AN OVERVIEW OF PATH PLANNING TECHNOLOGIES FOR UNMANNED AERIAL VEHICLES

by

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Unmanned aerial vehicles, due to their superior maneuverability and reduced costs can easily perform tasks that are too difficult and complex to be performed with manned aircraft, under all conditions. In order to cope with various obstacles and operate in complex and unstable environmental conditions, the unmanned aerial vehicles must first plan its path. One of the most important problems to investigated in order to find an optimal path between the starting point and the target point of the unmanned aerial vehicles is path planning and choosing the appropriate algorithm. These algorithms find the optimal and shortest path, and also provide a collision-free environment for unmanned aerial vehicles. It is important to have path planning algorithms to calculate a safe path to the final destination in the shortest possible time. However, algorithms are not guaranteed to provide full performance in each path planning situation. Also, each algorithm has some specifications, these specifications make it possible to make them suitable in complex situations. Although there are many studies in path planning literature, this subject is still an active research area considering the high maneuverability of unmanned aerial vehicles. In this study, the most used methods of graph search, sampling-based algorithms and computational intelligence-based algorithms, which have become one of the important technologies for unmanned aerial vehicles and have been the subject of extensive research, are examined and their pros and cons are emphasized. In addition, studies conducted in the field of unmanned aerial vehicles with these algorithms are also briefly mentioned.

Key words: *unmanned aerial vehicle, path planning, sampling-based algorithms, graph search, computational intelligence-based algorithms*

Introduction

Unmanned aerial vehicles (UAV) is a semi-autonomous aerial vehicle that can be remotely controlled and operated using the electronic intelligence and control subsystem. In recent years, the continuous improvement of the capabilities of UAV allows UAV to easily perform many time-consuming tasks in complex environments due to artificial intelligence-based algorithms, low cost sensors, enhanced computational capacity and significantly improved cost performances. The UAV navigation aims to guide a UAV to desired points along a collision-free and efficient path without human intervention. In recent years, UAV have come to the fore with their maneuverability for tasks that are too difficult and complex to be performed with manned aircraft. At this point, the first problem to be solved in order to ensure a certain level of autonomy is path planning (PP). In previous years, the best path was chosen according to the shortest

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distance between the starting point and target point. But nowadays, in determining the best path, not only the path traveled but also energy consumption*, etc.* situations are also effective [1]. Considering more parameters besides the distance, we can express the PP problem as a multi-objective optimization problem. In recent years, the popularity of UAV has increased and they have been widely used for different purposes. While UAV are limited to primarily military uses, they are also widely used in commercial and industrial areas due to the increase in power and technology capacities of these vehicles [2]. The potential applications of UAV include optical remote sensing [3], real-time vehicle detection [4], disaster management [5], data collection for scientific research [6], aerial forest fire detection [7], *etc.* can be given as an example. In parallel with the widespread use of UAV in many different fields, the problem of PP has become a very important research subject. A PP problem is about finding a flyable path between the starting and target location while safely passing obstacles in the underlying 3-D environment map, simultaneously meeting one or more optimization objectives such as time, distance and energy consumption [8]. During its flight to fulfill a mission, the UAV needs to analyze its position, environment, obstacles and other essential information calculate and find the safest path. Depending on the complex and different scenarios and environments in which UAV operate, choosing appropriate algorithms for PP is an important issue and extensive research is being conducted in this area [9]. Although there are many types of UAV PP algorithm (PPA), PP still faces many problems during the actual flight of UAV. Although graph search algorithms have powerful search capabilities, the success of PP rate can be low in the unknown environmental conditions. Computational intelligence-based algorithms respond faster than graph search algorithms and can better handle UAV in dynamic environments. Therefore, hybridization is a suitable method to combine the advantages of different algorithms. In this study, the most used methods of graph search, sampling-based algorithms and computational intelligence-based algorithms, which have become one of the important technologies for UAV and have been the subject of extensive research, are examined and their pros and cons are emphasized. In addition, studies conducted in the field of UAV with these algorithms are also briefly mentioned.

