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Longitudinal parameter identification of a small unmanned aerial vehicle based on modified particle swarm optimization

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Abstract This paper describes a longitudinal parameter identification procedure for a small unmanned aerial vehicle (UAV) through modified particle swam optimization (PSO). The procedure is demonstrated using a small UAV equipped with only an micro-electro-mechanical systems (MEMS) inertial measuring element and a global positioning system (GPS) receiver to provide test information. A small UAV longitudinal parameter mathematical model is derived and the modified method is proposed based on PSO with selective particle regeneration (SRPSO). Once modified PSO is applied to the mathematical model, the simulation results show that the mathematical model is correct, and aerodynamic parameters and coefficients of the propeller can be identified accurately. Results are compared with those of PSO and SRPSO and the comparison shows that the proposed method is more robust and faster than the other methods for the longitudinal parameter identification of the small UAV. Some parameter identification results are affected slightly by noise, but the identification results are very good overall. Eventually, experimental validation is employed to test the proposed method, which demonstrates the usefulness of this method.

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1. Introduction

Small unmanned aerial vehicles (UAVs) have the potential to act as low-cost tools in a variety of both civilian and military applications including traffic monitoring, border patrol and search and rescue. In recent years, there has been a tremendous growth in research emphasizing control of UAVs either in isolation or in teams, where aerodynamic parameters are the basis of their control system design.

At present, theoretical calculations and experimental methods are the main methodologies used to obtain aerodynamic parameters for small UAVs. The theoretical calculation methods include the engineering calculation method[1] and the computational fluid dynamics (CFD) method,[2] while the experimental methods include the wind tunnel experiments[3,4] and the identification test method.[5–7] The accuracy of the parameters is lower when the engineering and CFD methods are used, while the wind tunnel experiments usually require

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long cycles and therefore can become costly. By only relying on the relationship between inputs and outputs, the identification test method can identify UAV aerodynamic parameters easily by selecting an appropriate identification method and is quite suitable for small UAVs.

Aerodynamic parameter identification is the most fully developed field in conventional aircraft system identification, which has been successfully applied in aircraft and missiles.[8] Suk et al.[9] used maximum likelihood estimation and extended Kalman filters to identify the system and evaluate the stability of a UAV in 2003. Tang and Shi[10] used a numerically robust least-squares estimator in the frequency domain to identify the aircraft flutter modal parameters in 2008. Burchett[11] used an improved gradient-based method to estimate the aerodynamic coefficients of a symmetric projectile from free flight range data. Wu and Wang[12] designed signals to excite the longitudinal motion of a fly-by-wire passenger airliner to identify the aerodynamic parameters in 2013.

In conventional aircraft system identification, various test technologies are needed for flight data. Generally, the technologies can be divided into external parameters measurement and internal parameters measurement in two ways. The instantaneous position, trajectories, velocity and acceleration etc. can be measured by external parameters measurement. These data can then be compared with the data measured by airborne systems to test the accuracy of the airborne systems. External parameters measurement equipment includes photography, radar measurement and laser measurement etc. Internal parameters measurement equipment includes global positioning system (GPS) receiver, angular velocity gyroscope, accelerometer, angular accelerometer, altimeter, airspeed meter and so on.

Currently, for small UAVs, external parameters measurement equipment is nonexistent and onboard test equipment is limited in quantity because of space limitations and cost. In this paper, the small UAVs studied only use an micro-electro-mechanical systems (MEMS) inertial measurement element and a GPS receiver to provide test information. The problem with using such devices is that only a minimal amount of information can be collected and the signal-to-noise ratio is low. Therefore, aerodynamic parameter identification for small UAVs is even more challenging.[13]

Intelligent identification algorithms have been widely used in the field of parameter identification with the development of optimization theories.[14,15] Particle swarm optimization (PSO) is a new heuristic algorithm proposed by Kennedy and Eberhart,[16] and it has been successfully applied in many research and application areas in recent years. Examples include plans and scheduling,[17–19] data clustering,[20] power flow analysis,[21] pattern recognition[22] and layout design.[23] In 2010, PSO was applied towards aerodynamic parameter estimation to replace gradient-based optimization methods by Zhang et al.[24] which proved that PSO was an effective method to estimate aerodynamic parameters. However, it was found that the convergence of PSO was slow when solving complex problems and the search may be occasionally trapped in local minima. In order to improve the performance of the algorithm, many attempts have been made. PSO with selective particle regeneration (SRPSO) was proposed by Tsai and Kao[25] in 2009. SRPSO was applied to solve continuous multimodal function optimization, demonstrating that SRPSO was better than PSO in many respects and SRPSO was a more efficient, accurate and robust method. SRPSO was later applied to solve data clustering problems by Tsai and Kao.[26]

