Downloaded by Beihang University At 00:44 22 July 2015 (PT)

Predator-prey biogeography-based optimization for parameters identification of UCAV flight control system

Weiren Zhu and Haibin Duan
State Key Laboratory of Virtual Reality Technology and Systems, Beijing University of Aeronautics and Astronautics, Beijing, China

Abstract
Purpose – The purpose of this paper is to propose a novel Unmanned Combat Air Vehicle (UCAV) flight controller parameters identification method, which is based on predator-prey Biogeography-Based Optimization (PPBBO) algorithm, with the objective of optimizing the whole UCAV system design process.
Design/methodology/approach – The hybrid model of predator-prey theory and biogeography-based optimization (BBO) algorithm is established for parameters identification of UCAV. This proposed method identifies controller parameters and reduces the computational complexity.
Findings – The basic BBO is improved by modifying the search strategy and adding some limits, so that it can be better applied to the parameters identification problem. Comparative experimental results demonstrated the feasibility and effectiveness of the proposed method: it can guarantee finding the optimal controller parameters, with the rapid convergence.
Practical implications – The proposed PPBBO algorithm can be easily applied to practice and can help the design of the UCAV flight control system, which will considerably increase the autonomy of the UCAV.
Originality/value – A hybrid model of predator-prey theory and BBO algorithm is proposed for parameters identification of UCAV, and a PPBBO-based software platform for UCAV controller design is also developed.

Keywords Unmanned combat air vehicle (UCAV), Predator-prey theory, Biogeography-Based Optimization (BBO), Parameters identification

Paper type Research paper

Introduction

Flight control system, which is a complicated multi-input and multi-output nonlinear system, is an essential part of the simulation training system design of Uninhabited Combat Aerial Vehicle (UCAV), which also directly determines the whole system's performance (Jin and Gu, 2009; Duan and Li, 2012). For the strong coupling of the inputs, the selection of the controller parameters is a tough problem in the design process of the flight control system (Duan *et al.*, 2010). Presently, cut and try method is commonly used to identify all the control loop parameters of flight control system. But this design method is low efficient and depends on the experience of the designers, as the flight control system will be more complex with the improvement of the aircraft performances, and these are becoming the bottleneck of the flight control system design (Duan and Li, 2012; Benini and Chiereghin, 2013).

Recently, many researchers focus on the method of finding optimal controller parameters for the system by computer, which has strong ability of logic and fast operation. Identifying controller parameters based on bio-inspired computing methods is one of the hottest topics. Genetic Algorithm (GA) is utilized to optimize the selection of the fixed control parameters of the flight control systems (Li *et al.*, 2009). Juang *et al.* (2008) design an intelligent aircraft automatic landing controller that uses recurrent neural networks with genetic algorithms to improve the performance of conventional automatic landing system. To reduce the design effort of nonlinear flight control laws, Rydlo *et al.* (2013) introduced an assisting flight control system on board of a light sport aircraft through an innovative approach which utilizes classical control theory along with flight envelope protection algorithms. Qi *et al.* (2009) apply a multivariable Proportional-Integral-Derivative (PID) neural network to design the flight control system of small-scale unmanned helicopter on the hardware platform. Sun *et al.* (2007) present a design method of a large envelope wavelet neural network gain scheduling flight control law based on Particle Swarm Optimization (PSO) algorithm. Duan *et al.* (2013a, 2013b) presented a novel network control method based on trophallaxis

The current issue and full text archive of this journal is available on Emerald Insight at: **www.emeraldinsight.com/1748-8842.htm**

Emerald

Aircraft Engineering and Aerospace Technology: An International Journal
87/3 (2015) 249–259
© Emerald Group Publishing Limited [ISSN 1748-8842]
[DOI 10.1108/AEAT-06-2013-0112]

This work was partially supported by National Key Basic Research Program of China (973 Project) under grant #2013CB035503 and #2014CB046401, Natural Science Foundation of China (NSFC) under grant # 61333004 and #61273054, National Magnetic Confinement Fusion Research Program of China under grant # 2012GB102006, Top-Notch Young Talents Program of China, Program for New Century Excellent Talents in University of China under grant #NCET-10-0021 and Aeronautical Foundation of China under grant #20135851042.

Received 17 June 2013
Revised 6 April 2014
Accepted 6 April 2014

Aircraft Engineering and Aerospace Technology: An International Journal
Volume 87 · Number 3 · 2015 · 249–259

Downloaded by Beihang University At 00:44 22 July 2015 (PT)

mechanism for the formation flight problem of multiple Unmanned Aerial Vehicles (UAVs).

However, the above methods have deficiencies of slow convergence and complex computing procedure. Some researchers try to use other intelligent algorithms to solve this problem. Duan *et al.* (2013a, 2013b) apply an improved PSO algorithm to identify PID parameters for UCAV flight control system. Sun and Duan (2013) proposed a new kind of Artificial Bee Colony (ABC) algorithm for pendulum-like oscillation control of an Unmanned Rotorcraft (UR) and improved the stabilizing performance of the UR's stare and hover. Li *et al.* (2012) proposed an improved Gravitational Search Algorithm to solve the UAV path planning problem considering the UAV flight constraints.

BBO algorithm is a new evolutionary optimization algorithm based on the science of biogeography for global optimization (Simon, 2008). BBO works based on two mechanisms: migration and mutation. BBO has some features in common with other population-based optimization algorithms like PSO and GA, such as the ability to share information between candidate solutions. However, BBO has certain features which overcome several demerits of the conventional methods. One of the characteristics of BBO is that it maintains solutions from one iteration to the next and improved the solutions by migration (Simon *et al.*, 2011). Furthermore, we introduced the predator-prey theory to improve the robustness of basic BBO algorithm considering its outstanding performance in jumping out of local best solution, and the comparative experimental results verified that our proposed method manifest better performance than the original BBO algorithm.

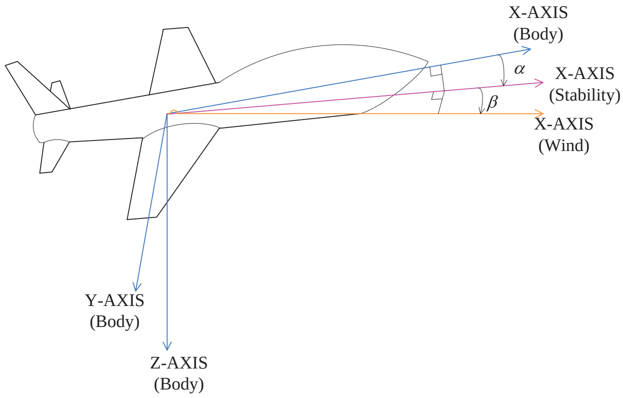
While using BBO to optimize flight control systems, we focus on the time domain responses by different PID parameters of the UCAV flight control system, in a form suitable for search and optimization by means of the proposed BBO algorithm. We use BBO algorithm to evaluate the fitness function which is determined by the dynamics response of different parameters of the flight control system. There are two problems need to be solved. First, the UCAV model selected is very important. Second, it is very crucial for BBO algorithm to choose the fitness function because there is no obvious mapping relationship between the UCAV controller and the property index. Therefore, how to evaluate each habitat's quality turns out to be a key issue which must to be resolved.

