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UAV Path Planning and Simulation Based on PSO with Greedy Initialization and 2-Opt Local Search

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Abstract. Unmanned Aerial Vehicle path planning is a key technology for realizing autonomous flight, which belongs to a typical NP-hard optimization problem. Genetic algorithm (GA) suffers from slow convergence speed and low iteration efficiency, whereas the standard particle swarm optimization (PSO) algorithm is prone to premature convergence and falling into local optima. In this paper,Greedy Initialization and 2-opt Local Search Particle Swarm Optimization (GILS-PSO) is proposed. A three-dimensional flight environment containing static obstacles and fixed waypoints is constructed for simulation verification. The performance of the algorithm is enhanced by means of greedy initialization, permutation encoding, adaptive inertia weight, and 2-opt local search. Under the same experimental scenario, the fitness convergence characteristics of them, are compared and analyzed.The results show that GILS-PSO is significantly superior in terms of convergence speed and optimal fitness. The optimal path planned by GILS-PSO is applied to a quadrotor UAV simulation system based on cascade PID control, and the feasibility of the scheme is verified by analyzing position, velocity, attitude angles, and angular velocity. The proposed method can provide an effective solution for offline three-dimensional path planning of unmanned aerial vehicles.

Keywords: UAV, Path planning, GA, PSO

1. Introduction

With the wide application of Unmanned Aerial Vehicle (UAV) technology in surveying and mapping, inspection, emergency rescue and other fields [1], autonomous flight capability has become its core competitiveness [2]. Path planning, as a key link to realize autonomous flight, directly determines flight efficiency and safety. Currently, UAVs mostly operate in complex three-dimensional environments, requiring avoidance of static obstacles and accurate traversal of fixed waypoints. This type of path planning problem is a typical NP-hard optimization problem, and traditional planning methods can hardly meet the requirements of efficient and optimal path planning. As the application scenarios of UAVs continue to expand, the requirements for real-time performance and optimality of path planning keep rising. Therefore, it is urgent to optimize intelligent algorithms to improve path planning performance and provide reliable technical support for UAV autonomous flight.

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In the field of UAV path planning, genetic algorithm (GA) [3, 4] and particle swarm optimization (PSO) algorithm [5] are two of the most widely used intelligent optimization algorithms, but both have obvious defects. GA tends to have slow convergence speed and low iteration efficiency in the iteration process; the randomness of its crossover and mutation operations also leads to insufficient algorithm stability, making it difficult to quickly obtain the optimal path. Standard PSO has the hidden danger of premature convergence, and particles are prone to fall into local optimal solutions during the update process, resulting in insufficient accuracy of the planned path [6]. In addition, it has poor adaptability to complex three-dimensional flight scenarios and cannot meet the path planning needs in practical applications.

To solve the above defects of the algorithms and improve the efficiency and accuracy of path planning, this paper proposes a greedy initialization and 2-opt local search particle swarm optimization (GILS-PSO). A greedy initialization strategy is introduced to optimize the quality of the initial population and reduce the blindness of the initial iteration of the algorithm [7]. Combined with the 2-opt local search algorithm, local optimization of the optimal solution is performed to avoid the algorithm falling into local optima [8, 9]. At the same time, permutation encoding and adaptive inertia weight are adopted for auxiliary optimization: permutation encoding improves the rationality of path encoding [10], and adaptive inertia weight balances the global exploration and local exploitation capabilities of the algorithm [6, 11], further enhancing the convergence performance and planning effect of the algorithm. In the Matlab environment, a three-dimensional flight map containing fixed waypoints and random obstacles is constructed to compare and analyze the fitness convergence characteristics of GA, standard PSO and GILS-PSO. The optimal path planned by GILS-PSO is connected to a quadrotor UAV simulation system based on cascade PID control [12], and the feasibility of the algorithm is verified by analyzing motion characteristic curves such as position and velocity. The results show that the proposed algorithm can effectively make up for the defects of traditional algorithms and significantly improve the UAV path planning performance.