Path planning

The PP is a necessary activity for autonomous vehicles and robots, the process of using accumulated sensor data and initial information enable it to find the best path to reach a target location. The main purpose of UAV PP is to find the optimal flight path of more than one UAV between the start and destination points in a safe, efficient and minimum cost, without colliding with obstacles in the environment and without entering the no-fly zone [10]. The PP problem for UAV is particularly difficult. For example, the dynamic limitations of the UAV, such as the minimum turning radius, should be considered in the PP process. The PP process must consider the sensor footprint as the aircraft follows a path, as well as aircraft dynamics [11]. There may be several places to visit before the UAV arrives at the target point, therefore, a consecutive paths may be required. Usually there will be several predefined points of interest on a known or partially known area/map [12]. The most important difference between general PP and UAV PP is that the UAV path search space is a 3-D space. As a result, the search range is a larger and more difficult problem to solve. Also, the PP problem is an NP-Hard problem with a continuous path finding task connecting a UAV from the starting point to the target point. The UAV PP problem is a typical constrained optimization problem. In order to plan a path for a UAV, many important factors should be considered such as its dynamics, the environment of the mission area, the safety and cost of the path. These factors exist either as an objective function that must be maximized or minimized, or as constraints that the path must conform to [10]. The two most important constraints for a UAV PP are that the path must be flyable and safety. The flyable of the paths satisfies the kinematic or movement constraints and determines the maneuverability of the UAV. The safety of the UAV is ensured by avoiding moving or fixed obstacles [12]. The PP consists of the two main steps: firstly, compilation of all available information in an effective and convenient configuration space, secondly, using a search algorithm to find the best path in space [2]. The PP problem is divided into two as online and offline PP [13]. Figure1 shows a PP model [14] as an example. Let the starting point be $P_S = (x_S, y_S)$ and the target point $P_t = (x_t, y_t)$ in the planning space 0_{xy}. Initially, P_S and P_t are connected by a straight line, and P_SP_t is evenly divided by $D + 1$. A line is then drawn perpendicular to P_SP_t at each segment point. Let us denote this set of lines as $L_1...L_d...L_D$. The $C = \{P_S, P_1,...P_d...P_D, P_t\}$ one point is selected from each line forming the set of discrete points, where $P_d = (x_d, y_d)$. The path is obtained by combining these selected points in succession. Then, the PP problem can be considered as the optimization of the co-ordinate series. The model can be simplified by transforming. The initial co-ordinate system 0_{xy} is converted to the new $0'_{x'y'}$ where P_S is the origin and P_SP_t is the x-axis. Then, the set C at $0'_{x'y'}$ is redefined as $C' = \{P'_S, P'_1,...P'_d... P'_D, P'_t\}$, where, $P'_S = (0, 0)$, $P'_1 = (x'_1, y'_1)$, $P'_d = (x'_d, y'_d)$, $P'_D = (x'_D, y'_D)$, and $P'_t = (|P_SP_t|, 0)$. Thus, the x-co-ordinate of any P'_d point is $x'_d = d/(D + 1)|P_SP_t|$ is expressed as a constant. Therefore, the process is reduced to optimizing only the y-co-ordinates, namely $\{y'_1...y'_d...y'_D,\}$. As a result, the amount of computation is significantly reduced [15].

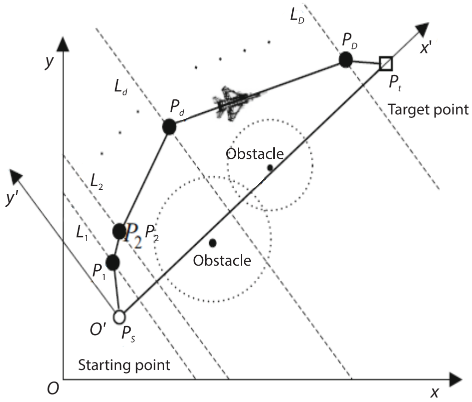

Figure 1. The model of PP [15]

Path planning algorithms

Graph search

The main idea of graph search algorithms are subclasses of search algorithms that aim to create tree-like paths to get from the starting point to the target point. These algorithms perceive the environment as vertices and nodes and are usually implemented in discrete and sparse environments. The most commonly used graph search algorithms are given.