The remainder of this paper is organized as follows. The next section introduces mathematic model of UCAV. Then, we describe how to design the flight control system in Matlab environment. PPBBO algorithm is presented followed by a description of the proposed method that is applied to UCAV flight control system design. The comparative results and platform are then given, followed by our concluding remarks.

Mathematical model of UCAV

The 6-DOF nonlinear model of UCAV is illustrated in this section, which is the prerequisite for simplifying and linearizing the mathematical model (Lombaerts, 2012; Luo *et al.*, 2011; Zhang and Duan, 2013). Figure 1 gives some information about the coordinate system of the aircraft.

Figure 1 Geometry of UCAV



UCAV nonlinear equations of 6-DOF can be deduced by the aerodynamic and kinematical equations as follows:

$$\dot{V} = \frac{1}{m}(P_x \cos\alpha \cos\beta - P_y \sin\alpha \cos\beta + P_z \sin\beta + Z \sin\beta - Q) \\ -g(\cos\alpha \cos\beta \sin\vartheta - \sin\alpha \cos\beta \cos\vartheta \cos\gamma - \sin\beta \cos\vartheta \sin\gamma) \quad (1)$$

$$\dot{\alpha} = -\frac{1}{mV\cos\beta}(P_x \sin\alpha + P_y \cos\alpha + Y) + \omega_z \\ - \tan\beta(\omega_x \cos\alpha - \omega_y \sin\alpha)\frac{\delta y}{\delta x} + \frac{g}{V\cos\beta}(\sin\alpha \sin\vartheta \\ + \cos\alpha \cos\vartheta \cos\gamma) \quad (2)$$

$$\dot{\beta} = \frac{1}{mV}(-P_x \cos\alpha \sin\beta + P_y \sin\alpha \sin\beta + P_z \cos\beta + Z) \\ + \omega_x \sin\alpha + \omega_y \cos\alpha + \frac{g}{V}(\cos\alpha \sin\beta \sin\vartheta \\ - \sin\alpha \sin\beta \cos\vartheta \cos\gamma + \cos\beta \sin\gamma \cos\vartheta) \quad (3)$$

where m is the mass of UCAV; α is angle of attack; β is sideslip angle; ϑ is pitch angle; γ is roll angle. P is engine thrust; X, Y, Z are the projections of aerodynamic force in body axis. ω_x, ω_y, ω_z denote the coordinate components of angular rates. These three equations already contain three forces in the body axis which are generated by the thrust vector:

$$\dot{\omega}_x = b_{11}\omega_y\omega_z + b_{12}\omega_x\omega_z + \frac{I_y(M_x + M_{px}) + I_{xy}(M_y + M_{py})}{I_xI_y - I_{xy}^2} \quad (4)$$

$$\dot{\omega}_y = b_{21}\omega_y\omega_z + b_{22}\omega_x\omega_z + \frac{I_{xy}(M_x + M_{px}) + I_x(M_y + M_{py})}{I_xI_y - I_{xy}^2} \quad (5)$$

$$\dot{\omega}_z = \frac{I_x - I_y}{I_z}\omega_x\omega_y + \frac{I_{xy}}{I_z}(\omega_x^2 - \omega_y^2) + \frac{(M_z + M_{pz})}{I_z} \quad (6)$$

$$b_{11} = \frac{I_y^2 - I_yI_z - I_{xy}^2}{I_xI_y - I_{xy}^2} \quad (7)$$

$$b_{22} = \frac{I_x I_z - I_x^2 - I_{xy}^2}{I_x I_y - I_{xy}^2} \tag{8}$$

$$b_{12} = \frac{I_{xy}(I_z - I_y - I_x)}{I_x I_y - I_{xy}^2} \tag{9}$$

$$b_{21} = \frac{I_{xy}(I_y - I_z - I_x)}{I_x I_y - I_{xy}^2} \tag{10}$$

where I_x, I_y, I_z and M_x, M_y, M_z denote the coordinate components of inertia moment and resultant moment, respectively.

In the body axis, we have:

$$\dot{\gamma} = \omega_x - \tan\vartheta(\omega_y \cos\gamma - \omega_z \sin\gamma) \tag{11}$$

$$\dot{\vartheta} = \omega_y \sin\gamma + \omega_z \cos\gamma \tag{12}$$

$$\psi = \frac{1}{\cos\vartheta}(\omega_y \cos\gamma - \omega_z \sin\gamma) \tag{13}$$

where ψ is the drift angle. Aerodynamic equations can be described as:

$$Y = C_y qS,\ C_y = C_y(\alpha, \delta_z),\ Z = \sum C_z qS,$$
$$\sum C_z = C_z(\alpha, \delta_x) + C_z(\alpha, \delta_y)$$

$$Q = C_x qS,\ C_x = C_x(\alpha, \delta_z)$$

where δ_x, δ_y, δ_z are the coordinate components of deflection angles of the controlling surface. Aerodynamic moments can be given by:

$$M_x = \sum m_x qsl,\ \sum m_x = m_x^{\beta}\beta + m_x(\alpha, \delta_x) + m_x(\alpha, \delta_y) + m_x^{\omega x}\omega_x \frac{l}{2V} + m_x^{\omega y}\omega_y \frac{l}{2V}$$

$$M_y = \sum m_y qsl,\ \sum m_y = m_y^{\beta}\beta + m_y(\alpha, \delta_x) + m_y(\alpha, \delta_y) + m_y^{\omega x}\omega_x \frac{l}{2V} + m_y^{\omega y}\omega_y \frac{l}{2V}$$

$$M_z = \sum m_z qsb_A,\ \sum m_z = m_z(\alpha, \delta_z) + m_z^{\omega z}\omega_z \frac{b_A}{V} + m_z^{\dot{\alpha}}\dot{\alpha}\frac{b_A}{V}$$

When the height and mach are fixed, aerodynamic coefficients $C_y(\alpha, \delta_z)$, $C_x(\alpha, \delta_z)$, $C_z(\alpha, \delta_x)$, $C_z(\alpha, \delta_y)$, $m_x(\alpha, \delta_x)$, $m_x(\alpha, \delta_y)$, $m_y(\alpha, \delta_x)$, $m_y(\alpha, \delta_y)$, $m_z(\alpha, \delta_z)$ are the functions of the height, mach, attack angle and control surface. Aerodynamic derivatives $m_z^{\omega z}$, $m_z^{\dot{\alpha}}$, m_x^{β}, $m_x^{\omega x}$, $m_x^{\omega y}$, m_y^{β}, $m_y^{\omega x}$, $m_y^{\omega y}$ are specified values.

