A Review on Energy Efficient Path Planning Algorithms for Unmanned Air Vehicles

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Abstract. Unmanned Aerial Vehicle (UAV) is a type of autonomous vehicle for which energy efficient path planning is a crucial issue. The use of UAV has been increased to replace humans in performing risky missions at adversarial environments and thus, the requirement of path planning with efficient energy consumption is necessary. This study analyses all the available path planning algorithms in terms of energy efficiency for a UAV. At the same time, the consideration is also given to the computation time, path length and completeness because UAV must compute a stealthy and minimal path length to save energy. Its range is limited and hence, time spent over a surveyed territory should be minimal, which in turn makes path length always a factor in any algorithm. Also the path must have a realistic trajectory and should be feasible for the UAV.

Keywords: Energy efficient, UAV, Path planning, Optimal path.

1 Introduction

The use of UAVs has been increased to perform missions, such as weather forecasting, traffic control and rescue people [1]. The mission may be in a cluttered and obstacle-rich environment; for example in an urban area and hence, it is important for a UAV to adopt a path planning algorithm ensuring the traversed path to be collision-free and optimal in terms of path length. However, optimal path only is not enough as it may cause the UAV to consume more energy than a suboptimal one. Most common problem of UAV path planning is to fly from a given starting point to a target point through a set of obstacles [2]. These obstacles may not be fixed at one location and can pop up during the fly. An energy efficient path planning must ensure that the method/algorithm can create a safe and optimal path and, simultaneously can minimize the travel duration and save energy/fuel. This paper discusses different approaches of path planning which also considers the energy consumption and path length.

The configuration space (C-space), which is a most commonly used technique for path planning, provides detailed position information of all points in the system and is the space for all configurations. It assumes that the UAV as a point and adds the area of the obstacles so that the path planning can be done more efficiently. C-space is obtained by adding the UAV radius while sliding it along the edge of the obstacles

R. Alfred et al. (eds.), *Computational Science and Technology*, Lecture Notes in Electrical Engineering 481, https://doi.org/10.1007/978-981-13-2622-6_51

and the border of the search space. An illustration of a C-space for a circular UAV is shown in Fig. 1.

In Fig.1(a), the obstacle-free area is represented by the white background while the solid dark area represents the obstacles' region. The UAV is denoted by a black dot circled with gray color and three pre-planned paths are represented by dotted, semi-dotted and solid lines to reach the target/goal configuration Q_{goal} from start/initial configuration Q_{init} considering that the C-space is not created. Conversely, when the workspace is considered as C-space, as shown in Fig. 1(b), the UAV has only one feasible path. This also reveals that the free space Q_{free} has been reduced while the obstacles' region Q_{obs} has been increased. Therefore, C-space denotes the real free space area for the movement of UAV and ensures that the vehicle or UAV must not collide with the obstacle. The popularity of C-space method in path planning is due to its use of uniform framework to compare and evaluate various algorithms [4]. The UAV's or robot's path planning can be classified in three ways namely combinatorial, sampling based and biologically inspired methods as illustrated in Fig. 2.

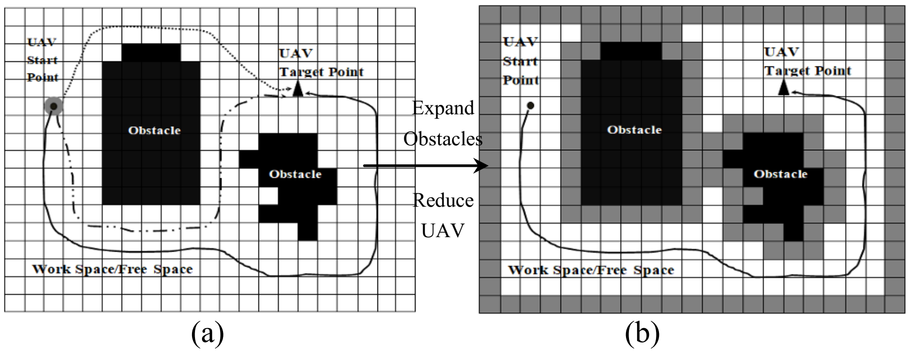

Fig. 1. Configuration space for a UAV path planning

2 Combinatorial Path Planning

Combinatorial method applies C-space concept to the workspace representation methods such as cell decomposition (CD), potential field (PF), visibility graph (VG) and Voronoi diagram (VD), to name a few, coupled with graph search algorithms like Dijkstra's, A-star, Breadth First Search and Depth First Search so that a collision-free energy efficient path can be found [5]. Researchers already proposed several techniques on path planning classified as roadmap method such as VG and VD, and other methods like CD and PF. The C-space representation allows efficient path planning techniques based on roadmap and cell decomposition to obtain a solution. The roadmap captures the connectivity within Q_{free} using a graph or network of paths. In a roadmap, nodes are considered as points in Q_{free} and two nodes are adjoined by an edge that must be within Q_{free}. A set of collision-free paths from an initial configuration Q_{init} to a goal configuration Q_{goal} builds the roadmap that uses several steps for path planning. Firstly, it connects the nodes with edges in free C-space area to build a network of graph. After that Q_{init} and Q_{goal} are associated with the network to conclude the roadmap. A series of line segments constructs a collision-free optimal path that can be explored within Q_{free}.