Voronoi diagram

The Voronoi diagram (VD) used for roadmaps is a connected graph created by forming polygons around obstacles. It also defines nodes that are equidistant from all points surrounded by obstacles. It is used to divide the surface into zones based on the distance to waypoints in a given plane, as shown in the fig. 2. First, each edge of the polygons is created by drawing a series of lines perpendicular to the lines joining the center of the obstacles. They are then adjusted to meet at the minimum set of vertices. A search

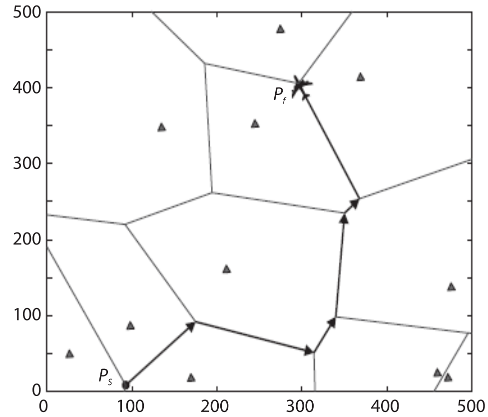

Figure 2. The VD: polygonal fences around obstacles [12]

algorithm such as A^* can then be used to find a path connecting the first and final vertex [12]. The path created as a graph from the VD is quite safe as the obstacles are far away on all sides of the path. Chen *et al.* [16] used VD to design roadmaps and find obstacles, and also proposed the coherence theory for optimality of UAV. Shen *et al.* [17] proposed a version of the VD to divide the low altitude sharing area into multiple areas [18]. In fig. 2, obstacles are represented by points and possible flight paths by lines. The VD can be defined: $P = \{p_1, p_2,..., p_i,..., p_n\}$ be the set of points called sites in a 2-D Euclidean plane. A VD divides space into regions around each site. Here, all points in the region around p_i are closer than any point in P. The Voronoi region $V(p_i)$ for each p_i is denoted:

$$V\left(p_i\right)=\left\{x:\left|p_i-x\right|\leq\left|p_j-x\right|,\forall j\neq i\right\} \tag{1}$$

The $V(p_i)$ region consists of all points that are closer to p_i than any other site. The region set of all sites forms the VD $V(P)$ [19].

The A^* algorithm

The A^* algorithm, introduced by Hart *et al.* [20], is a popular graph PPA. The A^* is an informed incremental heuristic search algorithm, or a common type of best-first search, that consists of an iterative process. The algorithm runs based on the lowest cost static path tree from the starting point to the final target point. In this sense it is a modification of Dijkstra's [21] algorithm and runs similarly. The purpose of A^* algorithm is to find the shortest path and directs its search towards the shortest path states with a heuristic function. Thus, the efficacy of the A^* algorithm is better than Dijkstra [22]. This algorithm is used in some cases in the dynamic environments. The A^* algorithm uses the least cost path and evaluates this cost:

$$f\left(n\right)=g\left(n\right)+h\left(n\right) \tag{2}$$

where n is the location of the UAV, $f(n)$ – the cost of the path from the starting point to the target point, $g(n)$ – the actual cost from node n to the first node, and $h(n)$ – the heuristic function that estimates the cost of the optimal path from n nodes to the target node. The heuristic is the minimum cost evaluation value of the A* algorithm from any node to the target node. This function also helps to reduce the number of passing nodes. Thus, the selection of the heuristic function has a direct effect on the efficacy of the algorithm. Euclidean distance, Manhattan distance, Chebyshev distance and diagonal distances can be used as heuristic functions of the algorithm. These distances are given by the following eqs. (3)-(6), where (x_p, y_p) is the co-ordinates of the target node and (x_q, y_q) is the co-ordinates of any node.

