Active disturbance rejection control for small unmanned helicopters via Levy flight-based pigeon-inspired optimization

Dai Feng Zhang, Haibin Duan and Yijun Yang

Science and Technology on Aircraft Control Laboratory, Beihang University, Beijing, China

Abstract

Purpose – The purpose of this paper is to propose a control approach for small unmanned helicopters, and a novel swarm intelligence algorithm is used to optimize the parameters of the proposed controller.

Design/methodology/approach – Small unmanned helicopters have many advantages over other unmanned aerial vehicles. However, the manual operation process is difficult because the model is always unstable and coupling. In this paper, a novel optimized active disturbance rejection control (ADRC) approach is presented for small unmanned helicopters. First, a linear attitude model is built in hovering condition according to small perturbation linearization. To realize decoupling, this model is divided into two parts, and each part is equipped with an ADRC controller. Finally, a novel Levy flight-based pigeon-inspired optimization (LFPIO) algorithm is developed to find the optimal ADRC parameters and enhance the performance of controller.

Findings – This paper applies ADRC method to the attitude control of small unmanned helicopters so that it can be implemented in practical flight under complex environments. Besides, a novel LFPIO algorithm is proposed to optimize the parameters of ADRC and is proved to be more efficient than other homogenous methods.

Originality/value – ADRC method can enhance the response and robustness of unmanned helicopters which make it valuable in actual environments. The proposed LFPIO algorithm is proved to be an effective swarm intelligence optimizer, and it is convenient and valuable to apply it in other optimized systems.

Keywords Parameter optimization, Active disturbance rejection control, Levy flight-based pigeon-inspired optimization, Small unmanned helicopters

Paper type Research paper

Introduction

As a common type of unmanned aerial vehicles (UAVs), unmanned helicopters overcome many obstacles in UAV flight. For example, when implementing rescue or other critical missions, it is always necessary for UAVs to hover in the air. However, the wing aircrafts cannot finish. On the contrary, unmanned helicopters could complete a variety of special actions including hover; therefore, it's easy to execute these critical missions. However, the operation process is hard for helicopter pilots because of its instable and nonlinear coupling model. Hovering flight is an important action for small unmanned helicopters in many emergences, and it has aroused interests among scholars to study the model in hovering flight. To realize autonomous flight, it is important to design high-performance attitude controller. In recent years, there are a lot of proposed advanced control methods for unmanned helicopters, such as the $H_\infty$ method (Cai et al., 2011; Ismaila et al., 2011), backstepping (Lu et al., 2015), adaptive control (Sheng et al., 2014), fuzzy control (Ho et al., 2008) and artificial intelligence (Nodland et al., 2013). Nevertheless, these methods are rarely applied in practical engineering because of their complicated structure and high requirement to computing device. Active disturbance rejection control (ADRC) (Tang et al., 2015) stems from proportional–integral–derivative controller (PID controller) algorithm; thus, it does not need high computation power and the exact object model. Besides, ADRC modifies the traditional PID structure and solves the inherent contradiction between overshoot and rise time in PID, which provides precise performance and high robustness simultaneously.

The parameters of ADRC are usually adjusted by some empirical formula (Han, 2009) and cannot be changed during the flight process. But sometimes we need to adjust parameters dynamically to make them adaptable. Hence, a parameter optimizing strategy is needed. Traditional parameter optimizing
Composition and modeling of small unmanned helicopter

The basic composition of a small unmanned helicopter mainly consists of three components as the main rotor, the fuselage and the tail rotor. The main rotor is responsible for the ascension and turning, which ensures to provide enough elevation force for flight. Therefore, the main rotor is the uppermost constituent, whereas its dynamic characteristics are very complicated. Meanwhile, in some cases such as high speed movement and large maneuver, the aerodynamics of fuselage are usually less certain. But in this paper, we mainly discuss the hovering state in actual flight which only permits low forward speed and little flexibility. Thus, the main rotor dynamics are simpler to determine and the fuselage dynamics can be neglected. Tail rotor is used to balance the torque force produced by main rotor and is responsible for the yaw actions. Due to instability of the tail system, an angular vector control system (AVCS) is used to stabilize the yaw channel which is a closed-loop subsystem based on PID controller (Yang et al., 2013). Figure 1 shows the model helicopter in this paper.