2. Overview

The PSO algorithm simulates the cooperative foraging behavior of bird flocks, maps potential solutions of optimization problems to particles in the solution space, and converges to the global optimal solution by tracking their historical optimal solution (pbest) and the group's global optimal solution (gbest) to dynamically adjust motion parameters.The core formulas of the algorithm are as follows:

$$v_{i,d}^{t+1} = \omega v_{i,d}^{t} + c_1 r_1 \left(pbest_{i,d} - \chi_{i,d}^{t} \right) + c_2 r_2 \left(gbest_{d} - \chi_{i,d}^{t} \right) \tag{1}$$

$$\chi_{i,d}^{t+1} = \chi_{i,d}^{t} + v_{i,d}^{t+1} \tag{2}$$

Among them, ω is the inertia weight, c_1 and c_2 are learning factors, r_1 and r_2 are random numbers in $[0, 1]$, and pbest and gbest are individual and group optimal positions, respectively.

PSO has a concise structure and is easy to implement with fast initial convergence speed. Nevertheless, this algorithm contains obvious inherent drawbacks. It is susceptible to premature convergence and fails to effectively escape from local optima, which leads to limited optimization accuracy [5, 6]. Core parameters usually require manual adjustment according to empirical knowledge, and inappropriate parameter matching will weaken the overall search performance [11].

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In addition, standard PSO cannot maintain stable convergence in complex high-dimensional scenarios, and it is likely to generate iterative oscillation and search stagnation during the optimization process [10].

3. GILS-PSO

3.1. Greedy strategy

The overall optimization performance of the GILS-PSO algorithm depends on initial population quality and population diversity. Different from standard PSO with complete random initialization this study adopts a hybrid generation mode.It combines greedy selection and random arrangement to balance search direction and population richness [13, 14]. The greedy rule selects the next waypoint with the shortest Euclidean distance as the transition standard.The core selection criterion is expressed as

$$L_{i,j} = min \left\| P_j - P_i \right\| \tag{3}$$

P_i and P_j denote coordinates of current waypoint and unvisited waypoint. $L_{i,j}$ represents the shortest distance between two nodes. Partially greedy individuals guarantee basic path quality while random individuals maintain population diversity. This hybrid mode reduces search blindness in early iteration and strengthens the overall optimization potential [8, 13].

3.2. Permutation encoding strategy

Standard PSO is designed for continuous optimization and cannot adapt to discrete waypoint sequence constraints [10, 7]. This paper adopts permutation encoding to realize the conversion between discrete paths and continuous vectors. Each waypoint is assigned a unique number and mapped into particle position vectors. Particles complete velocity and position update in continuous space following basic PSO rules. The updated vector data is restored to feasible waypoint sequences through sorting mapping. This simple and efficient encoding method solves the discrete adaptation problem of traditional PSO [10]. It makes the improved algorithm directly applicable to UAV discrete path planning tasks.

3.3. Adaptive inertia weight strategy

Inertia weight controls the global exploration and local exploitation capability of particles. Fixed weight in conventional PSO easily causes unbalanced search performance in different stages [6, 11]. This paper adopts a linear adaptive weight adjustment method with dynamic iteration update. The core calculation formula is given by

$$\omega = \omega_{\max} - \left(\omega_{\max} - \omega_{min}\right() \frac{iter}{max_iter} \left) \right. \tag{4}$$

ω is the real time inertia weight. $iter$ and max_iter represent current iteration and maximum iteration. ω_{max} and ω_{min} are the upper and lower bounds of weight. Larger weight is reserved in early search for global expansion. Gradually reduced weight in later iteration enhances local fine search ability. Dynamic weight adjustment balances dual search performance and improves convergence accuracy [5, 6].

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3.4. Opt local search strategy

Global iteration of PSO is prone to local optimum and redundant path distribution. 2-opt local search is embedded into the iteration process for path local refinement. It replaces original connecting edges and reconstructs partial path segments. The core optimization criterion judges path quality by distance difference before and after reconstruction.

$$\Delta L = L_{new} - L_{old} \tag{5}$$

L_{old} means the original path length and L_{new} is the length after 2-opt reconstruction. The algorithm accepts the new path only when ΔL keeps a negative value. This local search mechanism assists particles in jumping out of local optimum. It optimizes crossed and redundant routes and further improves overall path rationality [9, 15].

