Differential Evolution Parameter Identification of Multi-Rotor Unmanned Aerial Vehicle (UAV) based on Gradient Prey Acceleration Strategy

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***Abstract* — In order to improve the parameter identification precision of multi-rotor UAV, a differential evolution parameter identification method of multi-rotor UAV based on gradient prey acceleration strategy has been proposed. Firstly, research shall be carried out to the aerodynamic parameter model of multi-rotor UAV, and the parameter identification fitness function of multi-rotor UAV model shall be designed based on the observed quantity and numerical integration result of dynamics; secondly, the research on the differential evolutionary algorithms is executed, and initialization, full-search variation and gradient local search of the chaos achieve the performance promotion of differential evolution algorithms; finally, the aerodynamic parameter identification of multi-rotor UAV is achieved by using the algorithms mentioned, and the comparison validation of identification effect is completed.**

Keywords - gradient prey; multi-rotor uav; differential evolution; parameter identification

I. INTRODUCTION

In recent years, the multi-rotor UAV technology has been in fast development. Compared with the manned aircraft, UAV has a series of advantages such as manned limit, small size and low cost etc, it is required in large amount in the markets of aerial photo, plant protection and military reconnaissance etc. Flight control system is the core part for UAV to achieve the above tasks, and the basis of design is to obtain the description model and aerodynamic parameter for predicting the movement characteristics of UAV.

Differential Evolution (hereinafter referred to as DE) is a new evolution computing technology, which has good optimal performance; however, when it is multimodal function and when the searching space is large, the algorithm convergence speed is slow, and it is easy in early-ripe status, in order to improve the performance of DE, some scholars have proposed methods of improvement. In literature [1], it designs the self-adaption converging factor to construct self-adjusting weighted centroid variable strategy, which can improve the local reinforcement ability in the later period of the algorithm; in literature [2], multi-population DE is proposed, and it is used to solve the optimization problem of multiple extreme values; in literature [3], the acceleration and transfer operation are introduced into DE, where the acceleration operation uses the gradient information to guide the optimal individual to a much optimal area, and in order to prevent the premature convergence of the algorithm, when the dispersity of the population is lower than certain threshold value, new individual can be generated in the region adjacent to the most optimal individual through transfer operation, and the old individual can be replaced, so that the diversity of the population can be maintained; in literature [4], triangle method variation is introduced into DE, the individual is treated as the central point of a super triangle, along with three edges of the super triangle which consists of 3 groups of weighted difference vectors, different step sizes are adopted to separately to produce new variation individuals, so that the probability of algorithm jumping out from the local minimal point can be increased; in literature [5], a generalized variation strategy frame is proposed, which can make users select suitable mutation operation type, and at the same time, it is also good for developing new mutation operator; in literature [6], the self-adaption control parameters improved differential evolution algorithm (SACPMDE) and differential evolution algorithm (ASMDE) bases on group fitness variance self-adaption twice variant are proposed. Literature [7] proposes DERL algorithm.

These improved algorithms are based on the algorithm parameters improvement and variation method improvement. The Thesis adopts prey algorithms to search the whole situation, and it adopts gradient acceleration search algorithm to search the whole situation, and a kind of deep-prey twice-gradient acceleration differential evolution algorithm is designed, and it uses the algorithm mentioned above to make identification on the description model and aerodynamic parameters of UAV motion characteristics.

II. AERODYNAMIC PARAMETERS MODEL

As for multi-rotor UAV, its elastic motion can be ignored, rigid-body six degrees of freedom dynamic differential equation is adopted as the master control equation, and the inertia moment of the dynamical system it ignored. As for the pneumatic identification within the normal flight scope of UAV in low-speed and small-size, the pneumatic mathematical model of the lift force, resistance, side force, rolling moment, pitch moment and yawing moment coefficient C_L , C_D , C_Q , C_l , C_m and C_n are expressed as follows:

$$\begin{cases} C_L = C_{L0} + C_{L\alpha}\Delta\alpha + C_{Lq}\dfrac{q\bar{c}}{2V^*} + C_{LV}\dfrac{V-V_*}{V^*} + C_{L\delta e}\delta_e \\ C_D = C_{D0} + C_{D\alpha}\Delta\alpha + C_{D\alpha^2}\Delta\alpha^2 + C_{DV}\dfrac{V-V_*}{V_*} \\ C_Q = C_{Q0} + C_{Q\beta}\beta + C_{Qp}\dfrac{qb}{2V_*} + C_{Qr}\dfrac{rb}{2V_*} + C_{Q\delta_r}\delta_r + C_{QV}\dfrac{V-V_*}{V_*} \\ C_l = C_{l0} + C_{l\beta}\beta + C_{lp}\dfrac{pb}{2V_*} + C_{lr}\dfrac{rb}{2V_*} + C_{l\delta_a}\delta_a + C_{l\delta_r}\delta_r \\ C_m = C_{m0} + C_{m\alpha}\Delta\alpha + C_{mq}\dfrac{q\bar{c}}{2V_*} + C_{mV}\dfrac{V-V_*}{V_*} + C_{m\delta e}\delta_e \\ C_n = C_{n0} + C_{n\beta}\beta + C_{np}\dfrac{pb}{2V_*} + C_{nr}\dfrac{rb}{2V_*} + C_{n\delta_a}\delta_a + C_{n\delta_r}\delta_r \end{cases} \quad (1)$$

Where, V_* is the working point balancing airspeed; compared with the general linear pneumatic model, C_{Q0}, C_{l0}, C_{n0} is introduced into the model, and it mainly considers the asymmetric effect of external force which truly exists in the actual flight, and the measuring error also introduces the asymmetric apparent, however, as for the nature of the aerodynamic modeling, the error of this part needs to be filtered out, and the error which fails to be filtered out successfully shall be reflected in the asymmetric items as well; C_{LV} , C_{QV} and C_{mV} are the aerodynamic derivatives caused by velocity changes, although the flight speed is in low Mach number, the propelling system has influence which cannot be neglected on the aerodynamic characteristics, such derivative is introduced so identify the influence of speed changes on the pneumatic coupling of propelling system.

The observation equation used in the aerodynamic identification is:

$$\begin{cases} V_m = V + v_V, \alpha_m = \alpha + v_a, \beta_m = \beta + v_\beta \\ p_m = p + v_p, q_m = q + v_q, r_m = r + v_r \\ \phi_m = \phi + v_\phi, \theta_m = \theta + v_\theta, \psi_m = \psi + v_\psi \\ a_{xm} = \dfrac{\bar{q}S}{m}(-C_D\cos\alpha\cos\beta - C_Q\cos\alpha\sin\beta + C_L\sin\alpha) + \dfrac{T}{m} + v_{ax} \\ a_{ym} = \dfrac{\bar{q}S}{m}(-C_D\sin\beta + C_Q\cos\beta) + v_{ay} \\ a_{zm} = \dfrac{\bar{q}S}{m}(-C_D\sin\alpha\cos\beta - C_Q\sin\alpha\sin\beta - C_L\cos\alpha) + v_{az} \end{cases} \quad (2)$$

Where, all quantity with subscript “m” are the observed quantity, it is the actual measured value that includes measurement noise v, which is recorded as Z , and the modification value with measurement noise deducted equals to six free degrees dynamical-equation differential-equation numerical integration result, which is recorded as Y.

In accordance with measurement Z and the dynamics numerical integration result Y, the fitness function is designed as follows:

$$J = (Z-Y)^T Q(z-Y) \quad (3)$$

Where, Q is the weighted matrix. By using optimization algorithm, the parameters to be identified in the aerodynamics model are optimized, so that the fitness function value is the minimum, then the identification of aerodynamic parameters can be completed.

III. DIFFERENTIAL EVOLUTION

A. Basic DE Algorithms (Differential Evolution)

DE is an algorithm based on group evolution, which has the features of memorizing the most optimal solution of individual and sharing the information in the population group, which means it can optimize the solution to the problems through the cooperation and competition among individuals of the population [8].