Figure 1 Small unmanned helicopter Trex600E

The mathematical model of small unmanned helicopters is surely nonlinear, highly coupling and time-variant. But in many cases as above, we are interested to study the hovering state in which the lift force is almost equal to gravity. In condition of hovering state, we can extract a linear model for small unmanned helicopters through small perturbation linearization (Cao et al., 2004; Ismaila et al., 2011). Normally, a small unmanned helicopter is assembled with four digital servos so that the system inputs contain four channels as lateral channel, longitudinal channel, height channel and yaw channel. Each channel is responsible for control to the corresponding subsystem. The height and yaw subsystems with AVCS are regarded as independent first-order model, and they are easy to operate (Yang et al., 2013). On the other hands, lateral and longitudinal attitude models are complicated and coupled. Therefore, we mainly focus on the modeling and control for these two subsystems. According to the characteristics of hovering state, the magnitude of main rotor lift force is almost equal to the gravity, and its direction is determined by \( a \) and \( b \) which define the tilting angle of the rotor tip-path-plane (TPP) in longitudinal and lateral directions (Tang et al., 2014). Taken together, the moments of main rotor can be described as:

\[
\begin{align*}
L_{mr} & = (k_a + mg) b \\
M_{mr} & = (k_b + mg) a
\end{align*}
\]

where \( k_a \) defines the spring constant of the rotor hub, and \( H \) is the geometric parameter of fuselage. According to the small perturbation linearization, the angular velocity \( \dot{\theta} \) in longitudinal channel and \( \dot{\psi} \) in lateral channel are proportional to the relative moments and tilting angles of TPP. According to some studies (Tang et al., 2014), the states \( a \) and \( b \) are approximate to first-order models and can be directly controlled by the system inputs \([\delta_{\text{a}} \, \delta_{\text{b}}\,] \). Thus, we obtain the linear model of small unmanned helicopters as following equations:

\[
\dot{x} = Ax + Bu
\]

\[
A = \begin{bmatrix}
0 & 0 & 0 & L_n \\
0 & 0 & M_x & 0 \\
-1 & -1/\tau & A_y & 0 \\
-1 & 0 & B_a & -1/\tau
\end{bmatrix}
\quad B = \begin{bmatrix}
0 & 0 \\
0 & 0 \\
A_{\text{a}} & A_{\text{b}} \\
B_{\text{a}} & B_{\text{b}}
\end{bmatrix}
\]

where \( x \) defines the state variables as \([p, q, a, b] \); \( u \) is the system inputs \([\delta_{\text{a}} \, \delta_{\text{b}}\,] \); \( L_n, M_x \) are the differential operators to relative states; and \( \tau \) defines the time constant of delay for tilting angles of TPP.

From the system matrix \( A \), we can conclude that state variables \( a \) and \( b \) are similar to second-order differentials to attitude angles and are directly relative to the system inputs \( u \). Because \( a \) and \( b \) are difficult to observe, some advanced control laws are not suitable for this system. Besides these two channels obviously exist cross coupling, which is troublesome for system running.

Active disturbance rejection control

ADRC is based on the classical PID algorithm. It succeeds some advantages of PID, such as the concept of using error to remove error. In addition, ADRC revises some drawbacks of PID and enhances the performance. The contradictions
between the overshoot and search speed always impede the performances of the classical PID algorithm. ADRC solves this problem with the component tracking differential (TD) and provides effectiveness and robustness through nonlinear state feedback (NLSEF) and extended state observer (ESO) (Han, 2009). Figure 2 shows the structure of our ADRC.