Suppose the mathematical model of UCAV can be simplified into nonlinear equations of 5-DOF when the thrust and the resistance of the UCAV are the same. Without consideration of the thrust vector, we have $\dot{V} = 0$, $P = Q$, $P_x = P \cdot G$, $P_y = P_z = 0$. The equations of the UCAV speed level off (Duan *et al.*, 2011; Zhang, 2004). At the same time, it is assumed that $I_{xy} \cdot I_x I_y - I_{xy}^2$, state variable $x = (\alpha, \beta, \omega_x, \omega_y, \omega_z)^T$. The UCAV nonlinear equations of 5-DOF are as follows:

$$\dot{\alpha} = -\frac{1}{mV\cos\beta}(P\sin\alpha + Y) + \omega_z - \tan\beta(\omega_x\cos\alpha - \omega_y\sin\alpha) + \frac{g}{V\cos\beta}(\sin\alpha\sin\vartheta + \cos\alpha\cos\vartheta\cos\gamma) \tag{14}$$

$$\dot{\beta} = \frac{1}{mV}(-P\cos\alpha\sin\beta + Z) + \omega_x\sin\alpha + \omega_y\cos\alpha + \frac{g}{V}(\cos\alpha\sin\beta\sin\vartheta - \sin\alpha\sin\beta\cos\vartheta\cos\gamma + \cos\beta\sin\gamma\cos\vartheta) \tag{15}$$

$$\dot{\omega}_x = \frac{I_y^2 - I_y I_z - I_{xy}^2}{I_x I_y - I_{xy}^2}\omega_y\omega_z + \frac{I_{xy}(I_z - I_y - I_x)}{I_x I_y - I_{xy}^2}\omega_x\omega_z + \frac{I_y \sum M_x}{I_x I_y - I_{xy}^2} b_{11}\omega_y\omega_z + b_{12}\omega_x\omega_z + \frac{I_y M_x}{I_x I_y - I_{xy}^2} \tag{16}$$

$$\dot{\omega}_y = \frac{I_{xy}(I_y - I_z - I_x)}{I_x I_y - I_{xy}^2}\omega_y\omega_z + \frac{I_x I_z - I_x^2 - I_{xy}^2}{I_x I_y - I_{xy}^2}\omega_x\omega_z + \frac{I_x \sum M_y}{I_x I_y - I_{xy}^2} b_{21}\omega_y\omega_z + b_{22}\omega_x\omega_z + \frac{I_x M_y}{I_x I_y - I_{xy}^2} \tag{17}$$

$$\dot{\omega}_z = \frac{I_x - I_y}{I_z}\omega_x\omega_y + \frac{I_{xy}}{I_z}(\omega_x^2 - \omega_y^2) + \frac{\sum M_z}{I_z}\frac{I_x - I_y}{I_z}\omega_x\omega_y + \frac{I_{xy}}{I_z}(\omega_x^2 - \omega_y^2) + \frac{M_z}{I_z} \tag{18}$$

In most cases, UCAV maintains steady, straight-level flight, equations (14)–(18) can be modeled as linear time invariant state-space perturbation models, with the nominal trajectory being steady-level trimmed flight. The linear model of UCAV is as follows:

$$\Delta\dot{\alpha} = \Delta\omega_z - (Y^{\alpha}\Delta\alpha + \Delta\delta_Z) \tag{19}$$

$$\Delta\dot{\omega}_z = M_z^{\alpha}\Delta\alpha + M_z^{\omega_z}\Delta\omega_z + M_z^{\delta_z}\Delta\delta_z \tag{20}$$

$$\Delta\dot{\beta} = \Delta\omega_y + Z^{\delta_x}\Delta\delta_x + Z^{\delta_y}\Delta\delta_y \tag{21}$$

$$\Delta\dot{\omega}_x = M_x^{\beta}\Delta\beta + M_x^{\omega_x}\Delta\omega_x + M_x^{\omega_y}\Delta\omega_y + M_x^{\delta_x}\Delta\delta_x + M_x^{\delta_y}\Delta\delta_y \tag{22}$$

$$\Delta\dot{\omega}_y = M_y^{\beta}\Delta\beta + M_y^{\omega_x}\Delta\omega_x + M_y^{\omega_y}\Delta\omega_y + M_y^{\delta_x}\Delta\delta_x + M_y^{\delta_y}\Delta\delta_y \tag{23}$$

We have the state equations:

$$\dot{x} = Ax + Bu$$
$$y = Cx$$

where the state variable$x = (\alpha, \omega_z, \beta, \omega_x, \omega_y)^T$ and the control surface$u = (\delta_z, \delta_x, \delta_y)^T$, and A, B, C can be denoted by:

Downloaded by Beihang University At 00:44 22 July 2015 (PT)

$$A=\begin{bmatrix} -Y^{\alpha} & 1 & 0 & 0 & 0 \\ M_z^{\alpha} & M_z^{\omega_z} & 0 & 0 & 0 \\ 0 & 0 & Z^{\beta} & 0 & 1 \\ 0 & 0 & M_x^{\beta} & M_x^{\omega_x} & M_x^{\omega_y} \\ 0 & 0 & M_y^{\beta} & M_y^{\omega_x} & M_y^{\omega_y} \end{bmatrix}, \quad B=\begin{bmatrix} -Y^{\delta_z} & 0 & 0 \\ M_z^{\delta_z} & 0 & 0 \\ 0 & Z^{\delta_x} & Z^{\delta_y} \\ 0 & M_x^{\delta_x} & M_x^{\delta_y} \\ 0 & M_y^{\delta_x} & M_y^{\delta_y} \end{bmatrix}, \quad C=\begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

UCAV flight control system design in Matlab environment

Based on the UCAV control augmentation system, the aircraft linear equations are generally obtained by a series of equilibrium points. The flight envelope of this UCAV must satisfy $0 \leq H \leq 18km$ and$0.6 \leq M \leq 2.2$. Figure 2 shows the general block diagram of our simulation system.

As shown in Figure 2, the UCAV system comprises four subsystems: control law, actuator, mathematical model and simulation result display.

Matrix K for the function of control law can be obtained from Matlab main program. Actuator module is responsible for control adjusting, which can also limit the amplitudes of control surface deflection angle. The actuator module can be shown with Figure 3.

The actuator module requires that deflection angle of the elevator must be less than that of aileron and rudder. To prevent the deflection angles of the control surface from deflecting too fast, the angle authority of the elevator is set at -18° to12°, aileron and rudder at -25° to 25°, and the angle rate authority of elevator and aileron at $50^{\circ}/s$, and rudder is at $80^{\circ}/s$. UCAV model module is displayed in Figure 4.

where matrix A and B are both obtained from the workspace of Matlab. Figure 5 shows the simulation result display module.

The control law $u = -Kx$ is used. K denotes the state feedback gain, and it can be illustrated with the following matrix:

$$K=\begin{bmatrix} k_1 & k_2 & 0 & 0 & 0 \\ 0 & 0 & k_3 & k_4 & k_5 \\ 0 & 0 & k_6 & k_7 & k_8 \end{bmatrix}$$

Predatory-prey BBO

BBO is a novel population-based optimization technique for solving global optimization problems. In the science of biogeography, a habitat is any island (area) that is geographically isolated from other habitats. Each habitat is considered as an individual and has its measure of goodness