The algorithm shall obtain a group of randomly initialized population at first:

$$X^0 = \left[x_1^0; x_2^0; \cdots; x_{N_p}^0 \right] \quad (4)$$

N_p is the population scale, through a series of regulated operation, No. s generation individuals are evolved into:

$$x_i^s = \left[x_{i,1}^s, x_{i,2}^s, \cdots, x_{i,D}^s \right] \quad (5)$$

Where, D is the dimension of the optimized problem.

Two parent different random individuals are deducted the third individual which is selected in random, a variation individual is generated, then in accordance with certain probability, the interlace operation between the parent individuals and variation individuals is executed, and a test individual is formed, then the selection operation between the parent individual and the test individual is carried out based on the size of the fitness function value, and the individual with much optimal fitness is selected as the filial generation, so that the evolution is proceeded in the most optimal direction.

B. Mutation Operation

DE/rand/1/bin 和 DE/best/2/bin:

The mutation can prevent the evolution from being dropped into the local extremum, and it has many methods, two basic mutation methods are listed here, DE/rand/1/bin and DE/best/2/bin;

$$\begin{aligned} x_m &= x_{s3}^s + F * \left(x_{s1}^s - x_{s2}^s \right) \\ x_m &= x_g^s + F * \left[\left(x_{s1}^s - x_{s2}^s \right) + \left(x_{s3}^s - x_{s4}^s \right) \right] \end{aligned} \quad (6)$$

In equation (6), $x_{s1}^s, x_{s2}^s, x_{s3}^s, x_{s4}^s$ are different random individuals; x_{gbest}^s is the individual with the best fitness in current population; $F \in [0,2]$ is the zoom factor.

C. Crossover Operation

The crossover strategy: it assumes that the individual x_i^s and x_{m} of the population produce the test individual x_{T} by crossover operation, and in order to ensure the evolution of the individual, firstly, through the random selection, a least single bit of x_{T} is contributed by x_{m}, other bits use crossover probability factor CR, and the crossover operation equation is:

$$x_{\text{T}j} = \begin{cases} x_{\text{m}j}, & \text{rand} \le \text{CR} \\ x_{ij}, & \text{rand} > \text{CR} \end{cases} \qquad j = 1, 2, \cdots, D \tag{7}$$

D. Selection Operation

The selection operation adopts the searching strategy of “greedy”, the one with high fitness value shall be selected as the filial generation:

$$x_i^{s+1} = \begin{cases} x_{\text{T}}, & f(x_{\text{T}}) < f(x_i^s) \\ x_i^s, & f(x_{\text{T}}) \ge f(x_i^s) \end{cases} \tag{8}$$

Repeat the above operation until the filial generation that meets the fitness value conditions is generated, finish [10~12]

IV. PS-GDE ALGORITHM

A. Initialization Based on Chaos

Logistic model is a typical representative of multiple chaotic traversal algorithm models, many scholars make this as the model of study design, and the form of which is as follows:

$$cx_i^{k+1} = u \cdot cx_i^k \cdot (1 - cx_i^k),\ i = 1, 2, \ldots, n \tag{9}$$

Where, cx_i^k is the value that is obtained by cx_i through No. k chaos evolution. When the following conditions are met: $u = 4$, $cx_i \in [0,1]$ and $cx_i \notin [0.25, 0.5, 0.75]$, the chaotic phenomenon of $\left[\frac{\partial f(\vec{x})}{\partial x_1}, \frac{\partial f(\vec{x})}{\partial x_2}, \ldots, \frac{\partial f(\vec{x})}{\partial x_n}\right]^{\text{T}}$ will occur, cx_i traverses within $[0,1]$, which is shown in Fig. 1.

When the value in variable is $x_i \in [a_i, b_i] \ne [0,1]$, generally it can be conversed through the following equation[16]:

$$cx_i = (x_i - a_i)/(b_i - a_i) \tag{10}$$

$$x_i = a_i + cx_i (b_i - a_i) \tag{11}$$

The main purpose of adopting logistic chaotic model to initialize the PS-GDE algorithm initial population is to make it dispersed in the algorithm optimizing area uniformly, and to ensure initial population seeds exist around the optimal value, and the main targets of that are two: one is that the diversity of the population can be ensured sufficiently, the other is that if the initial population seeds exist around the optimal value, it can prevent the influence of local disturbing peak from covering the influence of the optimal value on the algorithm, so that the premature convergence of the algorithm can be prevented, this practice has been studied and tried by many scholars.