Manhattan distance heuristic function:

$$h\left(n\right)=\left|x_p-x_q\right|+\left|y_p-y_q\right| \tag{3}$$

Eucklidean distance heuristic function:

$$h\left(n\right)=\sqrt{\left(x_p-x_q\right)^2+\left(y_p-y_q\right)^2} \tag{4}$$

Chebyshev distance heuristic function:

$$h\left(n\right)=\max\left(\left|x_p-x_q\right|,\left|y_p-y_q\right|\right) \tag{5}$$

Diagonal distance heuristic function:

$$h\left(n\right)=\left|x_p-x_q\right|+\left|y_p-y_q\right|+\left(\sqrt{2}-2\right)\min\left(\left|x_p-x_q\right|,\left|y_p-y_q\right|\right) \tag{6}$$

Considering its efficiency suitable for working in embedded systems, it is a much simpler and less computational algorithm than many other PPA. It provides the shortest paths by finding the optimal path with heuristic information. However, the computation time and memory requirement increase exponentially with the complexity of the map. With the A^* algorithm, UAV PP and obstacle avoidance, robot PP, intelligent transportation*, etc.* There are many studies in the literature in the field. Zhang *et al.* [23] proposed a heuristic for matching and parametric analysis using the A^* algorithm in the target planning phase. Gupta *et al.* [24] showed in their study that multiple UAV can overcome the single UAV failure problem during reconnaissance and surveillance, and they used the A^* algorithm for multiple UAV. Li *et al.* [25] suggested the using of the A^* algorithm to find the optimal path.

The D^* lite algorithm

A version of the D^* algorithm [26] is the D* Lite algorithm [27], it is not based on the original D^* but implements the same behaved. The D^* Lite is a dynamic graph search algorithm that can be used to solve hypothetical PP problems. It is a widely used algorithm for UAV, mobile robot and autonomous vehicle navigation. The D^* Lite is an algorithm that uses implicit search tree notation built on LPA* [28], an incremental heuristic search algorithm. The D^* Lite algorithm searches from the proposed vertex to the current vertex of a robot and uses heuristics for this. In case of encountering previously unknown obstacles, the algorithm will efficiently re-plan a new shortest path from its current location a specific target location if necessary. If the target location does not change and new obstacles are discovered frequently, D^* is more efficient than repeated A^* searches. Koenig and Likhachev [27] experimentally proved that D^* Lite has a strong algorithmic basis on rapid re-planning methods in artificial intelligence and robotics. The results in [27] show that in practice D^* Lite runs faster than the original D^* algorithm. The D^* and D^* Lite inherit the completeness and optimality characteristics of the A^* algorithm on which they are built. Also, compared to other variants of the D^* algorithm, D^* Lite is easier to understand. Starting from the target node S_{goal}, D^* Lite searches the collision-free space up to the starting vertex of S_{start}. The algorithm stores the estimated distance between each vertex $g(s)$ and the distance between each vertex and the target $rhs(s)$. The *rhs*-values are estimated:

$$rhs(s)=\begin{cases} 0 & s=s_{\mathrm{goal}} \\ \min_{s'\in succ(s)}\left(g(s')+c(s,s')\right) & \text{otherwise} \end{cases} \tag{7}$$

where s' is the neighbor of s, and $succ(s)$ are vertices that extending from s and $c(s, s')$ – the transfer cost from s to s'. If $g(s)$ is equal to $rhs(s)$, s is locally consistent, otherwise, it is locally inconsistent [29].

