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Parameter Estimation for a VTOL UAV Using Mutant Pigeon Inspired Optimization Algorithm with Dynamic OBL Strategy*

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***Abstract*— Inertial physical parameter estimation for a VTOL Unmanned Aerial Vehicle (UAV) is helpful to the control and calibration. A mutant pigeon-inspired optimization algorithm (MPIO) is proposed in this paper, which is based on dynamic opposition-based Learning (OBL) strategy. The mutant operator with nonlinear characteristic is employed to enhance the global searching ability and accelerate the convergence speed of the globally optimal pigeon. Meanwhile, the dynamic opposition-based learning strategy is introduced to facilitate the central pigeon of the swarm to explore the potential better region. The proposed algorithm is applied to the UAV system with the data from model test. The experimental results indicate that the proposed algorithm shows better performance in converging speed and overall search ability.**

I. Introduction

In the last decades, the wide applications of unmanned aerial vehicles in military, transportation, entertainment have come into view. Owing to its apparent advantages of zero casualties, high-speed overload, short operation time, and low life-cycle cost [1,2], unmanned aerial vehicles are indispensable throughout almost all aspects of our life. In each of these application areas there exit much problems faced by the engineers. In the area of control, one of the inevitable problems is that of parameter estimation for UAV system [3].

Different form other land transportation mobile robots, the model of the UAV is influenced by the gravity, aerodynamics forces, and turbulence [4]. The accuracy of model is depended on the parameters which are composed of the mass, aerodynamic coefficient and the moments of inertia. Also, the noise of measurement and data processing system have influence on the parameters. Since the parameters make the dynamic changes, it is necessary to obtain the accurate model for UAV control system via parameter estimation.

Considerable researches including theoretical and experimental parameter estimation approaches have been carried out for highly nonlinear, multivariable, strongly coupled UAV control system. It is noted that the most widely used technical for parameter estimation are Maximum likelihood (ML) and least square (LS). The parameter estimation for noisy input–output models could be dealt with Maximum likelihood identification, which does not require any particular assumption on the input process [5]. A frequency-domain LS method combined with time-frequency filtering was proposed for flight flutter model parameter identification [6]. However, there are problems with the parameter estimation of the above approaches. For instance, ML method is a local search algorithm and sensitive to initial value. LS method is sensitive to the measurement noise and needed to describe the dynamic model as a linear function of the parameter vector. Other UAV parameter identification strategies include extended and unscented Kalman filter [7], real-time neural network [8], etc.

Recently, bioinspired search and optimization methods, called Swarm Intelligence (SI) algorithms, provide an ideal and automated solution to parameter estimation for UAV control system using regularly measured data and properly defined objective functions. Common ones cover genetic algorithm (GA), ant swarm optimization (ASO), particle swarm optimization (PSO) and pigeon-inspired optimization (PIO). Xu [9] proposed a novel adaptive genetic algorithm identification method for small unmanned aerial rotorcraft. Sun [10] focused on the parameter identification of synchronous generator using ant swarm optimization method. B. Zafer [11] dealt with the dynamic modeling and identification of Staubli RX-60 robot using PSO and LS methods. Due to the implementation, low computation cost, and fast convergence speed in dealing with practical industrial problems, pigeon-inspired optimization (PIO) has recently been employed as an attractive optimization algorithm in system estimation, control and optimal [12-15]. In this paper, a dynamic mutant PIO algorithm combined with opposition-based learning strategy was proposed to identify the parameters of a VTOL unmanned aerial vehicle.

The remainder of this paper is organized as follows. In section II, the dynamic model of the VTOL UAV is provided and the estimation of full parameters is analyzed. In section III, it provides the brief review on PIO and the detailed description of improved PIO. Experimental results and analysis are given in section IV. Finally, conclusions and future work are presented in section V.