Figure 2 General block diagram

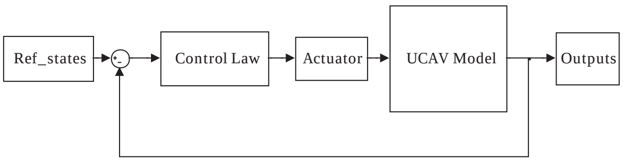


Figure 3 Actuator module of UCAV in Matlab environment

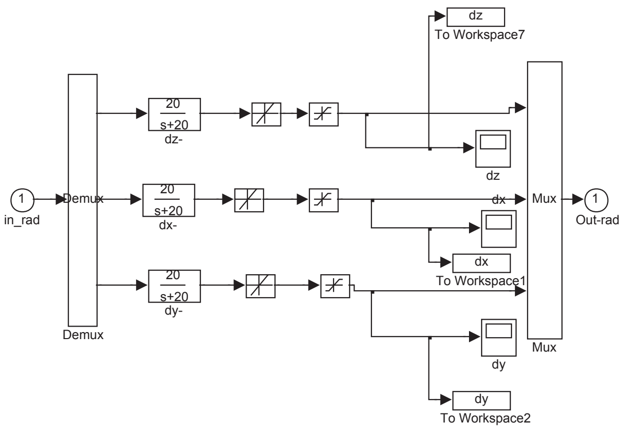


Figure 4 UCAV model module in Matlab environment

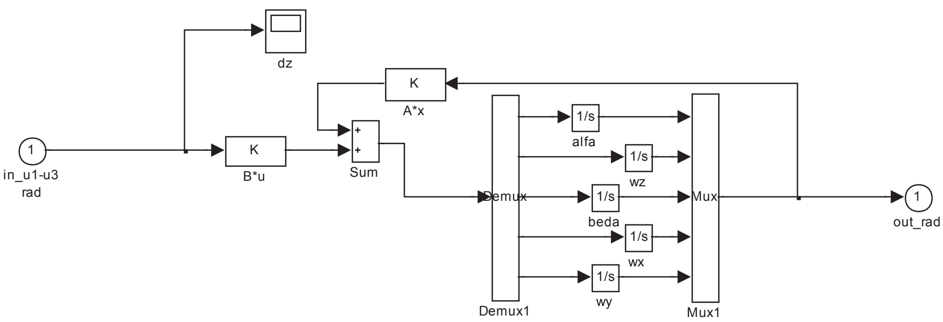
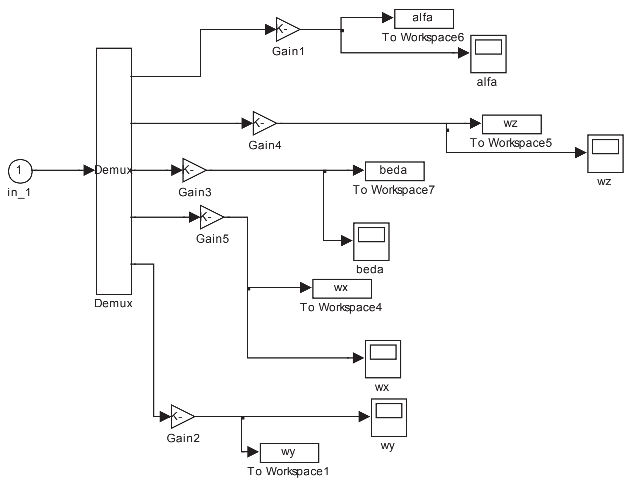


Figure 5 Simulation result display module in Matlab environment



Downloaded by Beihang University At 00:44 22 July 2015 (PT)

Figure 6 Species model of a habitat

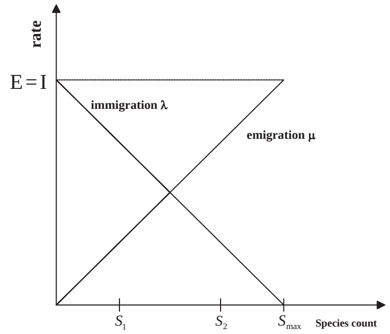


Figure 7 Algorithm for migration process of the BBO

```
for i = 1 to NP
   Select X_i with probability ∝ λ_i
   If X_i is selected then
      for j = 1 to NP do
         Select X_j with probability ∝ μ_j
            if X_j is selected then
               Randomly select a SIV from X_j
               Replace a random SIV in X_i with selected SIV of X_j
            end if
      end for
   end if
end for
```

Figure 8 Algorithm for mutation process of the BBO

```
for i = 1 to NP
   for j = 1 to D do
      Use λ_i and μ_i to compute the probability P_i using m(s) = m_max((1 - P_s)/P_max)
      Select a SIV H_i(j) with probability based on probability m_s
   if H_i(j) is selected then
      Replace H_i(j) with a randomly generated SIV
   end if
end for
```

for living which is known as the Habitat Suitability Index (HSI). Habitats that are well suited as residences for biological species are said to have a high HSI, while habitats that are not good, have a low HSI. Each of these features that characterize habitability is known as Suitability Index Variables (SIVs). The dynamics of the movement of the species among different habitats is mainly governed by two parameters called immigration rate (λ) and emigration rate (μ) and these two parameters depends upon the number of species in the habitats. From immigration graph of Figure 6, the equation

Figure 9 The pseudo code of PPBBO algorithm for UCAV flight controller

PROCEDURE Optimization of UCAV controller parameter based on the PPBBO algorithm

BEGIN

Step 1: Initialize the BBO parameters, such as the maximum species count S_{max} and the maximum migration rates *E* and *I* (see Figure4), the maximum mutation rate m_{max}, and an elitism parameter *Keep*. Initialize random population of *D*-dimensional parameters $x = (k_1, k_2, ..., k_D)$ where $k_i (i = 1, 2, ..., D)$ have the constrain of ± 10, which is set according to exact experience. Initialize a set of habitats, each habitat corresponding to a potential solution. Initialize the starting iteration *NC = 1*.

Step 2: According to the parameters of the generated habitats, calculate the cost of each solution formed by relative parameters by running simulation module of Simulink. The smaller the cost value is, the better performance the solution maintains. Based on the values of HSI, elite habitats are identified.

Step 3: Use immigration and emigration to modify each non-elite habitat probabilistically as described in Sec.3.1 and recomputed HSI of each modified habitat. Feasibility of a solution is verified when each SIV satisfies equality and inequality constraints of generator as mentioned in the specific problem.

Step 4 : Update the species count probability of each habitat. Then, perform mutation operation on the habitats as discussed in Section 3.2 and recomputed each of the HSI value of new habitats.

Step 5: Model the predator based on the worst solution as formula (30) demonstrates. Then, use formula (31) to provide the other solutions to maintain a distance from the predator.

Step 6: If $NC < NC_{max}$, go to Step 2. Otherwise, output the optimal parameters and optimal cost value.

End

for immigration rate λ_k and emigration rate μ_k for k number of species can be written as:

$$\lambda_k = I\left(1 - \frac{k}{n}\right) \tag{24}$$

$$\mu_k = E\left(\frac{k}{n}\right) \tag{25}$$

where E and I are the maximum emigration rate and maximum immigration rate, respectively, and $n = S_{max}$ is the maximum number of species in a habitat.

When $E = I$, combining (24) and (25), we can obtain:

$$\lambda_k + \mu_k = E \tag{26}$$

Downloaded by Beihang University At 00:44 22 July 2015 (PT)

Aircraft Engineering and Aerospace Technology: An International Journal
Volume 87 · Number 3 · 2015 · 249–259

Downloaded by Beihang University At 00:44 22 July 2015 (PT)

Mathematically, the concept of emigration and immigration can be represented by a probabilistic model. Now consider the probability P_s that the habitat contains exactly S species. P_s changes from time t to time $(t + \Delta t)$ as follows:

$$P_s(t + \Delta t) = P_s(t)(1 - \lambda_s \Delta t - \mu_s \Delta t) + P_{s-1}\lambda_{s-1}\Delta t + P_{s+1}\mu_{s+1}\Delta t \tag{27}$$

where λ_s and μ_s are the immigration and emigration rates when there are S species in the habitat. This equation holds because to have S species at time $(t + \Delta t)$, one of the following conditions must hold:

- there were S species at time t, and no immigration or emigration occurred between t and $(t + \Delta t)$;
- there were $(S - 1)$ species at time t, and one species immigrated; and
- there were $(S + 1)$ species at time t, and one species emigrated.

