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Adaptive sensitivity decision based path planning algorithm for unmanned aerial vehicle with improved particle swarm optimization

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Automatic path planning is an essential aspect of unmanned aerial vehicle (UAV) autonomy. This paper presents a three dimensional path planning algorithm based on adaptive sensitivity decision operator combined with particle swarm optimization (PSO) technique. In the proposed method, an adaptive sensitivity decision area is constructed to overcome the defects of local optimal and slow convergence. By using this specified area, the potential particle locations with high probabilities are determined and other candidates are deleted to improve computational capacity. Then the searching space of particles is constrained in a limited boundary to avoid premature state. In addition, the searching accuracy is enhanced by the relative particle directivity from current location. The objective function is redesigned by taking into account the distance to destination and UAV self-constraints. To evaluate the path length, the paired-sample T-Test is performed and the straight line rate (*SLR*) index is introduced. In the two scenarios applied in this paper, our proposed method is 35.4%, 21.6% and 49.5% better compared with other three tested optimization algorithms in the path cost on average. Correspondingly it is 9.6%, 12.8%, and 25.3% better in *SLR*, which is capable of generating higher quality paths efficiently for UAVs.

1. Introduction

Unmanned aerial vehicle (UAV) is an aircraft without pilots onboard that can be remotely controlled or can fly autonomously based on preprogrammed flight plans [1], which is an irresistible trend in the future. Due to their capabilities to work remotely and under extremely hazardous environments [2], the UAV is widely used in both civil and military tasks.

UAV path planning is one of the most important techniques in the autonomous process [3,4], and it has become especially crucial when UAVs were to be integrated into national airspace system (NAS). Path planning is often treated as a global optimization problem with mission, environment and UAV physical constraints. The optimality of a feasible path can be defined by different optimization criteria and fulfillment of mission constraints.

In the past few years, series of path planning algorithms have been proposed. Graph-based is one kind of such effective methods, including Voronoi diagram searching method [5], mathematical programming [6], A^* searching and D^* lite algorithm [7,8], and bi-level programming [9]. They all use an Eppstein's k-best algorithm [10] to find the optimal path. But it is difficult to consider the motion constraints of UAVs, which means it usually cannot be used in practical situations [11]. UAV self-constraint is indispensable when designing a flying path. Another category of path planning method, namely population-based evolutionary algorithm, can overcome these defects. It is believed to be an efficient and effective optimization technique to solve path planning problems, including genetic algorithm (GA) [2,3], particle swarm optimization (PSO) [11,12], firefly algorithm (FA) [13], ant colony optimization (ACO) [14,15], artificial bee colony (ABC) [16], differential evolution (DE) [17], memetic computing method [18] and their improved versions. For their simplicity and effectiveness, GA, PSO, and FA are the most popular and used in global optimization problem. GA is effective for its ease of implementation in both continuous and discrete problems and no extra requirements for the continuity in response functions. Many other improved GA techniques have been analyzed [5]. FA is recently developed to solve non-linear problems. All fireflies are unisexual and any individual will be attracted to others with higher brightness. Their brightness decreases as their mutual distance increases. By iterations of brightness ori-

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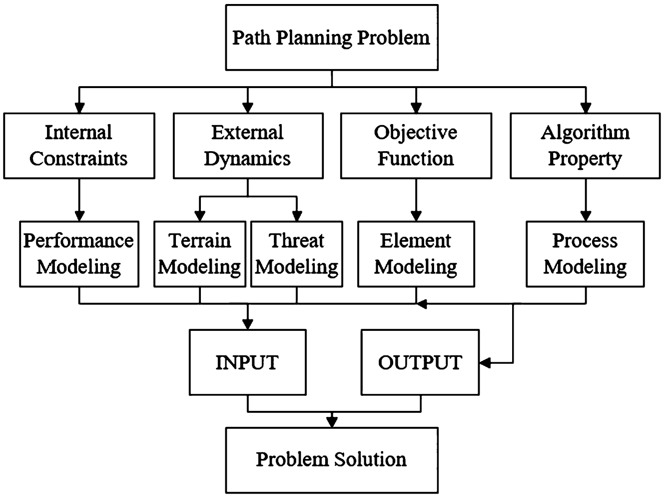

Fig. 1. Overall workflow of UAV path planning problem.

ented movements, the global optimal solutions can be achieved. Other FA related methods have been proposed [19].

Particle swarm optimization (PSO) is an evolutionary algorithm first proposed by Kennedy and Eberhart [12]. It is based on social behavior of bird schoolings. Each particle adjusts its flying position in the searching space in terms of its own flying and the whole swarm's flying experiences. Successful applications demonstrated that PSO is a promising and efficient optimization method. Many significant improvements were proposed [20]. However, PSO easily falls into premature and local optimal algorithms. The searching ability deteriorates in subsequent iterations, which lead to low accuracy of convergence and in some extreme situations solutions cannot be obtained.