II. Dynamic Model of the VTOL Unmanned Aerial Vehicle

Considering the process of take-off, there exist movements in axis X and Y with axis Z ignored. The force analysis is shown in figure 1. Axis $X-Y$ represents the inertial coordinate system, and $X_b - Y_b$ is the body axis system of VTOL UAV. Assuming the VTOL UAV is a single rigid body

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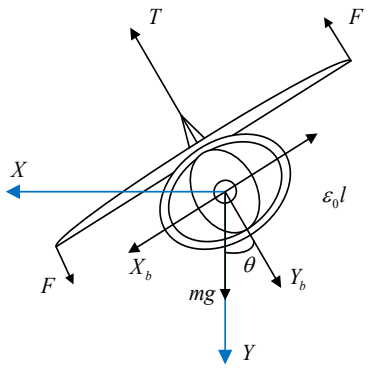
in the inertial frame, then it commonly simplified in following form [16]:

$$\begin{cases} -m\ddot{X} = -T\sin\theta + \varepsilon_0 l\cos\theta \\ -m\ddot{Y} = T\cos\theta + \varepsilon_0 l\sin\theta - mg \\ I_x\ddot{\theta} = l \end{cases} \tag{1}$$

Figure 1. Force analysis of VTOL UAV.



where T and l are inputs for control representing the thrust torque and rolling torque of the UAV. g is the acceleration of gravity. ε_0 is the coefficient that describes the coupled relationship between T and l. As one can see in equation (1), the model consists of two inputs which control three states. There are three physical parameters in the model, m, ε_0, and I_x.

Let $\left[X,\dot{X},Y,\dot{Y},\theta,\dot{\theta}\right]=\left[x_1,x_2,x_3,x_4,x_5,x_6\right]$, then the dynamic equilibrium equation could be stated as follows:

$$\begin{cases} \dot{x}_1 = x_2 \\ -m\dot{x}_2 = -T\sin x_5 + \varepsilon_0 l\cos x_5 \\ \dot{x}_3 = x_4 \\ -m\dot{x}_4 = T\cos x_5 + \varepsilon_0 l\sin x_5 - mg \\ \dot{x}_5 = x_6 \\ I_x\dot{x}_6 = l \end{cases} \tag{2}$$

Let $T=u_1$, $l=u_2$, $a_1=\frac{1}{m}$, $a_2=\frac{\varepsilon_0}{m}$, $a_3=\frac{1}{I_x}$, then the equation (2) could be expressed as follows:

$$\begin{cases} \dot{x}_1 = x_2 \\ \dot{x}_2 = a_1\sin x_5\cdot u_1 - a_2\cos x_5\cdot u_2 \\ \dot{x}_3 = x_4 \\ \dot{x}_4 = -a_1\cos x_5\cdot u_1 - a_2\sin x_5\cdot u_2 + g \\ \dot{x}_5 = x_6 \\ \dot{x}_6 = a_3\cdot u_2 \end{cases} \tag{3}$$

The above formula can be written as the calculation of matrixes:

$$\begin{bmatrix} \dot{x}_2 \\ \dot{x}_4 \\ \dot{x}_6 \end{bmatrix} = \begin{bmatrix} a_1\sin x_5\cdot u_1 - a_2\cos x_5\cdot u_2 \\ -a_1\cos x_5\cdot u_1 - a_2\sin x_5\cdot u_2 \\ a_3\cdot u_2 \end{bmatrix} + \begin{bmatrix} 0 \\ g \\ 0 \end{bmatrix} \tag{4}$$

The equation (4) could be converted to the following form:

$$\begin{bmatrix} \dot{x}_2 \\ \dot{x}_4 \\ \dot{x}_6 \end{bmatrix} = \begin{bmatrix} \sin x_5 & -\cos x_5 & 0 \\ -\cos x_5 & -\sin x_5 & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} a_1 & 0 \\ 0 & a_2 \\ 0 & a_3 \end{bmatrix} \begin{bmatrix} u_1 \\ u_2 \end{bmatrix} + \begin{bmatrix} 0 \\ g \\ 0 \end{bmatrix} \tag{5}$$

The above formula can be written as follows:

$$\mathbf{Y} = \mathbf{A}\tau \tag{6}$$

where $\mathbf{Y} = \begin{bmatrix} \sin x_5 & -\cos x_5 & 0 \\ -\cos x_5 & -\sin x_5 & 0 \\ 0 & 0 & 1 \end{bmatrix}^{-1} \left\{ \begin{bmatrix} \dot{x}_2 \\ \dot{x}_4 \\ \dot{x}_6 \end{bmatrix} - \begin{bmatrix} 0 \\ g \\ 0 \end{bmatrix} \right\}$,