If the increased time Δt is small enough, and the probability of more than one immigration or emigration can be ignored, then taking the limit of formula (27) as $\Delta t \to 0$ gives the following equation:

$$\dot{P}_s = \begin{cases} -(\lambda_s + \mu_s)P_s + \mu_{s+1}P_{s+1}, & S = 0 \\ -(\lambda_s + \mu_s)P_s + \lambda_{s-1}P_{s-1} + \mu_{s+1}P_{s+1}, & 1 \le S \le S_{\max} - 1 \\ -(\lambda_s + \mu_s)P_s + \lambda_{s-1}P_{s-1}, & S = S_{\max} \end{cases} \tag{28}$$

BBO concept is mainly based on the two operations: the migration operation and the mutation operation.

Migration

In the basic BBO algorithm, each of the candidate solutions for a problem is considered as a habitat and is associated with a fitness value called the HSI of a habitat. Low-HSI habitat represents an inferior solution and high-HSI habitat represents a good solution. The emigration and immigration rates of each solution are used to share features between habitats (The shared features do not disappear from the high-HSI solutions). Therefore, the migration operation, which is about emigration and immigration, is used to improve the solutions. For a D-dimensional optimization problem, a habitat is a $1 \times D$ array. The population consists of $NP = n$ parameters vector $X_i, i = 1, 2, \ldots, n$. One option for implementing the migration operator is shown in Figure 7.

A procedure of elitism is introduced to preserve some of the best habitats in the previous generation. These habitats are kept from the migration operation by setting their immigration rate λ to zero. This procedure, known as elitism operation, helps us to prevent best solutions from being corrupted due to the process of immigration.

Mutation

It is well known that due to some natural calamities or other events, HIS of a natural habitat might change suddenly from its equilibrium value. In BBO, this event is represented by the mutation of SIV. The species count probabilities are used to determine mutation rates. The probabilities of each species count are determined by the differential equation in (28). Mutation rate of each set of solution can be calculated in terms of species count probability using the following equation:

$$m(s) = m_{\max}\left(\frac{1 - P_s}{P_{\max}}\right) \tag{29}$$

where $m(s)$ is the mutation rate for habitat which contains S species, $m_{\max}$ is the maximum mutation rate and $P_{\max}$ is the maximum probability. The algorithm for mutation process of BBO is shown in Figure 7.

This mutation scheme makes both high and low HIS solutions likely to mutate, which gives them a chance for improving. The procedure of mutation tends to increase diversity among the population (Figure 8).

Due to the flexibility and robustness in solving optimization problems, BBO algorithm has already aroused intense interest. However, there still exist some flaws on this algorithm, such as the tendency to converge to local best solutions and the large number of iterations to reach the global optimal solution. To overcome these flaws of the original BBO algorithm, we propose a PPBBO integrated with the predator-prey concept in our work. After the mutation of each generation, conduct the predator-prey behavior to choose better solutions into next generation. In this way, our proposed algorithm takes the advantage of the predator-prey theory to make the individuals of sub-generations distributed ergodically in the predefined space and to increase the diversity of the population, as well as to increase the speed of finding the optimal solution.

In our algorithm, the predator is modeled based on the worst solution as equation (30) demonstrates:

$$P_{predator} = P_{worst} + \rho(1 - NC/NC_{\max}) \tag{30}$$

where $P_{predator}$ is the predator (a possible solution), P_{worst} is the worst solution in the population, NC is the current iteration, while $NC_{\max}$ is the maximum number of iterations and ρ is the hunting rate. To model the interactions between predator and prey, equation (31) is also used and this provides the solutions to maintain a distance from the predator:

Figure 10 Flow chart of the PPBBO

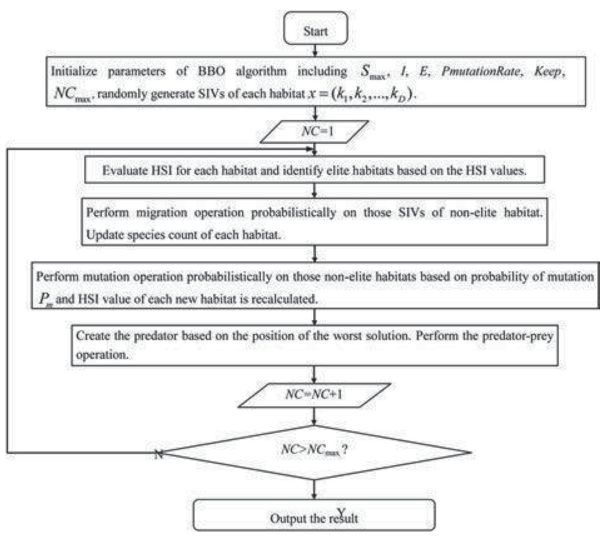
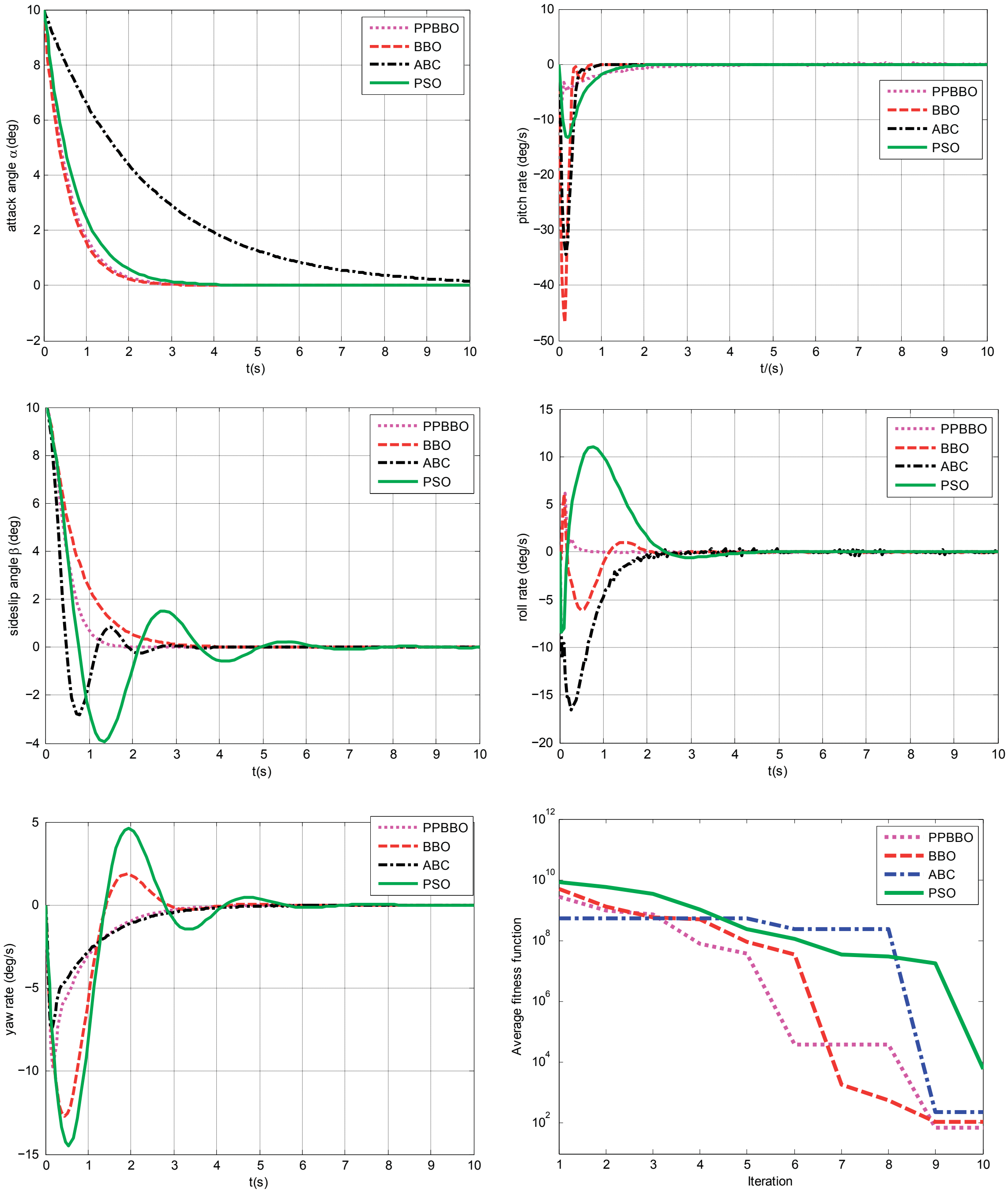