Sampling-based path planning methods

Sampling-based methods consist of rapidly exploring random trees (RRT) and probabilistic road map (PRM) and their versions. These methods require some predefined information of the workspace according to the 3-D environment, and they also rapidly generate optimal global solutions or near-optimal solutions. Because of their algorithmic simplicity, these methods are suitable for solving both single-query and real-time PP problems [8-18].

Probabilistic roadmap method

The PRM, a roadmap algorithm for UAV PP, was introduced by Kavraki *et al.* [30]. PRM consists of random nodes connected by straight edges. The PRM algorithm consists of two steps. The first is the learning phase. At this phase, nodes in the motion space are randomly sampled and adjacent nodes are searched at each node. Next, nodes are connected to create a collision-free roadmap. The second stage is the query phase. At this phase, heuristic search algorithm is used to search for feasible paths from the roadmap based on the starting point, destination point and roadmap information. The PRM method can avoid obstacles effectively, and it has also been reported to be a suitable method for solving motion planning problem in high dimensional space, even though it is based on Dijkstra's algorithm. However, in some applications, pre-computing a roadmap can be computationally challenging or even infeasible. If the number of iterations is not high enough, a feasible way may not be found. The thick line in fig. 3 shows that in roadmaps, the shortest path from source to destination is called PRM [18].

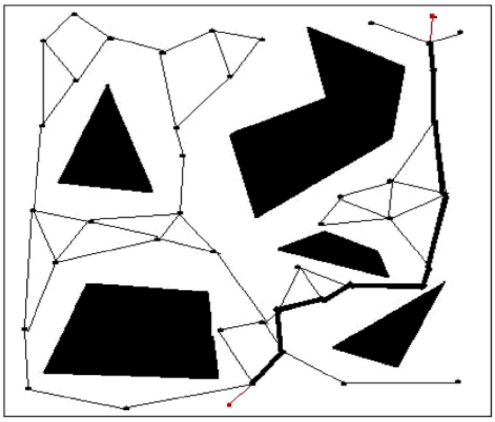

Figure 3. The PRM [18]

Rapid-exploring random trees

The RRT algorithm, a well-known method in the field of PP, was first introduced by LaValle in [31]. The RRT is a sampling-based method to solve the optimal PP problem. The algorithm has good performance and does not require a parameter tuning in applications as an incremental sampling search method. For the RRT to find a path, a given starting point and target must exist in the work area. The RRT is a tree growing algorithm that grows a tree from the starting point to the target point or from the target point to the starting point. This method quickly builds its tree to find its paths. Taking the starting point as the root node, a search tree is constructed by randomly removing the leaf nodes and the search tree can be extended over the entire space to find the target path. Starting from the first node, it starts generating a random node in the workspace and based on the distance between the nodes. It then chooses the node with the minimum distance from this random node in the tree. Meanwhile, the distance between the nodes, called the step size, is predefined. These nodes are added to the tree one by one and the process is repeated until the target point of all obstacle avoidance. The whole process eventually creates a tree-like structure and hence it is called rapid exploring random tree algorithm. There are many extended versions of RRT that are used in different applications. In addition, this algorithm is conceptually simple and very easy to implement. Although the algorithm can achieve probabilistic completeness, it is not guaranteed to reach optimality [32]. Also, the execution time and increased computation time with an unknown convergence rate can cause problems. Figure 4 shows the PP mechanism of the basic RRT algorithm in the presence of obstacles. The x_{init} is the starting node and x_{rand} is the target node. By collision detection of random sampling points in the

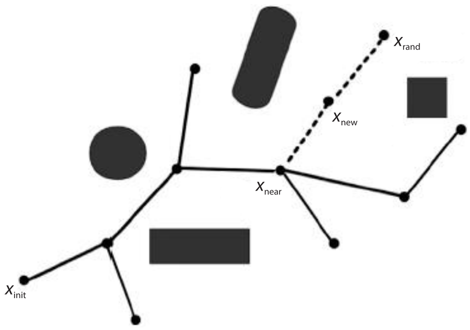

Figure 4. The PP mechanism of the basic RRT algorithm in the presence of obstacles [33]

state space, the nearest node x_{near} to the target node can be found, expanding the node x_{new} into the open undetected area [33].