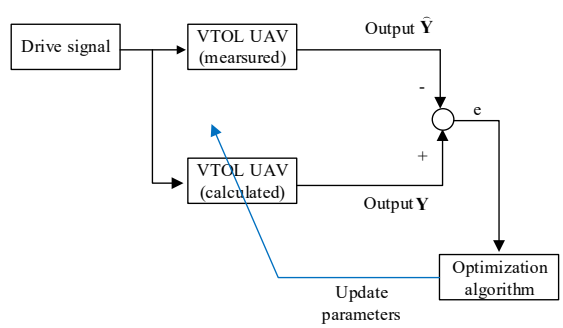
$\mathbf{A} = \begin{bmatrix} a_1 & 0 \\ 0 & a_2 \\ 0 & a_3 \end{bmatrix}$, $\tau = \begin{bmatrix} u_1 \\ u_2 \end{bmatrix}$.

Before the parameter estimation of swarm algorithms, it is necessary to conduct model test which generates the input and output data. By inputting the drive signal to UAV dynamic model, we could obtain the input vector $\hat{\tau}$ and output vector $\hat{\mathbf{Y}}$. The aim of parameter estimation is to minimize the error between calculated vector $\mathbf{Y}$ and the measured vector $\hat{\mathbf{Y}}$ when the specified drive signal works. The cost function of optimization algorithm can be claimed as follows:

$$J = \sum_{i=1}^{N} \frac{1}{2}(y_i - \hat{y}_i)^T (y_i - \hat{y}_i) \tag{7}$$

where N is the sampling numbers in model test. Therefore, the smaller value of cost function indicates the better solution that optimization algorithms found. The identification structure is depicted in figure 2.

Figure 2. System estimation structure.



III. Parameter Estimation Optimization with MPIO

Pigeon-inspired optimization is a novel proposed bio-inspired swarm intelligence optimization algorithm based on the special navigation behavior of the homing pigeons [17]. The basic PIO algorithm is easily to be trapped into the local

optimal value, our proposed MPIO algorithm with mutant operator and OBL strategy shows better performance in the balance of global exploration and local exploitation.

A. Principle of the basic PIO Algorithm

(1) Map and compass operator

At first, pigeons mainly update their position $\mathbf{X}_i = [x_{i1}, x_{i2} ... x_{iD}]$ and velocity $\mathbf{X}_i = [x_{i1}, x_{i2} ... x_{iD}]$ on the basis of the global optimal position $\mathbf{X}_{gbest}$ within the solution space. As the number of iterations increases, the new speed $\mathbf{V}_i$ and position $\mathbf{X}_i$ are updated as follows:

$$\mathbf{V}_i(n) = \mathbf{V}_i(n\text{-}1) \cdot \mathrm{e}^{-Rn} + rand \cdot (\mathbf{X}_{gbest} - \mathbf{X}_i(n\text{-}1)) \tag{8}$$

$$\mathbf{X}_i(n) = \mathbf{X}_i(n-1) + \mathbf{V}_i(n) \tag{9}$$

where n is the current time of iterations, ($0 \le n \le N_{c1max}$ and N_{c1max} is the maximum number of iterations), R represents the map and compass factor which is set to be between 0 to 1, rand is a number uniformly distributed between 0 and 1.

(2) Landmarks operator

As the pigeons approach their destination, the guidance tool change to the nearby landmarks. In the landmark operator, pigeons which are not familiar with the landmark, will gradually deviate from the track and be abandoned. Hence, the number of pigeons is reduced by half after each iteration. The number of pigeons at the n_{th} iteration can be defined as follows:

$$N_P(n) = \mathrm{ceil}(\frac{N_P(n-1)}{2}) \tag{10}$$

The rest of pigeons will use landmarks as a reference flight direction, which is denoted as $\mathbf{X}_{center}$. The position can be updated by the following equation:

$$\mathbf{X}_i(n) = \mathbf{X}_i(n-1) + \mathrm{rand} \cdot (\mathbf{X}_{center}(n) - \mathbf{X}_i(n-1)) \tag{11}$$