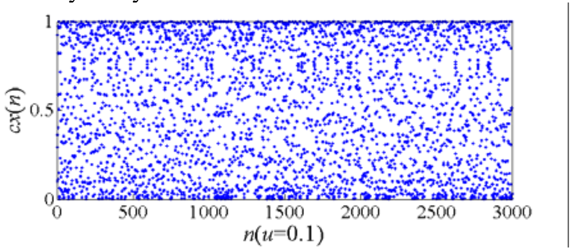

Figure 1. logistic model particle distribution

B. Improvement of Mutation Method

Through experiment and comparison, we can find out that the differential mutation method (standard or improved) given out in the past literatures, they are not very outstanding in the performance, and the direct result is that the algorithm easily in premature or the operation efficiency is too low, as for this, firstly, the research and improvement on the mutation method which is essential in affecting the performance of algorithm is to be carried out, and the improving method for differential mutation in the Thesis is as follows:

$$x_i^{t+1} = x_i^t + F(x_{r1}^t - x_i^t + x_{r2}^t - x_{r3}^t) \tag{12}$$

In the differential mutation mentioned in equation (12), individual x_i^t of generation t of differential population, the basis of its mutation method is its x_i^t (such as item 1 in the right side of equation (4)), the main idea of such treatment is to make individuals of the population can maintain their population diversity to the maximum after mutation with the premises of mutation optimizing can master the evolution direction in the whole situation around itself, such as the last item $x_{r2}^t - x_{r3}^t$ in the right side of equation (4), the main function of which is to add randomness to the mutation by disturbance on the mutation method, and the main target of such item is to design by maintaining the difference angle of individual after the mutation.

As for the selection of $r1, r2, r3$, we consider the direction of population evolution while making random selection, and by adopting such selection method, 3 unequal numbers $c1 \ne c2 \ne c3 \in Z[0,1]$ are generated randomly, the selection is carried out in accordance with the objective function value of its individuals, and as for the minimization problem, $r1$

seclection target is the minimum, and the target function value of $r3$ section is the maximum, which means:

(1) $r1 = \text{find}\{c1, c2, c3\}$,

$\text{s.t.} \quad \min\left\{\text{val}\left(x_{c1}^t\right), \text{val}\left(x_{c2}^t\right), \text{val}\left(x_{c3}^t\right)\right\}$

(2) $r2 = \text{find}\{c1, c2, c3\}$,

$\text{s.t.} \quad \text{mid}\left\{\text{val}\left(x_{c1}^t\right), \text{val}\left(x_{c2}^t\right), \text{val}\left(x_{c3}^t\right)\right\}$

(3) $r3 = \text{find}\{c1, c2, c3\}$,

$\text{s.t.} \quad \max\left\{\text{val}\left(x_{c1}^t\right), \text{val}\left(x_{c2}^t\right), \text{val}\left(x_{c3}^t\right)\right\}$

The main purpose of the sort order mentioned in above equation (1) ~ (3) $r1, r2, r3$ is to balance the over randomization mutation improvement in equation (12), and at the same time of giving consideration to differential evolution direction, the mutual supplementing can ensure the existence of individual difference, therefore, it is an mutation improvement scheme with high efficiency.

C. Local Area Searching Based on Gradient

As for function $f(\vec{x})$, $\vec{x} = (x_1, x_2, \dots, x_n)$, the gradient of which can be presented as [7]:

$$\Delta f(\vec{x}) = \left[\frac{\partial f(\vec{x})}{\partial x_1}, \frac{\partial f(\vec{x})}{\partial x_2}, \dots, \frac{\partial f(\vec{x})}{\partial x_n}\right]^{\mathrm{T}} \tag{13}$$

There is no doubt that the positive (negative) gradient of general function is the direction in which its value increasing (decreasing) fastest. When the differential individual adopts the linear displacement development in negative gradient direction in the process of making local deep searching, it shall achieve much effectively accelerate the operation efficiency of the algorithm. The linear searching adopts the golden section method, and the pseudo-code of the algorithm is as shown in Fig. 3.