In the field of UAV, Devaurs *et al.* [34] introduced an improved algorithm suitable for processing PP with threat zone and dynamic constraint. In this developed algorithm, the RRT algorithm was modified by deleting unnecessary nodes and creating a transition trajectory that increases the safety and maneuverability of the UAV. Li and Shim [35] propose a PPA based on RRT for fixed-wing drones UAV. Yang *et al.* [36] proposed an improved RRT algorithm for the obstacle avoidance problem.

Computational intelligence-based algorithms

Computational intelligence-based methods is a nature-inspired computational approach. Like graph-based methods, they are more useful in complex environments where mathematical modelling is not useful. They are also very effective methods to deal with uncertainty in PP.

Ant colony optimization

Ant colony optimization (ACO) was first introduced by Dorigo *et al.* [37, 38]. The ACO, like particle swarm optimization (PSO), is a heuristic optimization and probabilistic method that focuses on ant colony activity in foraging and creating paths after finding the source. In search of food, ants wander randomly, releasing a volatile chemical substance known as a pheromone on its trail and use it as feedback to get back to the nest. Path selection in other ants is based on the pheromone trail. The path that the ants travel the most contains the most pheromones and therefore, helps the next ant to choose the shortest path. The main idea behind the ACO algorithm, as mentioned previously, is that it uses the behavior of a single ant to represent a feasible solution the path optimization problem, and the behavior of the entire ant colony forms the solution space of the problem. As time goes on, the pheromone concentration accumulated in the shorter paths increases and this causes an increase in the number of ants that choose the path. As a result, all the ant will concentrate on the best path with positive feedback and the corresponding solution is the optimal solution the path optimization problem [13]. The ACO, an intelligent optimization algorithm, and its variants is a population-based evolutionary algorithm and can achieve global optimization through a parallel random search algorithm. According to different features of the problem, probabilistic heuristic algorithms have been developed to find the shortest path. The adaptive ACO algorithm has good global optimization ability and exhibits better optimization performance compared to other variants of the ACO algorithm [39]. The ACO has strong robustness compared to other heuristic algorithms as well as a better solution search ability. The algorithm has good scalability and can be used in dynamic applications. However, the convergence speed of the algorithm is slower in solving complex problems compared to other heuristic algorithms and requires a large number of parameters for tuning, resulting in high computational complexity. Convergence is guaranteed, however, the convergence time becomes uncertain as the complexity of the search space increases. The ACO algorithm has great and significant potential to accelerate and solve many complex tasks such as UAV PP and robot dynamic PP problems. In PP for UAV, ACO algorithms are often implemented by dividing a flying area into a grid and optimizing a path between a grid point and target point [13]. Consider a UAV flying from takeoff to destination using edges. In this case, the following assumption helps to choose the next edge of the path.

Assumption: Suppose k^{th} ant is at a node at time, t, the probability of transition is given:

$$p_{a,b}^{k}(t)=\frac{\tau_{a,b}^{\alpha}(t)\,\mu_{a,b}^{\beta}(t)}{\sum\limits_{b\in\text{accept}(a)}\tau_{a,b}^{\alpha}\mu_{a,b}^{\beta}(t)} \tag{8}$$

where $p^k_{a,b}(t)$ is the transition probability of the k^{th} ant from node a to node b, $\tau_{a,b}(t)$ – the pheromone at the edge (a, b), $\mu_{a,b}(t)$ – the feasibility of the transition from node a to node b, and accept(a) – the set of neighboring nodes of a. The α is the parameter controlling the effect $\tau_{a,b}(t)$ and β – the parameter controlling the effect $\mu_{a,b}(t)$. At the beginning of the algorithm, the initial pheromone ratio changes with respect to the edges. Then each ant that produces the result starts the next cycle of the algorithm and then resets the pheromone rate. The pheromone $\tau_{a,b}(t)$ at the edge (a, b):

$$\tau_{a,b}(t+1)=(1-\rho)\tau_{a,b}(t)+\sum_{k=1}^{m}\tau_{a,b}^{k}(t) \tag{9}$$

where ρ ($0 \leq \rho \leq 1$) is the evaporation rate of pheromone, m – the total number of ants, and $\Delta\tau^k_{a,b}(t)$ is the rate of pheromone at the edge (a, b) [40].