In summary, the GILS-PSO algorithm achieves deep integration of four improvement methods. The involved measures include greedy initialization permutation encoding adaptive inertia weight and 2-opt local search. These improved measures work together to address typical shortcomings of standard PSO when applied to UAV three dimensional path planning. Common limitations such as premature convergence weak adaptability to discrete problems and limited optimization accuracy can be effectively relieved through the above collaborative design. The proposed algorithm realizes overall promotion in multiple dimensions including initial population condition scenario adaptation capacity searching performance and final path rationality. Major implementation procedures of the GILS-PSO algorithm are presented in Figure 1.

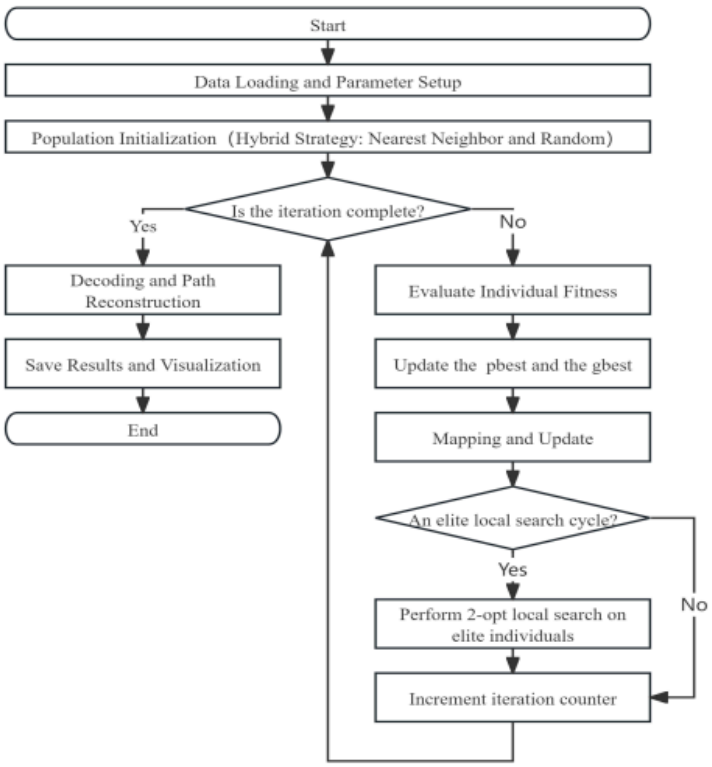

Figure 1. The main steps of the GILS-PSO algorithm

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4. Simulation experiments and result analysis

To evaluate the performance of GILS-PSO algorithm for UAV 3D path planning, a simulation environment with static obstacles and predefined waypoints is constructed in MATLAB. First, the A* algorithm is employed to precompute the shortest obstacle-free path between any two waypoints, forming a path cost matrix for subsequent algorithmic evaluation. The GA [3, 4], standard PSO [5], and GILS-PSO algorithms are then tested under identical conditions, with key parameters such as population size and maximum iterations kept consistent across all methods. The detailed parameter settings are listed in Table 1. During the experiments, the optimal path length in each generation is recorded to plot convergence curves, and 3D path visualizations are generated for qualitative comparison. The algorithms are assessed in terms of both convergence behavior and path optimization performance.

Table 1. Parameter settings of algorithms

Algorithm	Parameters
GA	$P_{crossover} = 0.9$, $P_{mutation} = 0.4$, $Tournament_k = 3$
PSO	$\omega = 0.8$, $c_1 = 1.0$, $c_2 = 2.0$
GILS-PSO	ω_{max} , ω_{min} , $c_1 = c_2 = 1.5$

The core optimization objective of the path planning problem is to minimize the total path length, which is defined as:

$$len = D\left(1, order\left(1\right) + 1\right) + \sum_{i=1}^{n-1} D\left(order\left(i\right) + 1, order\left(i+1\right) + 1\right) \tag{6}$$

where Len is the total flight path length of the UAV; $D\left(i, j\right)$ refers to the shortest distance between waypoint $i$and waypoint j. This distance matrix is calculated in advance with the astar algorithm. $order\left(s\right)$denotes the number of the sth accessed waypoint. It contains the overall arrangement information of the whole waypoint visiting sequence.