$\vec{t}_2 = \vec{a} + \beta\left(\vec{b} - \vec{a}\right); \quad f_2 = f\left(\vec{t}_2\right);$

$\vec{t}_1 = \vec{a} + \vec{b} - \vec{t}_2; \quad f_1 = f\left(\vec{t}_1\right);$

while $\left|\vec{t}_1 - \vec{t}_2\right| \geq \varepsilon$

  if $f_1 \leq f_2$

    $\vec{b} = \vec{t}_2; \vec{t}_2 = \vec{t}_1; f_2 = f_1;$

  else

    $\vec{a} = \vec{t}_1; \vec{t}_1 = \vec{t}_2; f_1 = f_2;$

    $\vec{t}_2 = \vec{a} + \beta\left(\vec{b} - \vec{a}\right); f_2 = f\left(\vec{t}_2\right);$

  end

end

$x_i^{t+1} = \dfrac{\vec{t}_1 + \vec{t}_2}{2};$

end

Figure 2. Pseudo-code of algorithm

$[\vec{a}, \vec{b}]$ is the gradient searching scope decided in trial, ε is the threshold value, and the relative optimal value listed here is $\varepsilon = 0.1$. The linear acceleration in the negative gradient direction makes the evolution of the differential individuals more effective, and it is good for the rapid convergence of the differential algorithm individual, and the displacement operation method of the negative gradient is easy, it only adds the time complexity of algorithmic improvement.

D. PS-GDE Algorithm Procedures

In the prey searching strategy, firstly, the relative optimal solution in the global search should be found out, then the searching in local area shall be carried out, a simplified form is listed hereby, the searching in local area is activated by the preset cycle, when the population evolutes to the integral multiple to the preset cycle, the searching of local area should be activated repeatedly to the much optimal individuals, which is relative to apply prey searching strategy for many times, and compared with the single prey searching algorithm, the repeat application of prey searching strategy can take advantage of the searching ability in whole situation and the local convergence of gradient searching algorithm, so that the rate of convergence can be accelerated, and the premature convergence of the population can be prevented. The algorithm steps of PS-GDE are as follows:

Step 1: in accordance with the requirement of the question, the population size *NP* and dimension *D* as well as algorithm termination evolution algebra *G* etc of PS-GDE should be decided, the initial searching scope of the algorithm is $\left[l^0, u^0\right]$, $s = 1$. The relevant parameters of prey searching: the trigger algebra of local prey searching is $NC = 20$, and the selection ratio of symples is $pr = 5\%$.

Step 2: in the $[l^0, u^0]$, the population P^1 with size of NP shall be initialized based on chaotic method, and the fitness of which is calculated;

Step 3: judge whether s is the integral multiple to NC, if it is the integral multiple, then turn to Step 4 and carry out the local area searching based on gradient, if it is not integral multiple, then turn to Step 5 and to carry out the global search based on the improved differential evolution algorithm;

Step 4: carry out the global searching, execute mutation in accordance with equation (12), and make crossover operation, and the fitness value of new individuals shall be calculated, and turn to Step 6;

Step 5: carry out the searching in local area, the specific algorithm steps are shown in the pseudo-code in Fig. 2.

Step 6: inspect whether the fitness value of current optimal individuals or iteration terminating algebra meet the end conditions set up, if they cannot meet the conditions, then PS-GDE algorithm evolution should be stopped and output the optimal solution, or turn to Step 3 to continue the algorithm evolution, and the evolution algebra $s = s + 1$ should be set up. The selection of prey searching parameters NC and pr shall influence the performance of the algorithm.