TD is used to trace the command input \( v_1 \) and configure the transition process by introducing transition reference \( v_1 \) and its differential \( v_2 \). TD obviously slows down the fierce change of error and provides a smooth and steady transition. The structure of TD is described as:

\[
\begin{align*}
fh & = fh\alpha n(v_1 - v_3, v_2, z_0, h) \\
v_1 & = v_1 + h\cdot v_2 \\
v_2 & = v_2 + h\cdot fh
\end{align*}
\]  
(3)

where the function \( fh\alpha n \) is the optimal control synthesis function, which derives from the discrete optimization theory (Han, 2009). \( h \) and \( r_0 \) denotes the step length and the speed constant of convergence. The iteration process of optimal control synthesis function are given as follows:

\[
\begin{align*}
d & = rh \\
d_0 & = rh^2 \\
y & = x_1 + hx_2 \\
a & = \sqrt{d^2 + 8|y|} \\
\frac{x_2 - \frac{(a_0 - d)}{2}}{h} & = x_1 + a, |y| > d_0 \\
\frac{x_2 + \frac{y}{h}}{a} & = x_1 + a, |y| \leq d_0 \\
u & = -\frac{r\cdot sign(y)}{d}, |a| \geq d \\
\frac{d}{a} & = -\frac{r\cdot sign(a)}{d}, |a| \leq d
\end{align*}
\]  
(4)

where \( sign(x) \) denotes the sign function.

Unlike traditional PID, ADRC introduces NLSEF to promote the efficiency of control inputs via some nonlinear combinations of system errors. ESO is essential for stability and robustness, which not only gives the precise observation of system variables through \( z_1 \) and \( z_2 \) but also provides the real-time unknown dynamics prediction through \( z_3 \). So we can use ESO to compensate the unwanted changes by following equation:

\[
u = u_0 - z_3
\]  
(5)

This process denotes feedback linearization. \( u_0 \) is the NLSEF output that represents the ideal control without considering unknown dynamics. When we compensate the practical control \( u \) by subtracting unknown dynamics \( z_3 \) from \( u_0 \), the original system is equivalent to a second-order integrator system with ideal control. Thus, the original model is decoupled. The flow of ESO computation is given as follows:

\[
\begin{align*}
e & = z_1 - y \\
f_\text{e} & = fal(\varepsilon, 0.5, h), f_{\varepsilon_1} = fal(\varepsilon, 0.25, h) \\
z_1 & = z_2 - \beta_0\varepsilon \\
z_2 & = z_3 - \beta_2 f_{\varepsilon_1} + u \\
z_3 & = -\beta_3 f_{\varepsilon_1}
\end{align*}
\]  
(6)

where \( y \) denotes the system output. The nonlinear function \( fal \) features fast tracking, and the structure is given as:

\[
\begin{align*}
fal(\varepsilon, \alpha, \delta) &= \begin{cases} \varepsilon & |\varepsilon| \leq \delta \\ 1 & |\varepsilon|^\alpha \cdot sign(\varepsilon), |\varepsilon| > \delta \end{cases}
\end{align*}
\]  
(7)

To apply ADRC to the attitude control of small unmanned helicopter, we separate the whole model into two parts. One refers to the lateral variables \( (p \) and \( b \)), and the other refers to the longitudinal ones \( (q \) and \( a \)). To decouple these two parts, we design a second-order ADRC like Figure 2 for each part, where the structure of TD and ESO adopts equations (2) and (4). NLSEF is selected as the following nonlinear error combination:

\[
u_0 = \beta_1 fal(\varepsilon_1, 0.5, h) + \beta_2 fal(\varepsilon_3, 0.25, h)
\]  
(8)

Because the original system inputs are coupled, the control value \( u \) needs to be transformed as:

\[
u_1 = \begin{bmatrix} A_{im} & A_{im}^{-1} \end{bmatrix} \cdot u
\]  
(9)

