RPnP Pose Estimation Optimized by Comprehensive Learning Pigeon-Inspired Optimization for Autonomous Aerial Refueling

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Abstract. The probe-and-drogue autonomous aerial refueling (AAR) needs the drogue's high-precision pose information in the docking. This paper proposes a novel optimized pose estimation method to improve the basic RPnP method's performance. To be specific, the RPnP method is adopted to estimate the drogue's real-time pose. Then, according to the reprojection error, the comprehensive learning pigeon-inspired optimization (CLPIO) is constructed to optimize the rotation axis selection of RPnP. The comprehensive learning (CL) strategy enhances the swarm diversity of the basic PIO, which can effectively avoid the algorithm trapping into the local optimum. The simulation results are given to prove the effectiveness of the proposed optimized RPnP method.

Keywords: Autonomous aerial refueling (AAR) · Comprehensive learning pigeon-inspired optimization (CLPIO) · Pose estimation

1 Introduction

Unmanned aerial vehicle (UAV) has been extensively applied to contemporary combat tasks, such as target tracking [1], cooperative attack [2], surveillance [3], and so on. To handle the conflict of the UAV endurance and payload, autonomous aerial refueling (AAR) [4] is regarded as a valid approach to deal with the abovementioned conflict for UAVs. In general, three approaches for aerial refueling are adopted: probe-and-drogue refueling (PDR) [5], boom-receptacle refueling (BRR) [6], and mixed refueling of PDR and BRR. Among the three aforementioned approaches, the PDR is superior in the aspects of the UAVs refueling together, wide-range refueling keep position, etc. Therefore, we mainly concentrate on the RDR technique.

In the docking process, due to the hose's flexibility, the multiple wind disturbances induce the hose and drogue to swing randomly all the time. Thus, the drogue's real-time high precision pose information is fundamentally required for the AAR docking. Compared with INS and DGPS, the vision navigation approach with a cheaper camera can

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satisfy the demands of the navigation's submeter-level accuracy and anti-electromagnetic interference ability. In the vision navigation system, the high-precision pose estimation method is the essential part. Among the pose estimation methods, Fischler et al. [7] firstly presented the perspective-*n*-point (PnP) approach to restore the pose information relying on the corresponding relation of the 3D points to 2D points. Lepetit et al. [8] developed the efficient perspective-*n*-point (EPnP) method to enhance the estimation precision of the PnP method, but the EPnP method was too complicated. Besides, the Levenberg-Marquardt (LM) method [9] was proposed by absorbing the advantage of solving the second derivative of the Hessian matrix through the Gauss-Newton method. Lu et al. [10] developed the Lu-Hager-Mjolsness (LHM) method, which was regarded as an efficient iterative pose estimation method. Moreover, a robust noniterative solution of PnP problem (RPnP) was proposed by Li et al. [11], which can realize the high-precise pose estimation using less computational complexity. Thus, we adopt the RPnP method to calculate the drogue's pose information in this paper. However, the rotation axis selection of the RPnP method affects a lot on the capability of pose estimation. Therefore, the modified pigeon-inspired optimization (PIO) algorithm is proposed to optimize the rotation axis of the RPnP method.

The PIO algorithm was first developed by Duan and Qiao [12] for path planning. Hereafter, the PIO algorithm has caught much attention in many practical applications. Li et al. [13] dealt with the UAV target detection problem via the edge potential function and a modified PIO. In [14], the multi-objective social learning PIO was presented to construct the obstacle avoidance approach for UAVs. Besides, the cooperative search-attack planning problem of UAVs was handled using a dynamic discrete PIO algorithm [2]. In this paper, the comprehensive learning (CL) strategy [15] is introduced into the basic PIO, called the comprehensive learning PIO (CLPIO), which can improve the swarm diversity of the original PIO. Thus, the CLPIO algorithm reduces the probability of trapping into the local optimum.

In this paper, an optimized RPnP method is developed to obtain the drogue's high-precision pose information for the AAR vision navigation system. We organize the remaining part of the paper as follows. In Sect. 2, the CLPIO algorithm is given. Section 3 presents the optimized RPnP method. Then, the simulation results are exhibited and discussed in Sect. 4. Section 5 summarizes this paper.

2 CLPIO Algorithm

2.1 PIO Algorithm

Motivated by long-and-close distance navigation mechanism of the homing pigeons, Duan and Qiao [12] first propose the original PIO algorithm constituted by two operators, i.e., map and compass operator, and landmark operator. The former operator simulates the pigeon's sun, magnetic field navigation of long distance. The latter operator is motivated by the landmark navigation of pigeons' vision in close distance. The pigeons' homing behaviors represent the optimization processes to search the optimal solution.