$$\mathbf{X}_{center}(n) = \frac{\sum_{i=1}^{N} \mathbf{X}_i(n) \cdot \mathrm{fitness}(\mathbf{X}_i(n))}{N_p \cdot \sum_{i=1}^{N} \mathrm{fitness}(\mathbf{X}_i(n))} \tag{12}$$

$$\mathrm{fitness}(\mathbf{X}_i(n)) = \begin{cases} \mathrm{f}_{\max}(\mathbf{X}_i(n)), & \text{case 1} \\ \dfrac{1}{\mathrm{f}_{\min}(\mathbf{X}_i(n) + \varepsilon)}, & \text{case 2} \end{cases} \tag{13}$$

where fitness is the cost function, case 1 and case 2 represent the maximization and minimization optimization problems respectively. After each iteration, pigeons' positions are closer to the center that is regarded as their destination. In this process, the landmark operator accelerates the speed of exploitation of local searching. The whole homing behavior of pigeons are shown in figure 3.

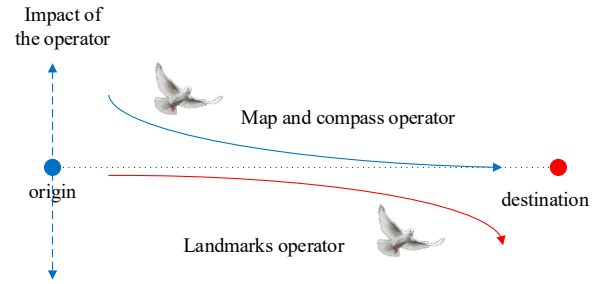


Figure 3. Process of pigeons homing behavior.

B. Mutant PIO Algorithm with Dynamic OBL Strategy

(1) Mutant operator

The dynamic mutant operator is proposed to enable global optimal solution $\mathbf{X}_{gbest}$ to learn the good experience from other elite individuals during the search process. Meanwhile, it can maintain the diversity of the swarm and accelerate the convergence speed. The mutant strategy is stated as follows:

$$\mathbf{X}_{gbest,\mathrm{d}} = \mathbf{X}_{gbest,\mathrm{d}} + \eta(n) \cdot (\mathbf{X}_{1,d} - \mathbf{X}_{2,d}) \tag{14}$$

$$\eta(n) = \mathrm{e}^{-\lambda\mu} \cdot \cos(2\pi\mu) \cdot (1 - \frac{n}{N}) \tag{15}$$

where $\eta(n)$ is a nonlinear multiscale mutation operator, the nonlinear variation coefficient λ is a constant parameter set to be 2 in this paper, μ is a number uniformly distributed between 0 and 1. It can be seen from the equation (13) that the mutation operator could obtain the large value at first and gradually decreases as the iteration increases. Conclusions could be drawn that the mutant operator is employed to facilitate the global exploration at first and implement the accuracy at the late evolution.

(2) Dynamic OBL strategy

The landmark operator $\mathbf{X}_{center}$ is used to guide the swarm flight direction during the late evolution. It is distinctly important to enhance the search ability to avoid being trapped into local optimum. The OBL method can help $\mathbf{X}_{center}$ explore potential better search areas [18]. The basic concept of OBL is that a search in the opposite direction is carried out simultaneously when a solution is exploited in a direction, which can be stated as follows:

$$\tilde{x} = a + b - x \tag{16}$$

where x is a real number on the interval $[a,b]$, and $\tilde{x}$ is the opposite number of x. The exploration performance of deterministic OBL is limited. In order to overcome the drawbacks of the original OBL and improve the $\mathbf{X}_{center}$ convergence speed, a dynamic OBL strategy using adaptive Gaussian distribution [19] is employed as follows:

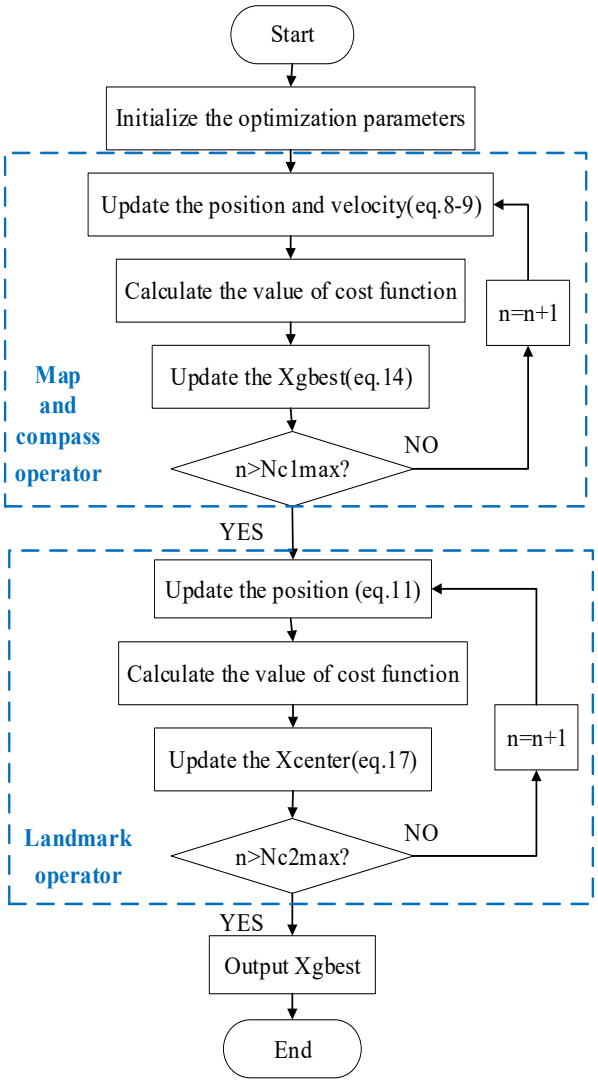
$$\mathbf{X}_{center\_new,d} = Gaussian(\mu, \sigma^2) \cdot (a_d - b_d) - \mathbf{X}_{center,d} \tag{17}$$

$$\sigma = \sigma_{\min} + (\sigma_{\max} - \sigma_{\min}) \cdot (1 - \frac{t}{T}) \tag{18}$$

where $a_d = \min(\mathbf{X}_{center,d})$, $b_d = \max(\mathbf{X}_{center,d})$, the Gaussian distribution is with a zero mean μ and linearly standard

decreased deviation σ to obtain the better dynamic search performance. The flow chart of the MPIO algorithm is depicted in figure 4.

Figure 4. Flow chart of the MPIO algorithm.



IV. Simulation Results and Analysis

In order to verify the feasibility and effectiveness of our proposed algorithm, the contrast experiments with PSO algorithm are conducted. In the tests, the size of swarm is set to be 100, and the maximum iteration is set to be 200. The evolutionary process is stopped until the maximum iterative generation is reached. The control parameters of the algorithms in the test are shown in the table I.

TABLE I. Contorl Parameters of Algorithms

Algorithm	*Variables*	*Description*	*Value*
PIO	$N_{c1\max}$	Maximum number of the Map and compass operator	120
	$N_{c2\max}$	Maximum number of the Landmark operator	80
	R	Map and compass operator	0.2
PSO	c_1	Learning efficient	1.3
	c_1	Learning efficient	1.7
	w	Inertial weight	0.8

The output data are obtained from the model test by using the drive signal. The drive signal in this paper is made up of sine wave. The contrast experimental results are shown in figures 5-8, and the convergence value of the algorithms are shown in table II.

TABLE II. Value of Cost Functionin

Algorithm	*Minimum value of cost function*
PSO	9.89433878235358e-19
MPSO	7.19809542180252e-19
PIO	5.60549499578212e-07
MPIO	**7.41945187328809e-30**

Figure 5. Cost function of four algorithms.

