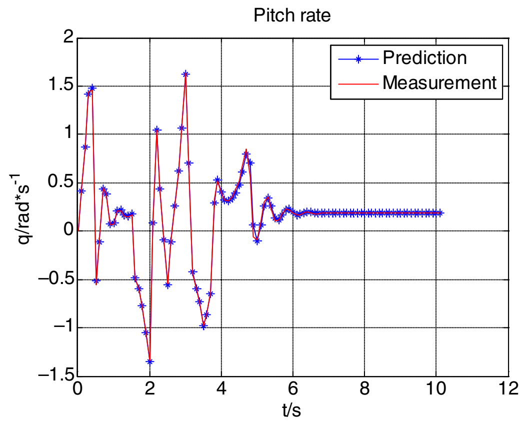


Table II SNR = 100db–identification value compared to the reference value

Parameter index	Reference value	Identification value (PIO)	Identification value (PSO)
1	1.86×10^{-2}	1.83×10^{-2}	1.93×10^{-2}
2	4.73×10^{-4}	5.78×10^{-4}	6.00×10^{-4}
3	1.52×10^{-4}	1.13×10^{-4}	1.77×10^{-4}
4	5.99×10^{-7}	6.81×10^{-7}	4.00×10^{-7}
5	4.08×10^{-6}	3.66×10^{-6}	3.00×10^{-6}
6	3.91×10^{-7}	3.55×10^{-7}	5.00×10^{-7}
7	1.30×10^{-8}	1.48×10^{-8}	1.00×10^{-8}
8	1.01×10^{-4}	5.64×10^{-5}	1.50×10^{-4}
9	4.14×10^{-4}	4.11×10^{-4}	5.00×10^{-4}
10	3.51×10^{-6}	3.80×10^{-6}	2.68×10^{-6}
11	4.70×10^{-6}	3.32×10^{-6}	4.15×10^{-6}
12	8.72×10^{-6}	7.48×10^{-6}	1.00×10^{-5}
13	1.70×10^{-7}	1.82×10^{-7}	2.86×10^{-7}

In Figure 9, the cost function curves of PIO and PSO are given out. Figures 10 and 11 show curves of the angle of attack and the pitch rate of prediction and measurement, respectively. Table III shows the identification values compared to the reference value. In this case, the PIO algorithm for the

Figure 9 SNR = 60db – cost function curve of PIO and PSO

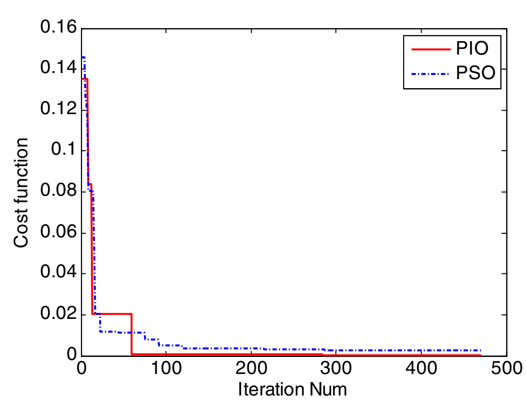


Figure 10 SNR = 60db – angle of attack curves of prediction and measurement

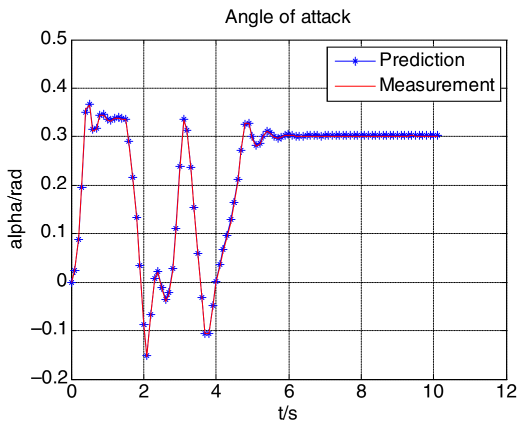


Figure 11 SNR = 60db – pitch rate curves of prediction and measurement

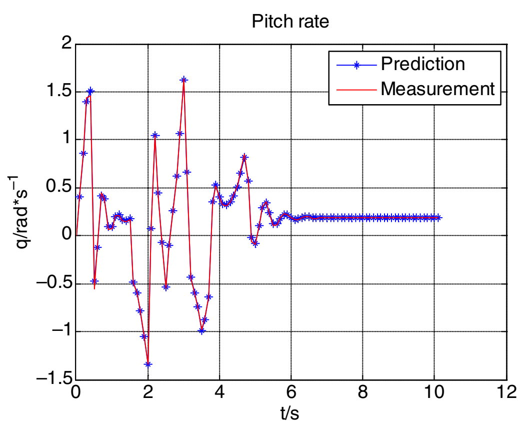


Table III SNR = 60db–identification value compared to the reference value

Parameter index	Reference value	Identification value (PIO)	Identification value (PSO)
1	1.86×10^{-2}	1.79×10^{-2}	1.73×10^{-2}
2	4.73×10^{-4}	4.49×10^{-4}	5.39×10^{-4}
3	1.52×10^{-4}	1.68×10^{-4}	1.00×10^{-4}
4	5.99×10^{-7}	5.53×10^{-7}	8.00×10^{-7}
5	4.08×10^{-6}	5.90×10^{-6}	3.73×10^{-6}
6	3.91×10^{-7}	3.28×10^{-7}	5.00×10^{-7}
7	1.30×10^{-8}	1.59×10^{-8}	1.98×10^{-8}
8	1.01×10^{-4}	9.46×10^{-5}	1.30×10^{-4}
9	4.14×10^{-4}	4.18×10^{-4}	5.00×10^{-4}
10	3.51×10^{-6}	3.07×10^{-6}	2.58×10^{-6}
11	4.70×10^{-6}	2.71×10^{-6}	5.75×10^{-6}
12	8.72×10^{-6}	5.42×10^{-6}	1.00×10^{-5}
13	1.70×10^{-7}	1.86×10^{-7}	2.99×10^{-7}

parameter identification can also offer acceptable results which verify the robustness of this algorithm.