**Levy flight-based pigeon-inspired optimization for active disturbance rejection control**

Although ADRC is able to decouple original system and provides strong robustness, it is still not desirable under changeable circumstances because static parameters cannot be adjusted and coped with various situations. Hence, we need to adopt a group of adjustable parameters to optimize the ADRC performance. PIO is one of the newest swarm intelligence optimizations that is aimed to solve the problems of optimal searching. PIO imitates the process that homing pigeons find paths. It is similar to some bio-inspired algorithms such as PSO in the bionic mechanism. Compared with PSO, PIO could provide a wider search space and is more efficient on controller optimization.

**Basic pigeon-inspired optimization algorithm**

Just as the process of homing pigeons searching path, basic PIO algorithm can be divided into two stages and each step contains a relative operator (Duan and Qiao, 2014). At the first stage, map and compass operators are adopted which is inspired by the natural phenomenon that pigeons use the sun and magnetic particles to sense home direction in the beginning of flight. This operator is given as:

\[
\begin{align*}
V(t) &= V(t-1) - e^{-\gamma} + rand \cdot (X(t) - X(t-1)) \\
X(t) &= X(t-1) + V(t)
\end{align*}
\]  
(10)
where $X_i$ and $V_i$ are the position and velocity of pigeon $i$, $R$ denotes map and compass factor, $rand$ is a random number between 0 and 1 and $X'_i$ denotes the current global best position.

When the pigeons fly close to their destination, they will rely on landmarks neighboring them. Landmark operator manifests this process with the following model:

$$N_i(t) = \frac{N_i(t-1)}{2}$$
$$X_i(t) = \frac{\sum X_i(t-1)f_{cost}(X_i(t-1))}{N_i(t)\sum f_{cost}(X_i(t-1))}$$ (11)

$$X_i(t) = X_i(t-1) + rand(X_i(t) - X_i(t-1))$$

where $N_i$ is the number of available pigeons toward the destination with half decreasing in every iteration. This means half pigeons will follow the other available pigeons in the next search process. $X_i$ is the center of available pigeons’ position as the reference of the swarms which represents the landmark, and the function $f_{cost}$ is the fitness function evaluating the quality of each pigeon. After these two steps, we can gain the convergent optimal solution.

**Levy flight-based pigeon-inspired optimization**

The basic PIO is more efficient than many homogeneous methods such as PSO and genetic algorithm. However, it also has some shortcomings to be improved such as the stochastic search space to be extended and the convergence speed to be accelerated. To improve the PIO algorithm, we introduce a novel Levy flight-based pigeon-inspired optimization (LFPIO) in which the two original operators are anew designed.

**Levy flight search operator**

Levy flight has been demonstrated that it is one of the best random walk models in which the step lengths have a probability distribution that is heavy-tailed (Barthelemy et al., 2008). In the process of walking, the step lengths are subject to Levy distribution. The simplified Levy flight can be described as follows:

$$L(s) \sim |s|^{-\delta}, 1 < \delta \leq 3$$ (12)

where $s$ denotes random step length. When searching an unknown and large-scale space, Levy flight is more effective than Brown motion (Chakravarti, 2004) because the variance $\sigma^2$ of Levy flight increases more rapidly. The two kinds of variances are shown as follows:

$$\sigma^2_B(s) \sim s$$ Brown motion
$$\sigma^2_L(s) \sim s^{-\delta}, 1 < \delta \leq 2$$ Levy flight

(13)