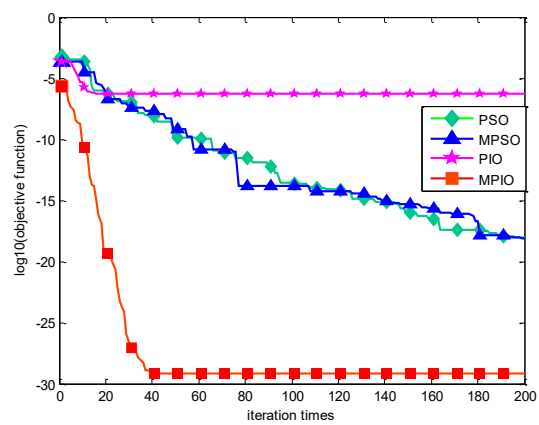


Figure 6. Estimation process of parameter m.

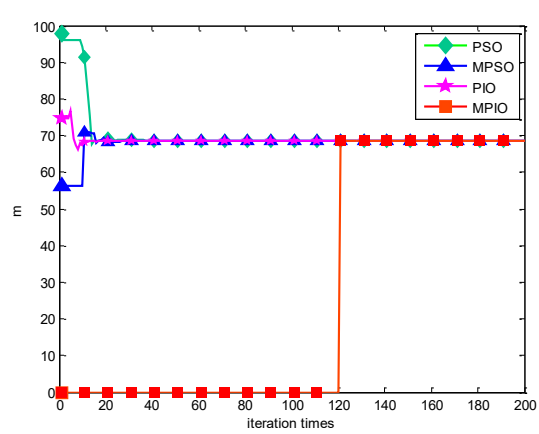


Figure 7. Estimation process of parameter ε_0 .

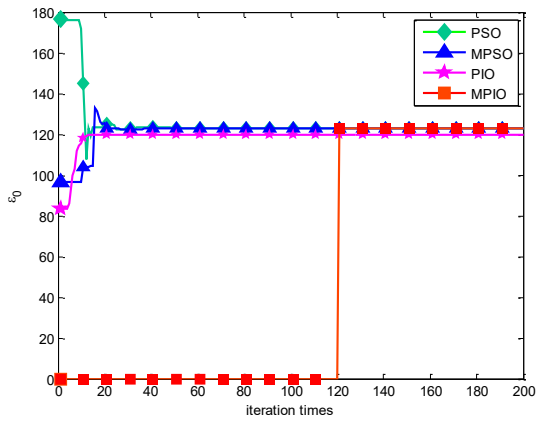
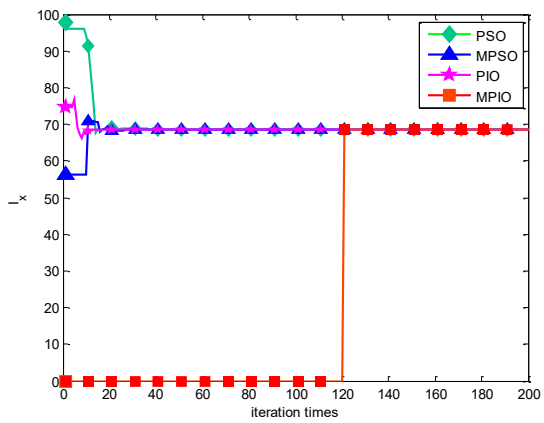


Figure 8. Estimation process of parameter I_x .



It is obvious in the figure 5 that the iterative curve of our proposed MPIO algorithm could find the optimal solution in short time which obtained the least value of cost function. The table II shows the value of cost function in four algorithms. It is obvious that the data of MPIO algorithm could reach the 10^{-30} level while others are bigger than 10^{-20} . The conclusions could be drawn that the mutant operator employed in MPIO algorithm facilitates the global explorative ability and implement the accuracy.

Figures 6-8 confirm the success of optimization process since parameters to be identified are all guided to their true value. As the mutant operator facilitates the global exploration, the MPIO algorithm has slow search speed at first. Then, due to the dynamic OBL strategy, it could obtain the more precise value of the parameters during the second period with the high convergence speed.

V. Conclusion

In this paper, we use the mutant PIO algorithm to estimate the unknow parameters for VTOL UAV. The mutant operator enhances the global searching ability and the dynamic opposition-based learning strategy facilitates the convergence. The experimental results indicate that our proposed algorithm is superior to other algorithms with good accuracy at the errors. Potentially, the parameter estimation method presented in this paper could be incorporated into dynamic control systems for on-line estimation.

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