(1) Map and compass operator:

The pigeons' velocity $\boldsymbol{V}_i^t = \left[v_{i,1}^t, v_{i,2}^t, \cdots, v_{i,D}^t\right]$ and position $\boldsymbol{X}_i^t = \left[x_{i,1}^t, x_{i,2}^t, \cdots, x_{i,D}^t\right]$ at current generation are defined beforehand. Then, we calculate the pigeons' velocities, positions as follows [5, 12]:

$$\boldsymbol{V}_i^t = e^{-R \cdot t} \cdot \boldsymbol{V}_i^{t-1} + rand \cdot \left(\boldsymbol{X}_{gbest} - \boldsymbol{X}_i^{t-1}\right) \tag{1}$$

$$\boldsymbol{X}_i^t = \boldsymbol{X}_i^{t-1} + \boldsymbol{V}_i^t \tag{2}$$

where t is the generation number, R denotes the speed factor, $rand$ denotes the random number, $rand \in [0, 1]$, $\boldsymbol{X}_{gbest}$ is the pigeons' global optimal position, the pigeons' number is N_p, $i = 1, 2, \cdots, N_p$.

(2) Landmark operator:

In the visual navigation processes, half of the pigeons will be eliminated due to loss of the optimization ability. The update rule of this operator is described as that the positions of pigeons follow the rest pigeons' center. Therefore, the pigeons' positions at current generation are calculated by [5, 12].

$$N_p^t = \left[\frac{N_p^{t-1}}{2}\right] \tag{3}$$

$$\boldsymbol{X}_c^{t-1} = \frac{\sum_{i=1}^{N_p^{t-1}} \boldsymbol{X}_i^{t-1} \cdot fitness\left(\boldsymbol{X}_i^{t-1}\right)}{\sum_{i=1}^{N_p^{t-1}} fitness\left(\boldsymbol{X}_i^{t-1}\right)} \tag{4}$$

$$\boldsymbol{X}_i^t = \boldsymbol{X}_i^{t-1} + rand \cdot \left(\boldsymbol{X}_c^{t-1} - \boldsymbol{X}_i^{t-1}\right) \tag{5}$$

where $[\cdot]$ is the ceil value of input number, N_p^t, N_p^{t-1} denote the number of the pigeons at two successive generations, $\boldsymbol{X}_c^{t-1}$ denotes the pigeons' center position, $fitness(\cdot)$ is the function for calculating the fitness values. This paper adopts the reprojection error as the fitness function, which will be minimized to optimize the RPnP method.

2.2 CLPIO Algorithm

The CL strategy [15] is adopted to improve the original PIO algorithm's swarm diversity, which enhances the algorithm's exploration ability in essence. Instead of only learning from the pigeon's own best position, the current pigeon follows the different pigeons' best positions for each dimension. The update exemplars are produced through the CL strategy as for the pigeons' learning objects.

(1) Modified map and compass operator:

The pigeons' velocities for each dimension are calculated using the following Eq. (6).

$$v_{i,d}^{t} = v_{i,d}^{t-1} \cdot e^{-R \cdot t} + rand1_{i,d} \cdot \left(x_{d,f_i(d)}^{pbest} - x_{i,d}^{t-1} \right) + rand2_{i,d} \cdot \left(x_{gbest,d} - x_{i,d}^{t-1} \right) \quad (6)$$

where d denotes the current dimension number, $x_{d,f_i(d)}^{pbest}$ is the position of the update exemplar, $f_i(d)$ is the update exemplar, $f_i(d) = [f_i(1), f_i(2), \cdots, f_i(D)]$ determines that the current pigeon learns from another's or its own best positions in the d-th dimension. $f_i(d)$ is decided based on the learning probability value Pc. The current pigeon's $Pc_{i,d}$ value for current dimension is calculated by:

$$Pc_{i,d} = a_p + b_p \cdot \frac{e^{10 \cdot (i-1) / N_p - 1} - 1}{e^{10} - 1} \quad (7)$$

where a_p, b_p denote the learning probability coefficient. If $rand_{i,d} > Pc_{i,d}$, the current pigeon's current dimension will follow its own best position. Otherwise, if $rand_{i,d} \leq Pc_{i,d}$, the current pigeon's current dimension will follow the best position of another pigeon. We determine the specific exemplar through the procedure of comparison selection. Besides, we update the learning exemplar when the fitness values of current pigeon are not promoted at a few continuous generations.