In Levy flight, some solutions execute local search, and others execute global search. This mechanism can balance the diversity and the convergence speed. At the same time, Levy flight can imitate the search behaviors of some animals such as the fish school and the pigeon flock. Hence, we use this mechanism to design the new search operator. Here, Levy flight can be implemented by Mantegna’s algorithm (Mantegna and Stanley, 1994), and the operator can be described as following equations:

$$s = \mu/|v|^{1/\gamma}$$
$$X_i = X_i(t-1) + s\cdot rand(X_i(t-1) - X_g)$$ (14)

$$\mu \sim N(0, \sigma^2_u), v \sim N(0, \sigma^2_v), \delta = 1.5$$

$$\sigma^2_u = \left[\frac{\Gamma(1 + \delta)\sin(\pi\delta/2)}{\Gamma(1 + \delta/2)2^{\delta-1}}\right]^{1/\delta}, \sigma_v = 1$$

where $N(0, \sigma^2)$ denotes the normal distribution, $s$ is the step length of Levy flight and $rand$ is a random number subject to normal distribution. In addition, the elite selection strategy is utilized to improve the ability of local search and described by the following equation:

$$X_i(t) = \begin{cases} X_p, & Iff_{cost}(X_p) < f(X_i(t-1)) \\ X_i(t-1), & Iff_{cost}(X_i) \geq f(X_i(t-1)) \end{cases}$$ (15)

**Revised landmark operator**

In basic PIO algorithm, the landmark operator can accelerate the convergence of algorithm. However, it easily leads to the premature convergence, and all solution will be trapped into local optima. To avoid the problem, we adopt the adaptive Logsig function to adjust the step length of search. Detailed equations are given as follows:

$$Step = Logsig\left(\frac{N_{\max} - t}{k}\right)$$
$$X_i(t) = X_i(t-1) + Step \cdot rand(X_p - X_i(t-1))$$ (16)

where $\zeta$ and $k$ are the adaptive parameters of Logsig function which decides when the search converges, and $N_{\max}$ is maximum iterations.

**Optimized active disturbance rejection control based on Levy flight-based pigeon-inspired optimization**

The parameters of ADRC include $r_0$ from TD, $\beta_{01}$ from ESO and $\beta_1, \beta_2$ from NLSEF. We usually set $r_0 = 0.0001/h^2$ according to experiences, so the parameters to be optimized for each ADRC are the rest five. Before we execute LFPIO, the fitness function need to be confirmed. Here, we select the characteristics of step response including steady state error, input limitations and rise time to assess the whole system performance. The fitness function is listed as follows, we expect it as small as enough:

$$f_{cost} = \int_{t_0}^{t_f} \omega_1(|e_1| + |e_2|)dt$$
$$+ \int_{t_0}^{t_f} \omega_2(u_1^2 + u_2^2)dt + \omega_3(t_{r1} + t_{r2})$$ (17)

where $\omega_1, \omega_2$ and $\omega_3$ are the weight values, $e$ and $u$ are errors and input controls for each subsystem and $t_r$ denotes the rise time. Because ADRC method could realize decoupling of the two attitude subsystems, the controller in each subsystem can execute parallely. Due to each ADRC has five parameters, the dimension of total LFPIO is ten. When we test each solution, substitute the parameters into ADRC process and set the step instruction. Then we can obtain the characteristics of step response in fixed period and, hence, gain the relative fitness value. Figure 3 shows the structure of whole system.

The detailed implementation procedure of LFPIO for ADRC optimization is described as follows:
**Comparative experiments**

To investigate the feasibility and effectiveness of our proposed optimized ADRC with LFPIO, a series of comparative experiments with PSO and basic PIO are conducted. To verify the robustness of the whole system, some certain disturbances are considered. The step instruction is set as one with step time zero. Select step length \( h \) as the sampling period 0.01 s and control period \( T \) as 1 s. Parameters of the helicopter model are given according to Ioannis et al. (2012). LFPIO maximum iteration \( N_{\text{max}} \) is 100, and according to the above, dimension \( D \) of total LFPIO is 10. The population of pigeons is 100 as the same number of candidate solutions. According to experiences, the five ADRC parameters can be adjusted in following ranges as \( \beta_{11} : [100,500] \), \( \beta_{22} : [100,1000] \), \( \beta_{33} : [1000,5000] \), \( \beta \) : [1,20] and \( \beta_{23} : [1,20] \). After debugging, we select the parameters \( \zeta \) and \( k \) in revised landmark operator as 0.5 and 15, respectively. To emphasize the control precision and rapidity, we set the weight values \( w_1 = 0.999 \), \( w_2 = 0.001 \) and \( w_3 = 0.2 \). To verify the effectiveness of LFPIO, the same parameters are adjusted in basic PIO and PSO, so the comparative results are obtained in Figures 5 to 7. In addition, an unexpected impulse wind disturbance with 6N·m and a stochastic wind disturbance with magnitude of 2N·m are added to the simulation experiments.