The convergence curves of the three algorithms are presented in Figure 2. The standard PSO converges rapidly in the early iterations but falls into local optimum around the 20th generation, with the final path length stabilizing at approximately 589 [5, 6]. The GA exhibits a slower convergence process, reaching stability around the 180th generation with a final path length of about 450 [3, 4]. In contrast, the GILS-PSO converges around the 100th generation, with the final path length stabilizing at approximately 340. Compared with the standard PSO and GA, the path length obtained by GILS-PSO is reduced by about 42.3% and 24.4%, respectively. Meanwhile, the proposed algorithm avoids the premature convergence issue of standard PSO and achieves a faster convergence rate than GA.

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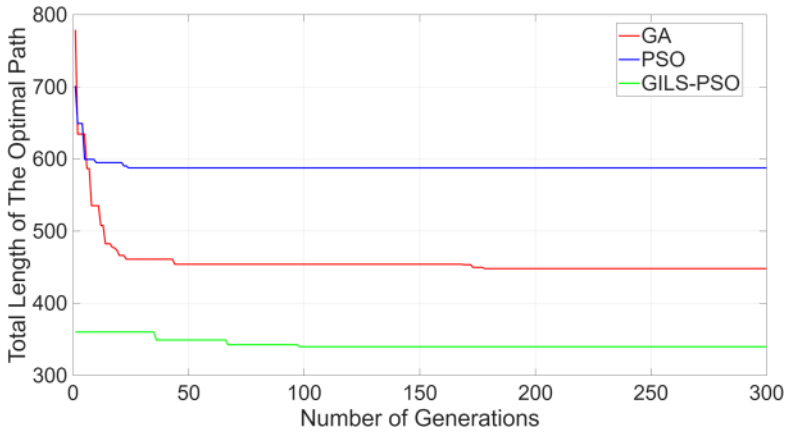

Figure 2. Convergence curves of GA, PSO and GILS-PSO

The 3D optimal paths generated by GILS-PSO are visualized in Figure 3. It can be intuitively observed that the path generated by the GILS-PSO algorithm shows better performance in obstacle avoidance and path smoothness, further verifying its feasibility and superiority in 3D path planning [1, 2, 13].

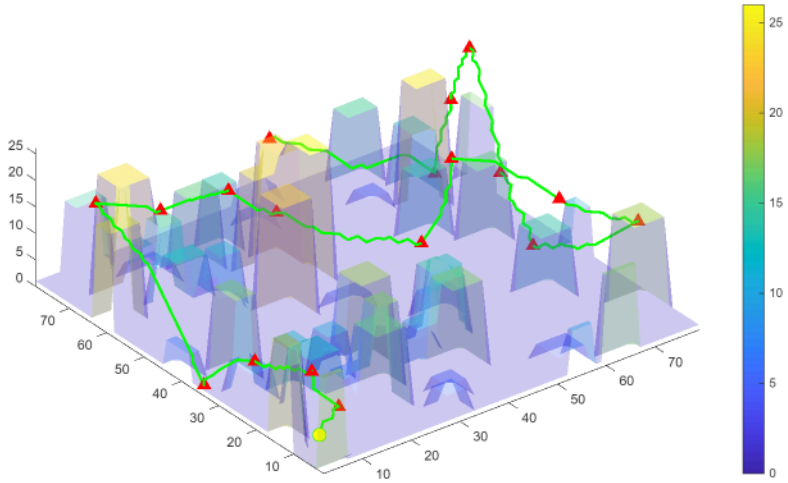

Figure 3. 3D optimal path visualization

Based on the path planning results, the optimal path generated by the GILS-PSO algorithm is imported into a quadrotor UAV simulation system with cascade PID control. The architecture of the system is illustrated in Figure 4. The system adopts a position outer-loop and attitude inner-loop double closed-loop control structure, and solves the UAV dynamic model using the Runge-Kutta numerical method to track the predefined waypoints [12].