(2) We do not modify the original landmark operator.

3 Optimized RPnP Pose Estimation Method

The basic RPnP method is a robust noniterative pose estimation method. For the matched markers, a line connecting two markers needs to be selected as the rotation axis, which is denoted as $\overrightarrow{P_{i0}P_{j0}}$. Then, we select the midpoint of $\overrightarrow{P_{i0}P_{j0}}$ as the original point to build a new reference frame $O_aX_aY_aZ_a$. The Z_a-axis holds the same direction as $\overrightarrow{P_{i0}P_{j0}}$. Next, the markers' world coordinates will be transformed to the new coordinates in $O_aX_aY_aZ_a$.

To choose the axis of rotation (i.e., Z_a), a series of subsets are constructed by taking arbitrary three markers of the point set. Every subset is able to establish a quartic polynomial according to the triangular geometry principle. Next, the least-squares residual method is employed to search the minimal value of all quartic polynomials' sum-of-squares. Then, the deepness of P_{i0} and P_{j0} can be obtained using the existent method [16]. Thus, we denote the rotation axis Z_a as $Z_a = \overrightarrow{P_{i0}P_{j0}} \Big/ \left\| \overrightarrow{P_{i0}P_{j0}} \right\|$.

When the Z_a-axis is obtained, we calculate the rotation matrix using (8), which transforms $O_aX_aY_aZ_a$ to the camera's reference frame.

$$R = R' rot(Z_c, \alpha) = \begin{bmatrix} r_1 & r_4 & r_7 \\ r_2 & r_5 & r_8 \\ r_3 & r_6 & r_9 \end{bmatrix} \begin{bmatrix} \cos\alpha & -\sin\alpha & 0 \\ \sin\alpha & \cos\alpha & 0 \\ 0 & 0 & 1 \end{bmatrix} \quad (8)$$

where R' denotes an orthogonal rotation matrix, $[r_7\ r_8\ r_9]^T$ is the same as Z_a, $rot(Z_c, \alpha)$ denotes the action that rotates α degrees around Z_c-axis. Based on the pinhole imaging principle, we project the 3-D markers to the 2-D image plane using (9).

$$\lambda_i \begin{bmatrix} u_i \\ v_i \\ 1 \end{bmatrix} = \begin{bmatrix} r_1 & r_4 & r_7 \\ r_2 & r_5 & r_8 \\ r_3 & r_6 & r_9 \end{bmatrix} \begin{bmatrix} \cos\alpha & -\sin\alpha & 0 \\ \sin\alpha & \cos\alpha & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x_i \\ y_i \\ z_i \end{bmatrix} + \begin{bmatrix} t_x \\ t_y \\ t_z \end{bmatrix} \tag{9}$$

where $\begin{bmatrix} u_i & v_i & 1 \end{bmatrix}^T$ is the normalized pixel coordinate, $\begin{bmatrix} x_i & y_i & z_i \end{bmatrix}^T$ is the markers' coordinates in $O_aX_aY_aZ_a$, the translation vector is presented as $\mathbf{t}$, $\mathbf{t} = \begin{bmatrix} t_x & t_y & t_z \end{bmatrix}^T$. The singular value decomposition (SVD) [11] approach is applied to acquire the solution of Eq. (9), and further we can get the variables vector $\begin{bmatrix} \cos\alpha & \sin\alpha & t_x & t_y & t_z & 1 \end{bmatrix}$. Finally, the markers' rotation matrix $\mathbf{R}$ and the translation vector $\mathbf{t}$ will be acquired.

Assuming that there are n markers, the basic RPnP method chooses one rotation axis among the $n(n-1)/2$ segments by calculating the corresponding projected lengths in the pixel plane. However, the computational process is not only complex but not optimal. The CLPIO algorithm is adopted to optimize the rotation axis of the RPnP method. The optimized RPnP method takes the reprojection error as the fitness function. After obtaining $\mathbf{R}$ and $\mathbf{t}$, we reproject the markers' world coordinates to the pixel plane. Through comparing the reprojected pixel coordinates and the original pixel coordinates, we find the minimum projection error among all the possible rotation axes, which is adopted as the optimized rotation axis for pose estimation.

