Parameter Estimation of an unmanned aerial vehicle using dandelion algorithm

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Abstract

In this study, we introduce a novel approach to the parameter estimation of Unmanned Aerial Vehicles (UAVs) utilizing the dandelion algorithm, a bio-inspired optimization technique that simulates the seed dispersal mechanism of dandelions. With UAVs increasingly becoming integral to various sectors, accurate parameter estimation emerges as a critical factor in ensuring their optimal performance and safety. Traditional parameter estimation methods often fall short, plagued by computational inefficiencies and a propensity for local optima, which can significantly hinder UAV operations. The dandelion algorithm, with its unique global search capabilities and adeptness in navigating multidimensional spaces, presents a solution that markedly enhances the precision and speed of parameter estimation. Through a series of simulations involving diverse UAV models, this study compares the performance of the dandelion algorithm against the conventional technique; the Particle Swarm Optimization (PSO), demonstrating its superior ability in achieving rapid convergence, higher accuracy, and an exceptional aptitude for avoiding local optima. Our findings not only underscore the algorithm's potential to revolutionize UAV parameter estimation but also highlight its applicability in advancing UAV technology and bio-inspired computational algorithms. This research contributes to the aerospace engineering field by offering an innovative, efficient alternative to existing parameter estimation methods, promising significant improvements in the design, operation, and safety of UAV systems across a spectrum of applications.

Keywords: Unmanned Aerial Vehicle, Dandelion Algorithm, UAVs, Parameter Estimation

1. Introduction

Unmanned Aerial Vehicles (UAVs) have brought an historic leap forward to the field of aerospace engineering which is increasingly developing [1-10]. Indeed, the precision and reliability of these complex flying robots have been vital in a wide range of areas, such as military missions, disaster control and environmental surveillance. The process of parameter estimation represents the core of realizing these properties and is a major way of improving performance and safety of UAV operations [11-27].

Some of the activities carried out in parameter estimation in UAVs include establishing the basic flight parameters including the aerodynamic coefficients that are crucial in the proper control and navigation during flight. Challenges that conventional approaches for parameter estimation usually face include computational inefficiency, local minimum susceptibility, and large flight data requirements. Meeting these challenges, this study evaluates the efficiency of the dandelion algorithm, which is known for its robustness, simplicity and the optimality of traversing the complex multidimensional spaces [28-43].

The metaheuristics can be used to solve many complicated problem [44-65] however, in this study we used the dandelion algorithm, which is based on the natural scattering behavior of dandelion seeds, utilizes a specific method of global optimization [66-83]. This paper explains how this bio-inspired algorithm has been customized for the UAV parameter estimation problem, describing the implementation of the algorithm and the theoretical

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characteristics that make it suitable for this application. Utilizing the unique exploration and exploitation capabilities of the dandelion algorithm, we show a substantial improvement in the accuracy and speed of parameters estimation for UAVs in comparison to conventional methods.

Our study employs a detailed simulation environment, in which UAV models of different complexity are passed through the parameter estimation by the dandelion algorithm. The outputs are compared to pre-set benchmarks demonstrating the superiority of the algorithm in attaining faster convergence rates, greater levels of accuracy, and impressive resistance to the perils of local optima. This study, however, improves the theoretical aspect of bio-inspired computational algorithms in aerospace engineering, but also outlines a feasible approach to one of the persistent problems with parameter estimation in UAVs, contributing to the design, operation, and safety of these flying machines. This paper presents a new methodology for parameter estimation for UAVs, based on the dandelion algorithm, a nature-inspired optimization technique, which imitates the seed dispersal process of dandelions.

2. Dynamics Model for a Quadcopter UAV

The quadcopter has a high nonlinear dynamic model that is described in [84, 85], and has the following discrete form:

$$x_{k+1} = x_k + T_s \dot{x}_k \tag{1}$$

$$y_{k+1} = y_k + T_s \dot{y}_k \tag{2}$$

$$z_{k+1} = z_k + T_s \dot{z}_k \tag{3}$$

$$\phi_{k+1} = \phi_k + T_s \left(p_k + T_{a\theta_k}\left(q_k S_{\phi_k} + r_k C_{\phi_k}\right)\right) \tag{4}$$

$$\theta_{k+1} = \theta_k + T_s\left(q_k C_{\phi_k} - r_k S_{\phi_k}\right) \tag{5}$$

$$\psi_{k+1} = \psi_k + \frac{T_s\left(q_k S_{\phi_k} + r_k C_{\phi_k}\right)}{C_{\theta_k}} \tag{6}$$

$$\dot{x}_{k+1} = \dot{x}_k + \frac{T_s}{m} M_{1,k} u_k \tag{7}$$

$$\dot{y}_{k+1} = \dot{y}_k - \frac{T_s}{m} M_{2,k} u_k \tag{8}$$

$$\dot{z}_{k+1} = \dot{z}_k + \frac{T_s}{m} M_{3,k} u_k - T_s g \tag{9}$$

$$p_{k+1} = p_k + \frac{T_s}{I_x}\left(q_k r_k \left(I_y - I_z\right) - J_R d q_k + L u_{1,k}\right) \tag{10}$$

$$q_{k+1} = q_k + \frac{T_s}{I_y}\ \left(p_k r_k (I_z - I_x) + J_R d r_k + L u_{2,k}\right) \tag{11}$$