Figure 11 Results of identifying controller parameters for UCAV based on PPBBO in case 1



Notes: (a) Comparison of attack angle responses; (b) comparison of pitch rate responses; (c) comparison of sideslip angle responses; (d) comparison of roll rate responses; (e) comparison of yaw rate responses and (f) evolution curves of four algorithms

$$\begin{cases} P_{NC+1} = P_{NC} + \rho e^{-|d|}, d > 0 \\ P_{NC+1} = P_{NC} - \rho e^{-|d|}, d < 0 \end{cases} \tag{31}$$

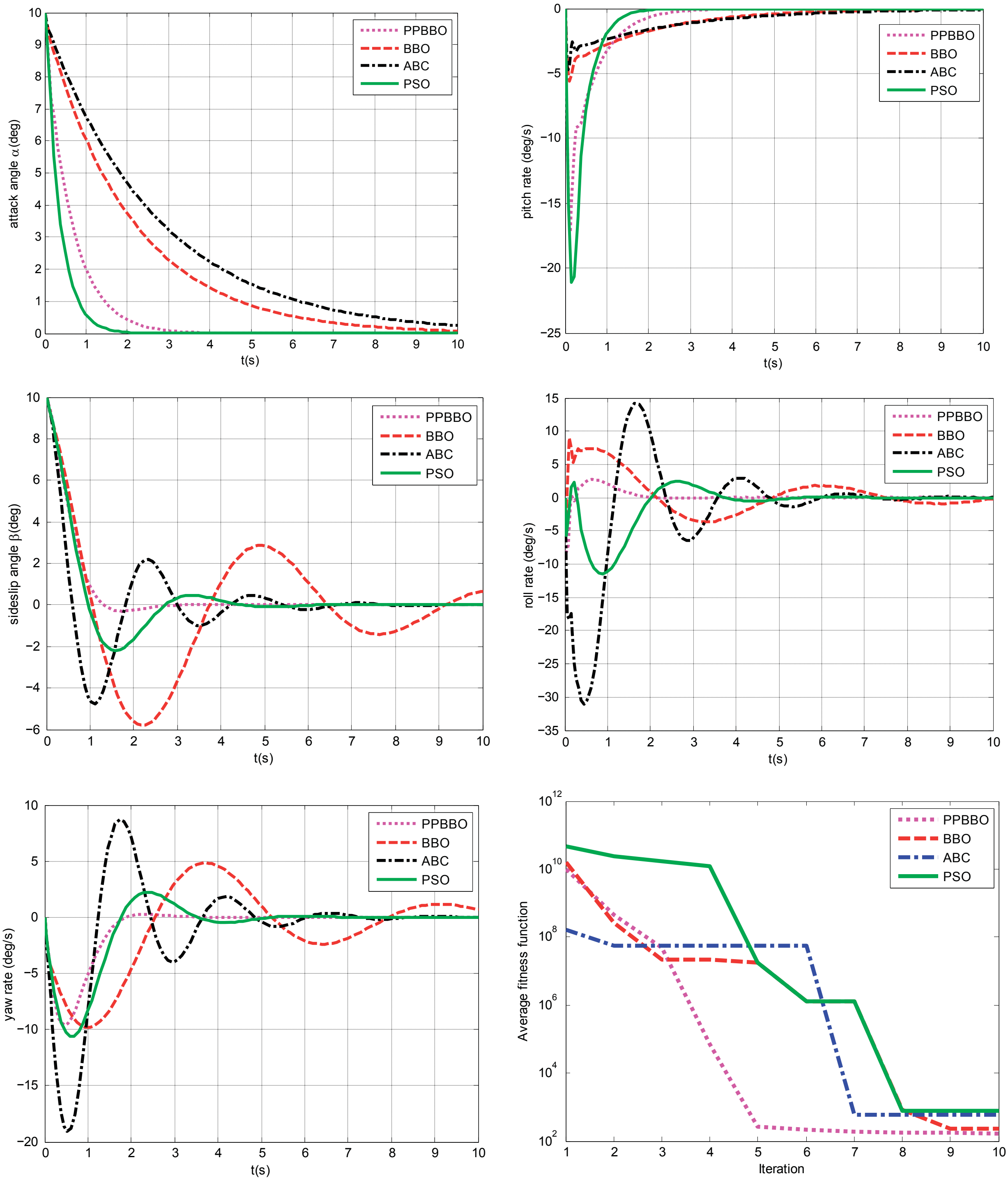
where d is the distance between the solution and the predator, and NC is the current iteration.

Table I Results of comparison between four algorithms in case 1

Algorithm	PPBBO	BBO	ABC	PSO
Minimum value	76.7692	105.0301	190.5187	150.4508

Downloaded by Beihang University At 00:44 22 July 2015 (PT)

Figure 12 Results of identifying controller parameters for UCAV based on PPBBO in case 2



Notes: (a) Comparison of attack angle responses; (b) comparison of pitch rate responses; (c) comparison of sideslip angle responses; (d) comparison of roll rate responses; (e) comparison of yaw rate responses and (f) evolution curves of four algorithms