**Figure 5** Comparative evolutionary curves of LFPIO, basic PIO and PSO

**Table I** Parameters with best fitness values listed in Table I and test the step responses with these parameters shown in Figure 6 and 7. To demonstrate the precision of ESO, tracking curves of unknown dynamics containing wind disturbances in the lateral channel are shown in Figure 8.

From Figure 5, it is obvious that the proposed LFPIO converges more quickly and is more stable than basic PIO and PSO. Meanwhile, LFPIO is more reliable in global optima searching because of its extended search space. Moreover, we
can conclude from Figures 6 to 8 that ESO can estimate the unknown dynamics and support the optimized ADRC to execute real-time disturbance compensation for ideal control, so this system could provide proper responses under hard conditions. Among the optimized parameters, LFPIO-based ones respond more effectively.

Conclusions
This paper presents an ADRC method applied to small unmanned helicopters. A linear attitude model based on hovering state and small perturbation linearization is given in this work. To realize decoupling and strong robustness of the whole system, a couple of ADRCs are arranged into two subsystems. Moreover, to promote the efficiency of each basic ADRC, a novel LFPIO algorithm is developed to optimize the five adaptive ADRC parameters. To extend the search space and proceed the convergence speed, the two original operators of basic PIO are replaced. The comparative simulation experiments with basic PIO and PSO show that the proposed LFPIO can give the good precision and stability of convergent globally optimal solution. Besides, ADRC system with LFPIO-based optimal parameters could provide the best tracking precision and lowest overshoots under certain disturbances.

In the future, we expect that our optimized ADRC could be used in practical flight and our proposed LFPIO could be applied and developed in other important optimization aspects.

References
Levy flight-based pigeon-inspired optimization
Daiyong Zhang, Haibin Duan and Yijun Yang


About the authors

*Daiyong Zhang* received his MSc degree in Control Science and Engineering from Beihang University (formerly Beijing University of Aeronautics and Astronautics, BUAA) in 2016. He is currently a PhD candidate with the School of Automation Science and Electrical Engineering, Beihang University. His current research interests include advanced flight control, bio-inspired computation and embedded system development.

*Haibin Duan* is currently a full Professor at School of Automation Science and Electrical Engineering, Beihang University (formerly Beijing University of Aeronautics and Astronautics, BUAA), Beijing, China. He received the PhD degree from Nanjing University of Aeronautics and Astronautics (NUAA) in 2005. He was an Academic Visitor of National University of Singapore (NUS) in 2007, a Senior Visiting Scholar of The University of Suwon (USW) of South Korea in 2011. He is currently an IEEE Senior Member and IFAC TC7.5 Technical Committee Member. He has published 3 monographs and over 60 peer-reviewed papers in international journals. His current research interests include bio-inspired computation, advanced flight control and biological computer vision. Haibin Duan is the corresponding author and can be contacted at: hbduan@buaa.edu.cn

*Yijun Yang* is currently a BSc candidate in the School of Automation Science and Electrical Engineering, Beihang University (formerly Beijing University of Aeronautics and Astronautics, BUAA). He is a Member of BUAA Bio-inspired Autonomous Flight Systems (BAPS) Research Group. His current research interests include computational intelligence techniques and their applications.