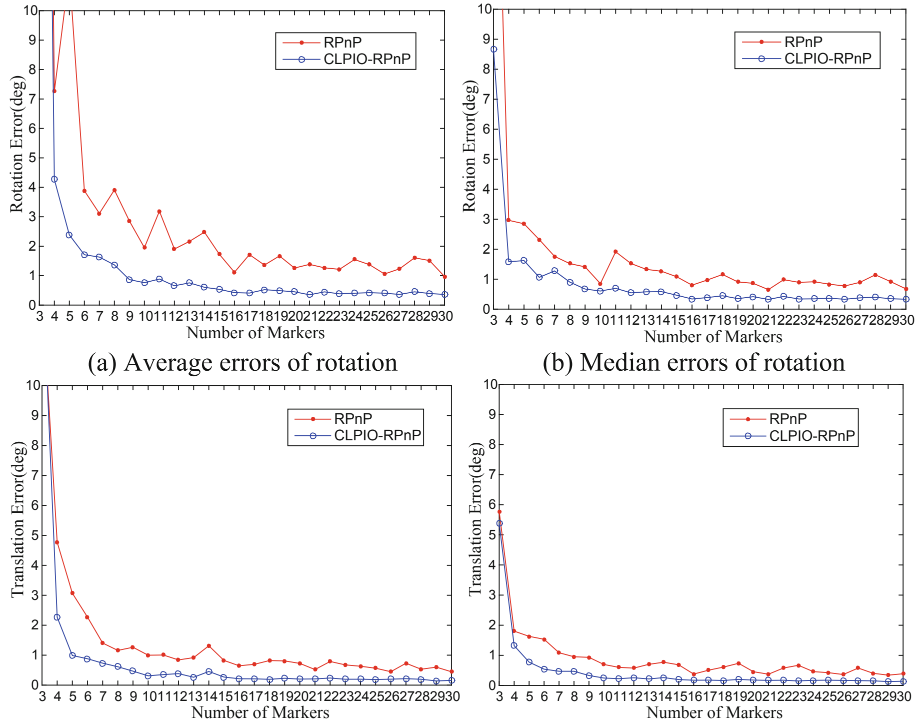
4 Simulation Results and Analysis

Several simulations are implemented to verify the effectiveness of the proposed optimized RPnP pose estimation method. We construct the simulation scenes satisfying the following conditions: 1) the number of markers changes from three to thirty; 2) the world coordinates corresponding to the markers are coplanar; 3) for a fixed number of markers, 30 sets of data are generated for pose estimation. We give the simulation parameters in Table 1.

Table 1. Parameters of simulations.

Parameters	Description	Value
N_p	Pigeons' number	10
T_{1max}	Maximum iteration of map and compass operator	7
T_{2max}	Maximum iteration of landmark operator	3
R	Speed factor	0.2
D	Search space's dimension	2
a_p, b_p	Learning probability coefficient	0.1, 0.25

Figure 1 illustrates the pose estimation errors for the RPnP and optimized RPnP method. As we can see that though the basic RPnP method has a good measurement accuracy, the optimized RPnP method further enhances the measurement accuracy, which demonstrates that the original selection criterion of the rotation axis is not optimal. Figure 2 gives the time costs for the RPnP and optimized RPnP methods. In comparison with the basic RPnP approach, the optimized RPnP method's time costs increase in an acceptable range. The reason is that the optimal rotation axis is determined by several pose estimation processes using the CLPIO algorithm. The proposed optimized RPnP method improves the pose estimation accuracy at a small time cost.



(a) Average errors of rotation

(b) Median errors of rotation

(c) Mean errors of translation

(d) Median errors of translation

Fig. 1. Pose estimation errors for the RPnP and optimized RPnP methods.

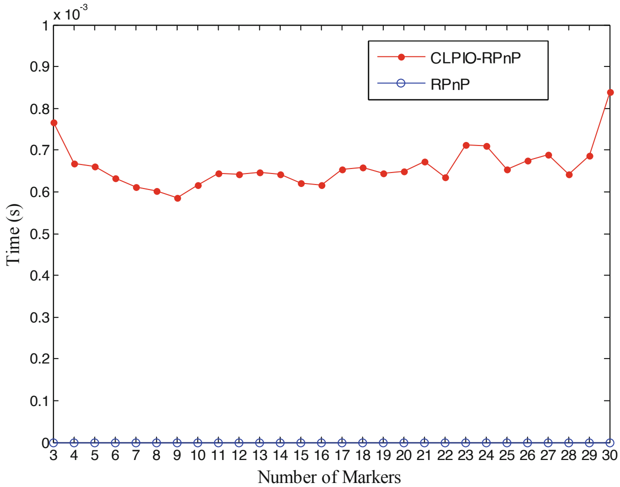


Fig. 2. Time costs for the RPnP and optimized RPnP methods.