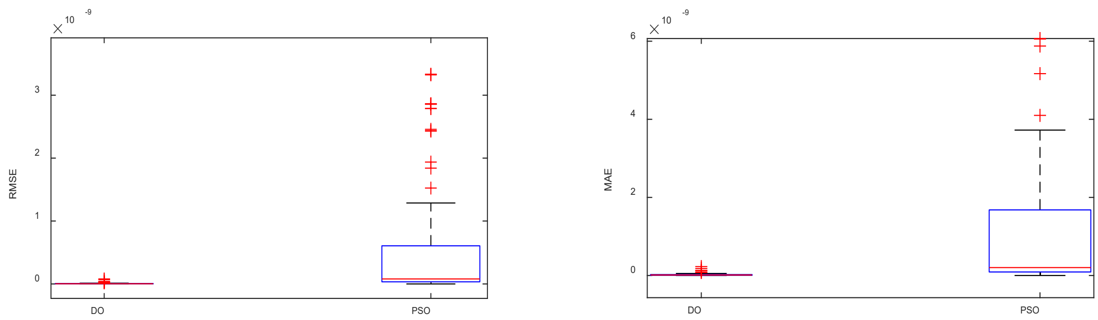
$$r_{k+1} = r_k + \frac{T_s}{I_z}\left(p_k q_k \left(I_x - I_y\right) + u_{3,k}\right) \tag{12}$$

Where $M_{1,k} = S_{\phi_k} C_{\psi_k} - C_{\phi_k} S_{\theta_k} S_{\psi_k}$, $M_{2,k} = S_{\phi_k} S_{\psi_k} + C_{\phi_k} S_{\theta_k} C_{\psi_k}$, $M_{3,k} = C_{\phi_k} C_{\theta_k}$, $C_x = \cos(x)$, $S_x = \sin(x)$, $T_{ax} = \tan(x)$, and $T_s = 0.001\, sec$. The UAV has position's components (x, y and z), velocity's components ($\dot{x}$, $\dot{y}$ and $\dot{z}$), orientaion's components (ϕ, θ and ψ), and their derivatives ($\dot{\phi}$, $\dot{\theta}$ and $\dot{\psi}$), where they are all measured with respect to the fixed frame. On the other hand, p, q and r are the angular rates described with respect to the UAV body's frame. u_x represents the input to the system. The rest of the terms are the UAV parameters including the mass (m), the inertias (J_R, I_x, I_y and I_z), dimensional terms (L) drag coefficient (d), and an input parameter (b). These parameters have the values of 0.52 kg, $6 \times 10^{-5}\, kgm^2, 6.228 \times 10^{-3}\, kgm^2, 6.225 \times 10^{-3}\, kgm^2, 1.1 \times 10^{-2}\, kgm^2, 0.232\, m, 7.5 \times 10^{-7}\, Nms^2$ and $3.13 \times 10^{-3}\, Ns^2$.

These parameters will be extracted from the measurement using the dandelion optimizer, which is discussed in [84, 85].

3. Results and discussion

The DO is used to obtain the parameters of an UAV drone from given measured states and inputs. The system is simulated using a Monte Carlo Simulation (MCS) that is repeated 100 times, in which each run lasts for 150 epochs. Each simulation uses 5 agents, and the results are compared to PSO. Figure 1 shows the root mean squared error (RMSE), and maximum absolute error (MAE) for the MCS. Figure 2 shows the simulation time. The histogram of the errors is shown in figure 3. Lastly, the convergence rate is shown in figure 4. The results reveal that both DO and PSO achieved an acceptable RMSE and MAE. However, the DO shows more robust and faster performance compared to PSO, with minimum variations in the errors. On the other side, PSO required less computational time.