V. EXPERIMENT ANALYSES

A. Experiment Settings

The simulated UAV is an UAV of low speed with straight-wing double-tail boom arrangement, the initial condition of simulation is straight-level flying status, and the trim parameters are as follows:

$$V_0 = 35m/S, \alpha_0 = 5.88°, h_0 = 200m$$
$$\delta_{e0} = -1.7°, T_0 = 220.87N \tag{14}$$

As for the vertical aerodynamic parameter identification, the vertical short-cycle and long-cycle mode of motion of the UAV needs to be activated, thus the combination of periodic signal with amplitude 11.46° and phase-step time interval 0.3s as well as the long pulse signal of 3s are designed as the simulation input signal, and about half of a long-period oscillation time can be reserved so as to achieve a much comprehensive long-period modal characteristics. Fig. 3 shows the response curve of speed, angle of attack, pitch angle rate and pitch angle output by six free degrees model, and we can see from the figure that by adopting "3211", the combination of signal and long pulse signal can successfully activate the obvious short-period and long-period motion model.

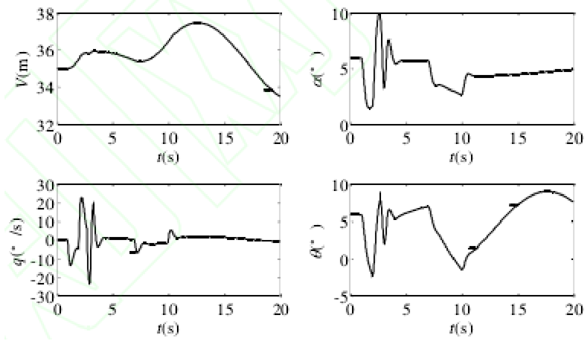

Figure 3. Vertical response curve

B. Comparison of Identification Results

GA, PSO and the algorithm in the Thesis are adopted to make aerodynamic parameter identification separately. The simulation test is divided into four groups based on the maximum interation steps 500, 1000, 1500 and 2000, and in the experiment of each group, 50 times identification tests shall be carried out, and as the initial analysis, the test shall not add noise observation. In order to evaluate three algorithms objectively, the parameters setting of them shall be consistent, and the same fitness function, population assize and upper and lower bound are adopted. The identification results are as shown in Table 1.

In Table 1, the comparison between parameters of three optimal algorithms which have successfully identified the part and the average value of the cost function. From the truth-value of identified parameters and the identification result, we can see that three algorithms have outstanding optimizing ability, and the principle of PSO algorithm is simple, and the mechanism of the information sharing in whole situation makes the algorithm efficiency improved largely, however, as the population location in the later period of the algorithm is concentrated, it fails to jump out of the most optimal mechanism in the local area, which makes it hard to jump out of the optimal in the local area. The algorithm in the Thesis has better searching ability in local area by comparing with the GA and PSO algorithm, and the identification value obtained from which is much accurate.

Table 1. Comparison of identification result

Parameter	True value	Identified mean value		
		GA	PSO	Proposed algorithm
C_{D0}	0.06	0.0569999	0.059909	0.06003
$C_{D\alpha}$	0.43	0.4199999	0.430754	0.42974
C_{L0}	0.385	0.3749999	0.385599	0.38474
$C_{L\alpha}$	4.78	4.7699994	4.773452	4.78275
C_{Lq}	10.47	10.451354	10.35328	10.4928
$C_{L\delta_e}$	0.201	0.2109999	0.198585	0.20180
C_{m0}	0.194	0.1839999	0.194544	0.19394
$C_{m\alpha}$	-2.12	-2.3200006	-2.321577	-2.11936
C_{mq}	-47.6	-47.51452	-47.63800	-47.5840
$C_{m\delta_e}$	-0.8	-0.8100001	-0.810625	-0.79974
Fitness value		121.57	289.38	84.26

VI. CONCLUSIONS

A multi-rotor UAV differential evolution parameter identification method based on gradient prey acceleration strategy is proposed in the Thesis, and the parameter identification fitness function of multi-rotor UAV model has been designed, and the aerodynamic parameter model identification of multi-rotor UAV has been achieved by using the improved differential evolution algorithm, and at last, the efficiency of the method mentioned is verified by experiment. Based on the identification result of flight test, it indicates that the aerodynamic parameter model structure set up in the Thesis can reflect the aerodynamic characteristics of small UAV in normal envelope flight, and it can ensure to achieve good aerodynamic identification result.

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