5 Conclusions

This paper develops an optimized RPnP method to acquire the high-precision pose information for AAR docking. The CL strategy is introduced into the basic PIO algorithm, called as CLPIO algorithm, to increase the global optimization capability. Then, the CLPIO algorithm is adopted to tackle with the optimal selection problem of the RPnP method's rotation axis according to the reprojection error of pose estimation. The simulation results show that the proposed optimized RPnP method can realize the higher precision pose estimation by increasing a little time cost, which verifies the proposed method's effectiveness. We will try to employ the proposed method to the real-time vision navigation system in the future.

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References

1. Sun, Y.B., Xia, K.W., Zou, Y., Fu, Q., He, X.Y.: Distributed output-feedback formation tracking control for clustered quad-rotors. IEEE Trans. Aerosp. Electron. Syst. **58**(3), 1894–1905 (2022)
2. Duan, H.B., Zhao, J.X., Deng, Y.M., Shi, Y.H., Ding, X.L.: Dynamic discrete pigeon-inspired optimization for multi-UAV cooperative search-attack mission planning. IEEE Trans. Aerosp. Electron. Syst. **57**(1), 706–720 (2021)
3. Nigam, N., Bieniawski, S., Kroo, I., Vian, J.: Control of multiple UAVs for persistent surveillance: algorithm and flight test results. IEEE Trans. Control Syst. Technol. **20**(5), 1236–1251 (2012)

4. Duan, H.B., Sun, Y.B., Shi, Y.H.: Bionic visual control for probe-and-drogue autonomous aerial refueling. IEEE Trans. Aerosp. Electron. Syst. **57**(2), 848–865 (2021)
5. Sun, Y.B., Liu, Z.J., Zou, Y., He, X.Y.: Active disturbance rejection controllers optimized via adaptive granularity learning distributed pigeon-inspired optimization for autonomous aerial refueling hose-drogue system. Aerosp. Sci. Technol. **124**, 107528 (2022)
6. Duan, H.B., Zhang, Q.F.: Visual measurement in simulation environment for vision-based UAV autonomous aerial refueling. IEEE Trans. Instrum. Meas. **64**(9), 2468–2480 (2015)
7. Fischler, M.A., Bolles, R.C.: Random sample consensus: a paradigm for model fitting with applications to image analysis and automated cartography. Commun. ACM **24**(6), 619–638 (1981)
8. Lepetit, V., Moreno N. F., Fua. P.: EPnP: an accurate O(n) solution to the PnP problem. Int. J. Comput. Vis. **81**(2), 155–166 (2009)
9. Marquardt, D.W.: An algorithm for least-squares estimation of nonlinear parameters. J. Soc. Ind. Appl. Math. **11**(2), 431–441 (1963)
10. Lu, C.P., Hager, G.D., Mjolsness, E.: Fast and globally convergent pose estimation from video images. IEEE Trans. Pattern Anal. Mach. Intell. **22**(6), 610–622 (2000)
11. Li, S.Q., Xu, C., Xie, M.: A robust O(n) solution to the perspective-n-point problem. IEEE Trans. Pattern Anal. Mach. Intell. **34**(7), 1444–1450 (2012)
12. Duan, H.B., Qiao, P.X.: Pigeon-inspired optimization: a new swarm intelligence optimizer for air robot path planning. Int. J. Intell. Comput. Cybern. **7**(1), 24–37 (2014)
13. Li, C., Duan, H.B.: Target detection approach for UAVs via improved pigeon-inspired optimization and edge potential function. Aerosp. Sci. Technol. **39**, 352–360 (2014)
14. Ruan, W.Y., Duan, H.B.: Multiple UAVs obstacle avoidance control via multi-objective social learning pigeon-inspired optimization. Frontiers of Information Technology & Electronic Engineering **21**(5), 740–748 (2020)
15. Liang, J.J., Qin, A.K., Suganthan, P.N., Baskar, S.: Comprehensive learning particle swarm optimizer for global optimization of multimodal functions. IEEE Trans. Evol. Comput. **10**(3), 281–295 (2006)
16. Li, S.Q., Xu, C.: A stable direct solution of perspective-three-point problem. J. Pattern Recogn. Artif. Intell. **25**(5), 627–642 (2011)