(a) (b)

Figure 1. MCS results

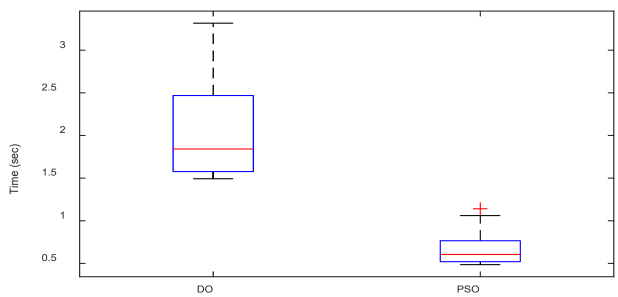


Figure 2. MCS simulation time

4. Conclusion

In concluding our investigation into the parameter estimation of Unmanned Aerial Vehicles (UAVs) using the dandelion algorithm, this research has illuminated the significant advantages of employing bio-inspired optimization techniques in aerospace engineering. Demonstrating marked improvements in accuracy, computational efficiency, and the ability to avoid local optima, the dandelion algorithm not only outperforms traditional parameter estimation methods but also opens new horizons for enhancing UAV performance and reliability. Our findings advocate for a broader integration of nature-inspired computational strategies in solving complex engineering challenges, suggesting that the future of UAV technology could greatly benefit from further explorations into bio-inspired algorithms. The potential for the dandelion algorithm to revolutionize UAV parameter estimation presents a compelling case for its adoption and further adaptation in the field, signaling a promising direction for advancing UAV capabilities and operational safety in diverse applications. This study, therefore, not only contributes a novel approach to the aerospace engineering literature but also sets a foundation for future research aimed at exploring and harnessing the power of bio-inspired solutions in technology development and optimization challenges.

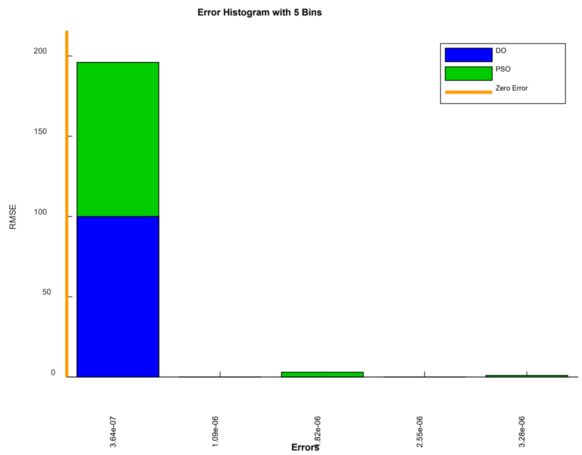


Figure 3. The histogram results of MCS for obtaining minimum value

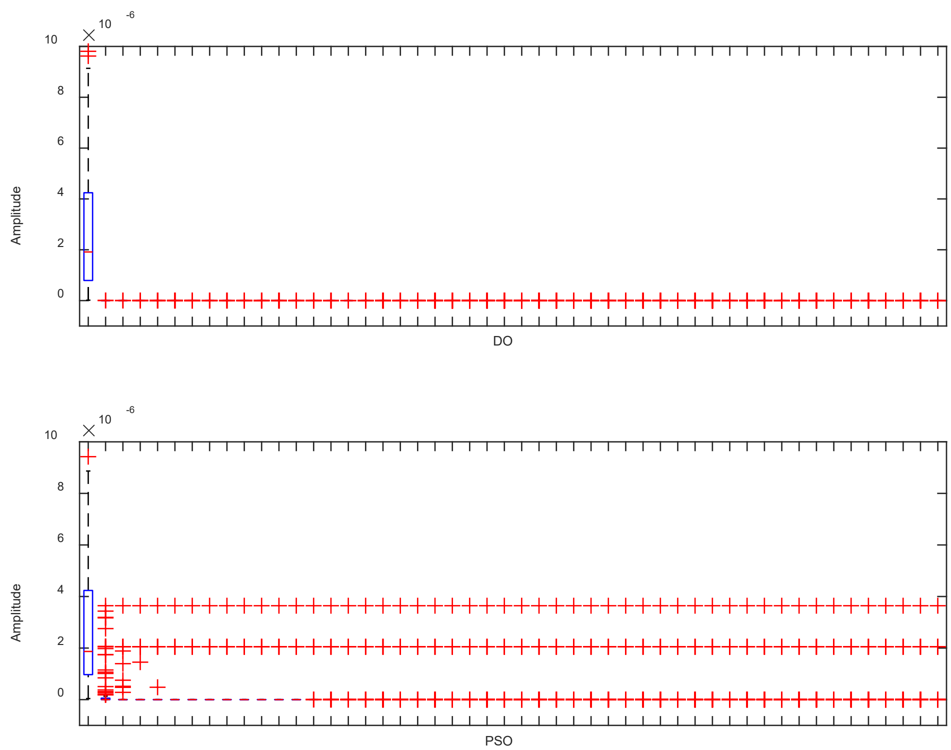


Figure 4. MCS's convergence rate for the simulations

Declaration

The final draft of this research paper has undergone a rigorous proofreading process, which included the utilization of advanced artificial intelligence (AI) technology.

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