Case 4: To further prove the robustness and performance of the identification algorithm, we make the SNR smaller. Let SNR be 26db.
The cost function curves are given out in Figure 12-14 show the angle of attack and the pitch rate curve of prediction and measurement, respectively. Table IV shows the identification values compared to the reference value.

In this case, the result shows that the algorithm is less sensitive to the measurement noise. We can get the acceptable identification results even the measurement noise is stronger. Compared to the gradient identification algorithm such as maximum likelihood method, the PIO algorithm for parameter identification can be used when the gradient information cannot be obtained easily. Compared the performance of PIO algorithm with PSO algorithm in the aerodynamic parameters identification, the PIO algorithm shows fast optimum-seeking speed and better cost function value in some conditions. It is a beneficial trial to apply PIO algorithm for solving the aerodynamic parameter identification.

Conclusion

In this paper, the aerodynamic parameters identification based on the PIO algorithm is given out. In the framework of this

Figure 12 SNR = 26db – cost function curve of PIO and PSO

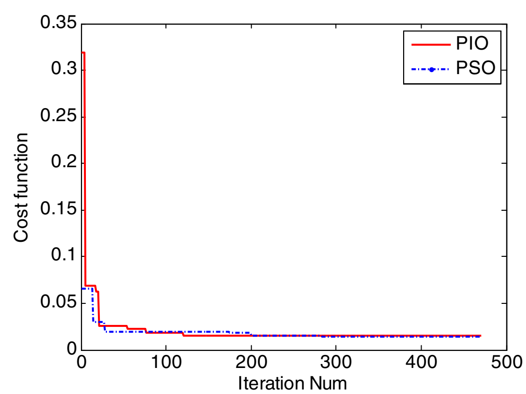


Figure 13 SNR = 26db – angle of attack curves of prediction and measurement

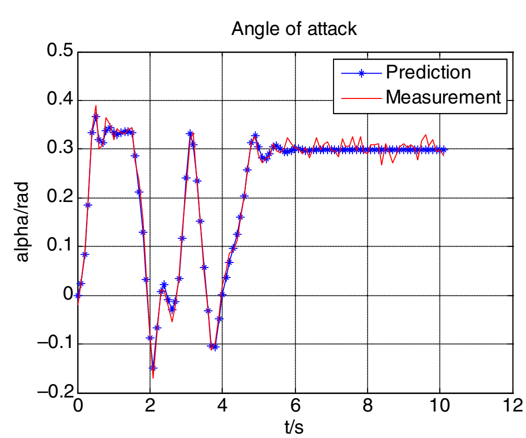


Figure 14 SNR = 26db – pitch rate curves of prediction and measurement

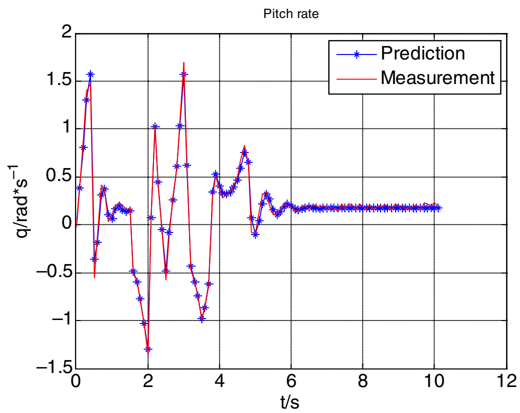


Table IV SNR = 26db–identification value compared to the reference value

Parameter index	Reference value	Identification value (PIO)	Identification value (PSO)
1	1.86×10^{-2}	1.66×10^{-2}	1.61×10^{-2}
2	4.73×10^{-4}	2.30×10^{-4}	2.08×10^{-4}
3	1.52×10^{-4}	1.36×10^{-4}	1.46×10^{-4}
4	5.99×10^{-7}	4.69×10^{-7}	7.58×10^{-7}
5	4.08×10^{-6}	5.05×10^{-6}	5.22×10^{-6}
6	3.91×10^{-7}	3.79×10^{-7}	3.94×10^{-7}
7	1.30×10^{-8}	1.36×10^{-8}	1.94×10^{-8}
8	1.01×10^{-4}	8.73×10^{-5}	1.50×10^{-4}
9	4.14×10^{-4}	4.87×10^{-4}	5.00×10^{-4}
10	3.51×10^{-6}	3.69×10^{-6}	3.97×10^{-6}
11	4.70×10^{-6}	5.60×10^{-6}	2.80×10^{-6}
12	8.72×10^{-6}	8.45×10^{-6}	1.00×10^{-5}
13	1.70×10^{-7}	1.31×10^{-7}	3.00×10^{-7}

solution for the parameter identification, the identification problem could be converted into the optimization problem. The complex differential calculation has been avoided compared to some classic gradient algorithm such as maximum likelihood method. The experimental results show that our proposed method is a feasible and robust way in aerodynamic parameters identification.

Our future work will focus on how to combine the modern swarm intelligence algorithm and the classic mathematic algorithm in the aerodynamic parameter identification area. This idea will allow us to exert the advantages of the two different methods fully and overcome their dependence on certain conditions.

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