Predatory-prey BBO for identifying controller parameters

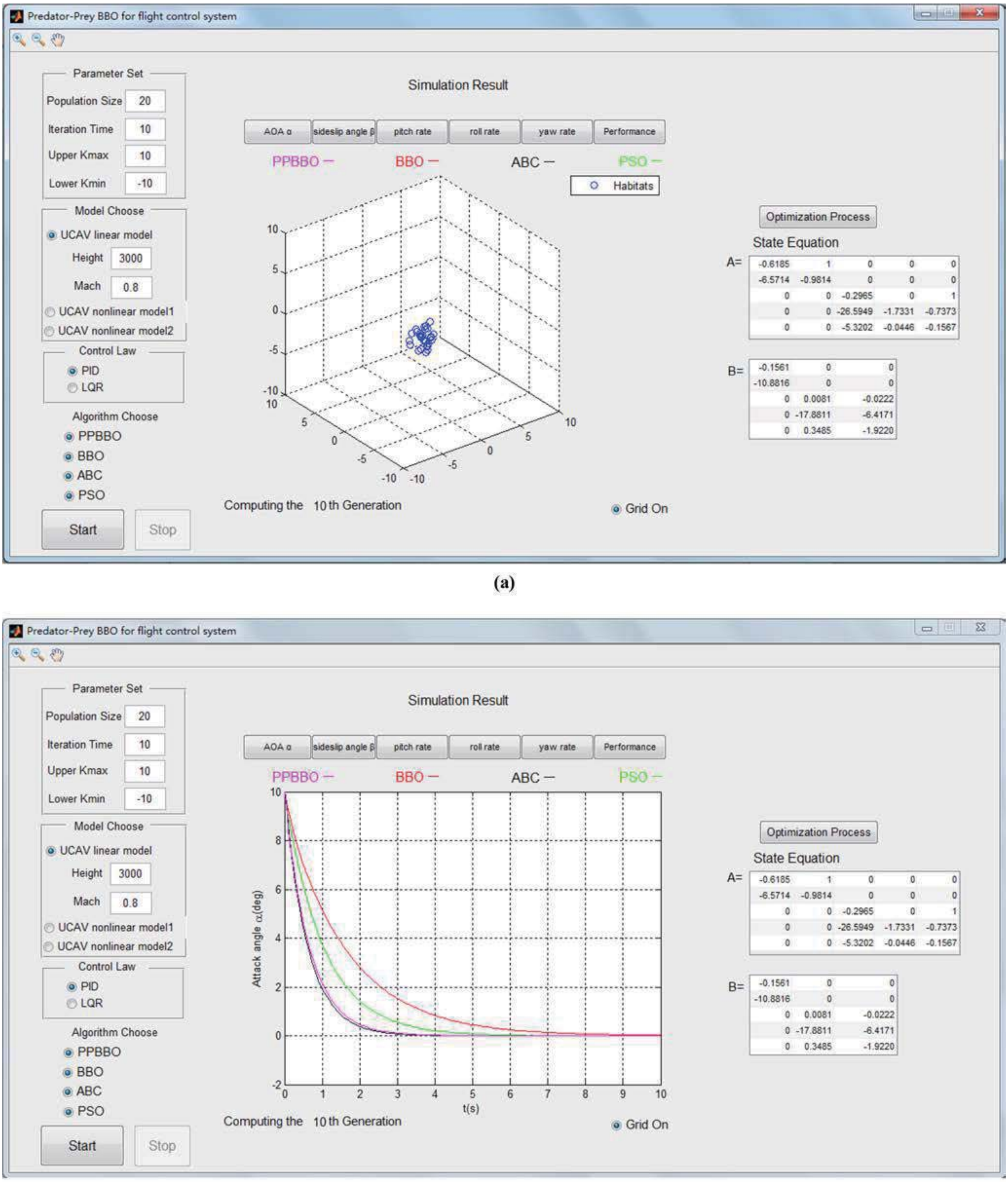
The parameters identification of the conventional flight controller can be treated as the typical continual spatial

Table II Results of comparison between four algorithms in case 2

Algorithm	PPBBO	BBO	ABC	PSO
Minimum value	170.2663	231.8397	408.8407	799.4569

Downloaded by Beihang University At 00:44 22 July 2015 (PT)

Figure 13 UCAV controller design software platform based on predator-prey PSO



(a)

(b)

Notes: (a) Sideslip angle response based on PPBBO; (b) convergence process interface of four algorithms

Downloaded by Beihang University At 00:44 22 July 2015 (PT)

Downloaded by Beihang University At 00:44 22 July 2015 (PT)

optimization problem (Duan, 2005). BBO is a novel way for solving this problem. BBO, which is a bio-inspired computation algorithm, can be applied to the design of flight control system to reduce the workload of conventional designer. The bounds of the control gain parameters are set, and BBO searches for the corresponding space automatically to find the optimal parameters. The process in conventional design is conducted manually, now it can be done automatically. Bio-inspired computation can be applied to promote the automation of conventional controller design (Zhang and An, 2008).

Using the proposed PPBBO algorithm to obtain the optimal parameters combination for the UCAV flight control system here, the fitness function is given by:

$$\mathcal{J} = \frac{1}{2}\int (x'Qx + u'Ru)dt \qquad (32)$$

where x is the error between the reference states and the aircraft current states, and u is the control vector. Q and R are diagonal positive matrix. Here the weighting matrices is chosen as $Q = \mathrm{diag}(80, 40, 30, 30, 30)$, $R = diag(50, 50, 50)$. The smaller $\mathcal{J}$ is, the better the solution is.

The suitability index variables of a habitat is defined by:

$$x = (k_1, k_2, \ldots, k_D)$$

where x has the constraint of ± 10, which is set according to experience.

The process of proposed PPBBO algorithm for solving UCAV controller parameters identification can be described with Figure 9.

The aforementioned flow chart of the PPBBO algorithm process can also be illustrated with Figure 10.

Experimental results and platform

To investigate the feasibility and effectiveness of the proposed PPBBO approach for identification of UCAV controller parameters, a series of experiments are conducted under some constrained conditions.

The initial parameters of both classical BBO algorithm and PPBBO in our experiments were adjusted as:

- *Populationsize*: Smax = 60;
- *Maximum possible immigration rate*: I = 1;
- *Maximum possible emigration rate*: E = 1;
- *Mutation probability*: PmutationRate = 0.2; and
- *Elitism parameter*: Keep = 5.

Case 1

In this case, the parameter values are initially set to $\Delta\alpha = 10^{\circ}$, $\Delta\beta = 10^{\circ}$, $NC_{\max} = 10$, $t = 10$ s, mach = 0.7, $H = 3{,}000$ m, where t is the simulating time of the controller. Comparison of the experiment results between our proposed PPBBO and the basic BBO approach are illustrated from Figure 11(a-e). To show the improvement of our proposed method, we also compared our presented approach with the basic ABC algorithm and PSO algorithm. Figure 11(f) shows the evolution curve of the four algorithms.

The final optimal results of the minimum fitness values are shown in Table I.

As indicated in Figure 11, as expected, the proposed algorithm performs better than the basic BBO, ABC and PSO approaches, apparently showing that our improved method can identify the parameters more stable than the other methods. Figure 11(f) also demonstrates that the proposed algorithm can converge to the optimal solution quickly.

Case 2

In this case, the parameter values are $\Delta\alpha = 10^{\circ}$, $\Delta\beta = 10^{\circ}$, $NC_{\max} = 10$, $t = 10$ s, mach = 1.3, $H = 13{,}000$ m, where t is the simulating time of the controller. Comparison of the experiment results between our proposed PPBBO and the basic BBO approach are illustrated from Figure 12(a-e). The performances of ABC and PSO algorithm are also included in the comparative experiments.

The final optimal result of the minimum fitness values are shown in Table II.