Zaza and Richards [41] applied a multi-colony approach based on ACO to minimize the delay time to complete the search and attack mission. The main challenge of using an ACO in a drone swarm for homing and attacking is path smoothing and pheromone updating. Gao *et al.* [42] introduced an iteration threshold in ACO to meet this challenge. Zhen *et al.* [43] proposed a hybrid approach of ACO and artificial potential field (APF) algorithm for collaborative mission planning of UAV swarm in an uncertain dynamic environment. Ma *et al.* [44] proposed an improved ACO algorithm for UAV PP in complex mountain areas for emergency rescue operation [45]. The new dynamic algorithm proposed by Huang *et al.* [46] combines potential field and ACO. While this algorithm takes into account both static and dynamic threats, it uses an artificial field to simulate the environment for collision-free PP for the UAV. Hao and Xu [47] integrated immune network optimization with ACO to improve the shortest path finding capability of a multi-UAV system for PP [32].

Particle swarm optimization

The PSO algorithm, introduced by Kennedy and Eberhart [48, 49], is a swarm intelligence-based optimization algorithm proposed to provide graphically simulation of group activity behaviors such as flocks of birds and groups of fish. In this method, each potential solution is considered as a particle with a random velocity and position in the search space, which is defined as the set of all probabilistic solutions for the problem to be optimized. Afterwards, continuously updates the position and velocity of each particle until the global best solution is found. Each particle gets its best position and velocity relative to the best solution (fitness) in the solution space. The i^{th} particle in the PSO algorithm updates its velocity and position at each T^{th} step:

$$V_i^{T+1}=WV_i^T+r_1C_1\left(P_{\text{best}}-X_i^T\right)+r_2C_2\left(G_{\text{best}}-X_i^T\right) \tag{10}$$

$$X_i^{T+1}=X_i^T+V_i^T \tag{11}$$

where X_i^T and V_i^T represent the position and velocity vector of the i^{th} particle in the swarm, W – the inertia weight to keep the balance between global and local search capability, and C_1, C_2 – the predefined by the user specifies the acceleration constant. The r_1 and r_2 are random numbers generated in the interval [0, 1] [45]. A representation of the PSO model is shown in fig.5. In fig.5, P_{best} is called the individual extremum, that is, the optimal solution that a particle finds. The G_{best} is called the global extremum, that is, the optimal solution in the whole swarm of particles. The whole process of the particle swarm optimization algorithm is to use the particles' velocity, V, current position X, P_{best} and G_{best} information iterate until an optimal solution is found [33]. Particle swarm algorithm is widely used in UAV PP problem. Although it is preferred in PP for target interception due to its low computational complexity, the local minimum can also get stuck [45]. In such problems, the motions of particles are guided by their best-known position in the search space and the best-known position of the entire swarm. As the optimized positions are calculated, they then guided the movements of each particle [13].