The main contribution of this paper is that it develops an optimization algorithm to solve the UAV path-generation problem, which can be suited in complicated environments [21]. An adaptive sensitivity decision operator combining PSO is designed. The defects of local optimal and slow convergence in PSO are solved by formulating this operator for each particle. The searching space of particles is constrained, which shortens the computation time and gets a higher accuracy of convergence compared with GA and FA. The objective function is redesigned by considering UAV self-constraints and distance to destination, which is more close to the actual scenarios than the graph-based ones. Experimental results demonstrate that the proposed method is capable of generating higher quality UAV paths more efficiently than other approaches.

2. Problem description

The path planning problem is illustrated in Fig. 1. There are four crucial parts, namely internal and external feature descriptions, objective function design and algorithm realization. The internal and external features include UAV performance settings, terrain and threat modeling. The UAV self-constraints are taken into account, such as flight altitude, minimum distance to the ground and so on. The characteristics of the flying space and threats are set in advance, including geographical range, topographical conditions, threat locations, threat levels, and so on. The objective function considers all the necessary elements that could influence the qualities of generated path, and how they influence the performances. Combining with PSO, a more applicable algorithm is proposed considering all the parts above. Finally, the process of algorithm is implemented and outputs the global optimal flying path, which could be followed by UAVs.

2.1. Terrain and threat modeling

External dynamics contains a set of limitations that are dictated to UAV's flying environment. Terrain features and threat areas are described in the following.

(1) Terrain modeling

In path planning problem it is reasonable to assume that the terrain constraint is known in advance and how to deal with a large amount of 3D terrain data is a key problem, especially when interpolation is made repeatedly to obtain elevation at various geographic locations. In this paper the cardinal spline [22] is taken into account for better local control, which overcomes the cubic splines. There is no need to solve a set of linear algebraic equations, which could be cumbersome by itself [23]. The cardinal splines can make a specified curve passing through all the control points, which is different from other types of splines.

The planned UAV path should not go through into the terrain and must avoid all the mountains or obstacles in 3D environment. The solutions should be penalized to have at least one point of the spline path inside the terrain. The total number of waypoints falling into the terrain can be denoted by J_{hit} with the following equation [24].

$$J_{hit} = \sum_i A_i \quad A_i = \begin{cases} 1 & \text{if } z_i < f(x_i, y_i) \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

where A_i is binary, which is determined by z_i and $f(x_i, y_i)$. $f(x_i, y_i)$ returns the altitude of terrain at any point (x_i, y_i). Correspondingly z_i is the UAV flight altitude at (x_i, y_i).

(2) Threat modeling

The deterministic threat is considered in this paper, such as radar, artillery, missile and so on. Once an UAV flies in the scope of threats, it has a probability to be found or taken down. Here a cylinder model in space is defined as a threat area with coordinate vector $P_T = [x_T \ y_T \ h_T \ r_T]^T$, where $(x_T \ y_T)^T$ is the center on the XOY plain, h_T is the covered height and r_T is the detected range. The exposure function for an UAV with coordinate $(x_U \ y_U \ z_U)^T$, is defined in equation (2).

$$J_{in} = \begin{cases} \frac{r_T^2 h_T}{(d_{XOY}^2 - z_U^2) z_U} L_T \\ \quad \text{if } z_U < h_T, \sqrt{(x_U - x_T)^2 + (y_U - y_T)^2} < r_T \\ 0 \quad \text{otherwise} \end{cases} \tag{2}$$

where $d_{XOY} = \sqrt{(x_U - x_T)^2 + (y_U - y_T)^2 + z_U^2}$ is the distance between UAV's current position and the threat center on XOY plain. L_T is the threat level of the corresponding threat.

(3) Flying map limits

In practical applications, each waypoint must be inside of the appointed flying space, out of which will be penalized. The following equation is defined to record the number of waypoints outside of the specified flying space.

$$J_{out} = \sum_i B_i \quad B_i = \begin{cases} 1 & (x_U, y_U, z_U)^T \notin S_F \\ 0 & \text{otherwise} \end{cases} \tag{3}$$

where S_F denotes the permitted flying space and is designed as a cube with fixed side length. $(x_U, y_U, z_U)^T$ is the position of UAV.

2.2. Path representation

The definition of path panning problem is a key task. The general definition is the creation of a plan to guide a point-like UAV from its starting location to a preset destination point [25]. The model used in our algorithm is shown in Fig. 2.