Although the initial conditions are much different from those of Experiment 1, the improved algorithm can find the optimal solution.

From the above experimental results, it is obvious that the proposed PPBBO approach could make the UCAV controlling system have better performance than the basic BBO approach. The state feedback gain obtained according to the PPBBO can guarantee fast response, precise control and strong robustness.

Based on the UCAV model and the proposed PPBBO algorithm, we developed a software platform of UCAV controller design. The graphical user interfaces of this platform are shown in Figure 13.

Conclusions

In this paper, a novel PPBBO algorithm for identifying parameters of UCAV flight control system is presented, which can reduce the workload of the designers during the process of designing complicated UCAV control system. In this approach, a new fitness function, which is proposed during design procedure, is proven appropriate and efficient by a series of comparative experimental results.

In the future, we will conduct further study on real-time and rapidity performance of this proposed bio-inspired computing method for the hypersonic vehicle flight control system.

References

Benini, E. and Chiereghin, N. (2013), "Turbofan multiobjective-multipoint optimization for UAV/UCAV applications", *Aircraft Engineering and Aerospace Technology*, Vol. 85 No. 5, pp. 366-381.

Duan, H.B. (2005), *Ant Colony Algorithms: Theory and Applications*, Science Press, Beijing.

Duan, H.B. and Li, P. (2012), "Progress in control approaches for hypersonic vehicle", *Science China Technological Sciences*, Vol. 55 No. 10, pp. 2965-2970.

Duan, H.B., Luo, Q.N. and Yu, Y.X. (2013a), "Trophallaxis network control approach to formation flight of multiple unmanned aerial vehicles", *Science China Technological Sciences*, Vol. 56 No. 5, pp. 1066-1074.

Duan, H.B., Shao, S., Su, B.W. and Zhang, L. (2010), "New development thoughts on the bio-inspired intelligence

Downloaded by Beihang University At 00:44 22 July 2015 (PT)

based control for unmanned combat aerial vehicle", *Science China Technological Sciences*, Vol. 53 No. 8, pp. 2025-2031.

Duan, H.B., Wei, X.X. and Dong, Z.N. (2013b), "Multiple UCAVs cooperative air combat simulation platform based on PSO, ACO, and game theory", *IEEE Aerospace and Electronic Systems Magazine*, Vol. 28 No. 7, pp. 12-19.

Duan, H.B., Zhang, Y.P. and Liu, S.Q. (2011), "Multiple UAVs/UGVs heterogeneous coordinated technique based on receding horizon control (RHC) and velocity vector control", *Science China Technological Sciences*, Vol. 54 No. 4, pp. 869-876.

Jin, G.D. and Gu, L.X. (2009), "UAV simulator-based simulation of flight control system", *Proceedings of the 2009 International Workshop on Intelligent Systems and Applications, Wuhan*, pp. 1-4.

Juang, J.G., Chiou, H.K. and Chien, L.H. (2008), "Analysis and comparison of aircraft landing control using recurrent neural networks and genetic algorithms approaches", *Neurocomputing*, Vol. 71 No. 16, pp. 3224-3228.

Li, C.Y., Jing, W.X. and Gao, C.S. (2009), "Adaptive back-stepping-based flight control system using integral filters", *Aerospace Science and Technology*, Vol. 13 No. 2, pp. 105-113.

Li, P. and Duan, H.B. (2012), "Path planning of unmanned aerial vehicle based on improved gravitational search algorithm", *Science China Technological Sciences*, Vol. 55 No. 10, pp. 2712-2719.

Lombaerts, T. (2012), "Aerodynamic model identification of frauke UAV", *AIAA Modeling and Simulation Technologies Conference*, Minneapolis, MN, pp. 13-16.

Luo, Y., Yeh, Y.H. and Ishihara, A.K. (2011), "Adaptive backstepping design for a longitudinal UAV model utilizing a fully tuned growing radial basis function network", *Proceedings of the AIAA lnfotech@ Aerospace Conference on Unleashing Unmanned Systems, St. Louis, MO*, pp. 1-23.

Qi, G.P., Song, P. and Li, K.J. (2009), "Multivariable PID neural network based flight control system for small-scale unmanned helicopter", *Proceedings of the 2009 IEEE International Conference on Information and Automation, Zhuhai, Macau*, pp. 1331-1335.

Rydlo, K., Rzucidlo, P. and Chudy, P. (2013), "Simulation and prototyping of FCS for sport aircraft", *Aircraft Engineering and Aerospace Technology*, Vol. 85 No. 6, pp. 475-486.

Simon, D. (2008), "Biogeography-based optimization", *IEEE Transactions on Evolutionary Computation*, Vol. 12 No. 6, pp. 702-713.

Simon, D., Ergezer, M., Dawei, D. and Rarick, R. (2011), "Markov models for biogeography-based optimization", *IEEE Transactions on Systems, Man, and Cybernetics, Part B: Cybernetics*, Vol. 41 No. 1, pp. 299-306.

Sun, C.H. and Duan, H.B. (2013), "Artificial bee colony optimized controller for unmanned rotorcraft pendulum", *Aircraft Engineering and Aerospace Technology*, Vol. 85 No. 2, pp. 104-114.

Sun, X., Zhang, W.G., Yin, W. and Li, A.-J. (2007), "Design of a large envelope wavelet neural network gain scheduling flight control law based on PSO algorithm", *Measurement & Control Technology*, Vol. 26 No. 10, pp. 34-36.

Zhang, M.T. and An, J.W. (2008), "Application of intelligent computation to promote the automation of flight control design", *Proceedings of the International Conference on Intelligent Computation Technology and Automation, Hunan*, Vol. 1, pp. 991-994.

Zhang, W.Y. (2004), "Study of intelligent robust design approach of large flight envelope flight control system", Master thesis, Beihang University, Beijing.

Zhang, Y.P. and Duan, H.B. (2013), "A directional control system for UCAV automatic takeoff roll", *Aircraft Engineering and Aerospace Technology*, Vol. 85 No. 1, pp. 48-61.

Further reading

Duan, H.B. and Li, P. (2014), *Bio-Inspired Computation in Unmanned Aerial Vehicles*, Springer-Verlag, Berlin.

Duan, H.B., Yu, Y.X. and Zhao, Z.Y. (2009), "Parameters identification of UCAV flight control system based on predator-prey particle swarm optimization", *Science China Information Sciences*, Vol. 56 No. 1, pp. 1-12.

Luo, Q.N. and Duan, H.B. (2013), "An improved artificial physics approach to multiple UAVs/UGVs heterogeneous coordination", *Science China Technological Sciences*, Vol. 56 No. 10, pp. 2473-2479.

About the authors

Weiren Zhu received his BSc in Automation Science from Beihang University (formerly Beijing University of Aeronautics and Astronautics, BUAA) in 2013. He is currently a post-graduate candidate with the School of Automation Science and Electrical Engineering, Beihang University. His current research interest includes advanced flight control, bio-inspired computation and intelligent information processing.

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 received the PhD from Nanjing University of Aeronautics and Astronautics (NUAA) in 2005. He was an academic visitor of National University of Singapore (NUS) in 2007, 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 three monographs and over 60 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

For instructions on how to order reprints of this article, please visit our website:
www.emeraldgrouppublishing.com/licensing/reprints.htm
Or contact us for further details: **permissions@emeraldinsight.com**