This paper proposes modified PSO (MPSO) to strengthen the local optimization ability and solution convergence efficiency, and then this approach is applied to parameters estimation of a small UAV. Herein, we deduce longitudinal aerodynamic parameters and a propeller dynamic mathematical model for a small UAV aimed at the limited in-flight test data. Other related parameters of the mathematical model are also identified based on MPSO. Simulation and an experimental test are conducted to evaluate the whole method.

2. Algorithm

2.1. Particle swarm optimization (PSO)

PSO is inspired by the social behaviors observed in flocks of birds and schools of fish. This intelligent algorithm has seen rapid development in recent years. PSO is initialized with a population of random solutions. Each particle represents a candidate solution in the solution space. The position of an individual particle is adjusted according to its own previous searching experience. The best solution is determined by its objective function value. The general procedure of PSO is as follows:

(1) Initialization. The algorithm randomly generates an initial population of potential solutions, called particles, and each particle is assigned a randomized velocity.
(2) Velocity and position update. The velocity update of a particle is dynamically adjusted, subject to its own best path history and those of its companions. Each particle updates its velocity and position via Eqs. (1) and (2).

$$\boldsymbol{V}_{\mathrm{id}}^{\mathrm{new}} = \omega \times \boldsymbol{V}_{\mathrm{id}}^{\mathrm{old}} + c_1 \times \xi \times \left(\boldsymbol{p}_{\mathrm{id}} - \boldsymbol{x}_{\mathrm{id}}^{\mathrm{old}}\right) + c_2 \times \xi \times \left(\boldsymbol{p}_{\mathrm{gd}} - \boldsymbol{x}_{\mathrm{id}}^{\mathrm{old}}\right) \tag{1}$$

$$\boldsymbol{x}_{\mathrm{id}}^{\mathrm{new}} = \boldsymbol{x}_{\mathrm{id}}^{\mathrm{old}} + \boldsymbol{V}_{\mathrm{id}}^{\mathrm{new}} \tag{2}$$

where $\boldsymbol{V}_{\mathrm{id}}^{\mathrm{old}}$ and $\boldsymbol{x}_{\mathrm{id}}^{\mathrm{old}}$ are respectively the particle's previous speed and position; $\boldsymbol{V}_{\mathrm{id}}^{\mathrm{new}}$ and $\boldsymbol{x}_{\mathrm{id}}^{\mathrm{new}}$ are respectively the particle's new speed and position; $\omega = 0.5 + \frac{\xi}{2}$ is the inertia weight coefficient, with ξ denoting a random number in the range of [0,1]; the cognition c_1 and the social parameter c_2 are acceleration coefficients that are conventionally set to a fixed value between 0 and 2; $\boldsymbol{p}_{\mathrm{id}}$ is the previous individual best position of the particle; $\boldsymbol{p}_{\mathrm{gd}}$ is the current global best position.

(3) Compute the desired optimization fitness function. Compare the fitness of each particle with its $\boldsymbol{p}_{\mathrm{id}}$, and if the current is better, update $\boldsymbol{p}_{\mathrm{gd}}$.
(4) Termination. Stop the algorithm if the stopping criterion is met; otherwise, go to step (2).

The determination of a particle's speed is based on the best individual position and the knowledge of the swarm's best trajectory. The quantity $\boldsymbol{p}_{\mathrm{id}} - \boldsymbol{x}_{\mathrm{id}}^{\mathrm{old}}$ represents the cognitive knowledge and $\boldsymbol{p}_{\mathrm{gd}} - \boldsymbol{x}_{\mathrm{id}}^{\mathrm{old}}$ corresponds to the social knowledge, while c_1 and c_2 determine the effects of the cognitive and social knowledge on the new velocity. A balanced setting

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