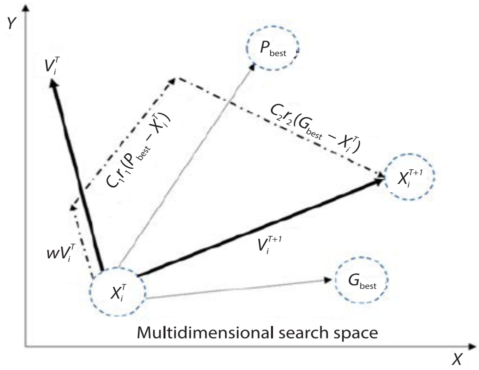

Figure 5. Representation of PSO model [45]

Shao *et al.* [50], the PSO developed in the study converged faster and produced an optimal solution. Dewang *et al.* [51] developed a method based on a new PSO called adaptive PSO and compared it with PSO in terms of path length and time in static settings. The method they developed reached the target in a shorter time compared to the traditional PSO method and successfully avoided obstacles [32]. Oh *et al.* [52] have proposed a modified version of PSO for interception moving targets by adapting graph theory in their work. Yihu and Siming [53] developed the adaptive particle swarm algorithm to prevent the UAV search path from falling into the local optimal solution.

Genetic algorithms

The GA is one of the intelligent optimization algorithms commonly used in UAV PP problems [8]. Discrete PPA, such as potential fields and grid-based methods, require significant memory and CPU performance. To overcome such problems and limitations, genetic algorithms are widely used in PP problems. The use of genetic algorithms provides advantages in terms of minimum memory requirement and efficient use of CPU resources, as well as covering a large search space and high processing capability. It also performs quite well in collision avoidance of the UAV swarm. However, it is not guaranteed that the solution found for the optimization problem will always be a global minimum. That is, the solution found may not always be the shortest path [39]. Low efficiency, high requirements for encoding, early-stage convergence and stagnation problem are other disadvantages [54]. In the application of GA in PP, the GA encodes the solutions of the optimization problem into chromosomes, that is, each PP candidate solution has a set of chromosomes or genotypes that can be mutated and changed. In each generation, GA evaluates the fitness of each solution in the population and keeps the chromosome in high fitness to the next generation. This process is repeated until the optimized solution is found. The fitness is usually the value of the objective function in the optimization problem [13-54]. According to the basic strategy of GA, the properties of the optimal path can be represented as objective functions [13]. Al-Taharwa *et al.* [55] explained the use of the GA approach in a PP problem in a non-dynamic environment. Arantes *et al.* [56] applied GA to PP during the emergency landing of UAV. As a result of their work, they showed that combining GA with a greedy approach would be beneficial for UAV PP. Liu *et al.* [57] expressed the PP problem of the UAV as a multi-objective optimization problem. In their work, proposed a new multigene structure to describe the way in which adaptive tuning, crossover and mutation strategies are adopted and adaptive differential multi-objective optimization algorithm is applied to avoid obstacles and achieve the optimal solution meet the flight constraints of the UAV. Oh and Suk [58] used genetic algorithm and evolutionary robot to develop the neural network controller for the obstacle avoidance problem in the multi-UAV scenario [54].

Conclusion

The UAV have many applications in different fields, from search and rescue, security and surveillance operations to product delivery and monitoring of forest lands. Research on UAV PP is discussed in three methodological categories: graph search approaches, sampling-based techniques, and computational intelligence-based algorithms. One of the biggest problems faced by autonomous UAV is obstacle avoidance. Many algorithms have been proposed in the literature that provide effective ways to deal with such problems. However, there are already some shortcomings and limitations that limit applications when operating in a large-scale geographic area. The PP is the most important and critical issue in the operation of UAV. In parallel with the rapid and continuous development of artificial intelligence, UAV PPA are constantly evolving. In this article, some of the most popular algorithms used in UAV PP are presented. At the same time, the advantages and disadvantages of each algorithm are briefly explained. In the study, studies in the literature related to the approaches described in three methodological categories are included. Each PPA has its own characteristics that make it applicable to different problems, and there are advantages of different algorithms. In many applications, there may be some shortcomings in using one of the existing algorithms. Therefore, hybrid methods obtained by improving algorithms and combining some of them are used in solving complex problems and more efficient solutions are obtained. As a result, researches on UAV PP in complex, dynamic and unsteady environments by combining different algorithms will be the main study subject of UAV PPA in the future.

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