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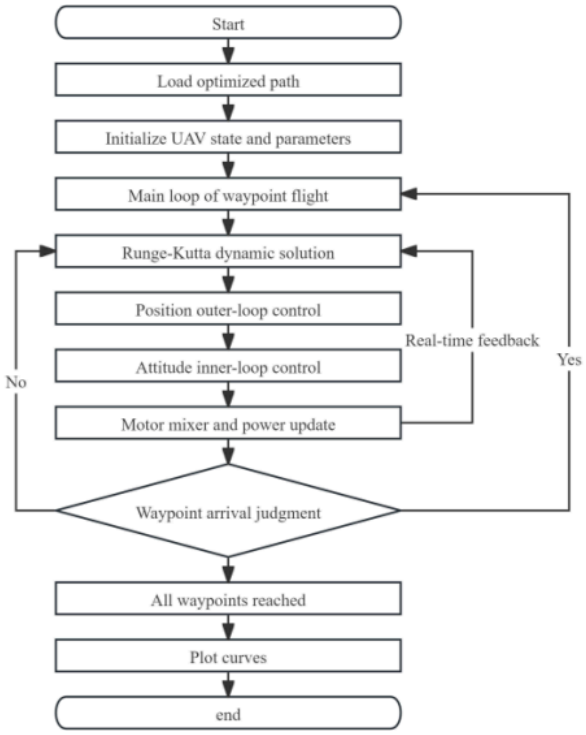

Figure 4. Quadrotor UAV simulation framework

During the simulation, the 3D position, linear velocity, attitude angles, and angular rates of the UAV are recorded and plotted, as shown in Figure 5 to Figure 8. The curves show that the UAV maintains small position tracking errors, smooth linear velocity variations, and reasonable fluctuations in attitude angles and angular rates without severe oscillations or overshoots. The results demonstrate that the cascade PID controller can stably track the path planned by GILS-PSO, with stable and timely response of the UAV motion states, verifying the feasibility and practical value of the paths generated by the proposed [12] algorithm.

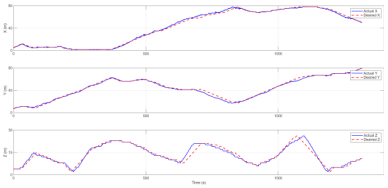

Figure 5. Position response

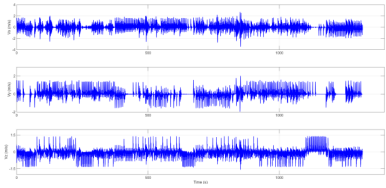

Figure 6. Linear velocity response

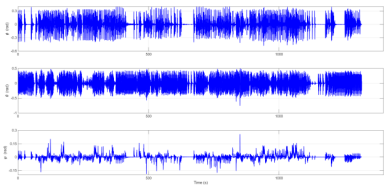

Figure 7. Attitude angles response

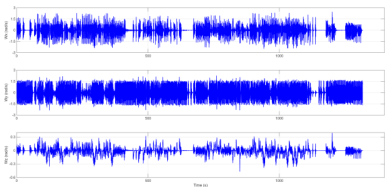

Figure 8. Angular velocity response

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5. Conclusion

This paper proposes a GILS-PSO algorithm for UAV 3D path planning with four improved strategies. It effectively solves premature convergence and low optimization accuracy of traditional PSO. Simulations are carried out in a MATLAB-built 3D static obstacle environment. The algorithm converges stably at the 100th generation, with path length reduced by 42.3% and 24.4% compared with standard PSO and GA respectively. Cascade PID quadrotor simulation verifies the path feasibility. Future work will focus on dynamic obstacle scenarios, multi-UAV cooperative planning and hardware-in-the-loop simulation.

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