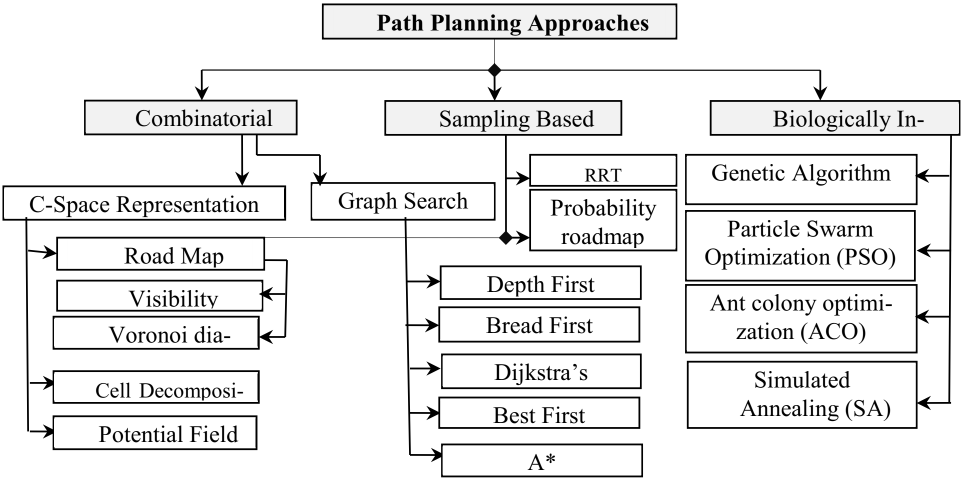

Fig. 2. Classification of path planning algorithms

Visibility Graph (VG). It is a popular and efficient path planning method under roadmap category where the available paths consist of waypoints that are also the nodes of obstacles and this makes the paths semi-collision-free. Vertices V of a VG graph comprise Qinit, Qgoal and the polygonal obstacles vertices [35]. The edges are made of the edges of obstacles and edges joining all pairs of vertices that lie in the Qfree. Lozano-Perez and Wesley initially proposed VG for path planning within an environment consisting polyhedral obstacles [7]. Oomen et al. used VG method in [9] to resolve the path planning of an autonomous mobile robot in an unexplored obstacle-filled environment. Research on the reduction of VG's complexity was projected in [2]. Both approaches claimed to be suitable and energy efficient for path planning in real-time. VG based algorithm, known as Equilateral Space Oriented Visibility Graph (ESOVG), was proposed to reduce the number of obstacles for a car-like robot during its path planning [11] and is capable of saving energy and finding optimal path with less computation time.

Voronoi Diagram (VD) - A set of regions built by dividing up the C-space makes the VD. Each region and all points in it correspond to one of the sites [12]. It generates Voronoi edge that is equidistant from all the points of the obstacles' area in C-space. Hence, it cannot generate optimal paths. A dynamic path planning for multi-robot was proposed to cover the sensor-based narrow environments assuming the energy capacities of the mobile robots based on generalised VD (GVD) graph [14]. A path planning method for Unmanned Surface Vehicle (USV), which operates at sea integrates the VD, VG and Dijkstra search algorithm and is able to find a collision-free and energy efficient path where up to 21 % energy can be saved [15].

Cell Decomposition (CD) – At outdoor environment it is a popular path planning method where the workspace is decomposed into discrete, non-overlapping, rectangular or polygonal shaped cells in between start and target points producing a continuous path [16] or connectivity graph. Here, the obstacle-free cells must be completely free from any obstacle or its part; else they are identified as occupied. There are several variants of CD including Regular Grid, Adaptive Cell Decomposition and Exact Cell Decomposition. Unfortunately, CD has several drawbacks like generation of infeasible solutions, combinatorial explosion and limited granularity. A cell decomposition approach for trade-off safe and short path was considered in [18] by choosing the weight values. Another cell decomposition method efficiently covers the optimised path over cells as per the distance between the centroids of cells and reduces the rate of energy consumption and operational time [19].

Potential Fields (PF) - In PF, Qgoal and obstacles have attractive and repulsive potentials respectively. The goal configuration and the obstacles produce a potential field at which the robot travels. PF was firstly suggested by Khatib [6], which considered a UAV as a point under the influence of the fields produced by Q_{init}, Q_{goal} and obstacles within C-space. The resultant force of the field on the robot determines the vehicle motion direction. As potential field method directs the vehicle towards a minimum in the field, it is not guaranteed that the minimum is the global minimum. A global off-line path planning approach is implemented using an energy-based approach known as Artificial Potential Field (APF) for Multi-Robot Systems (MRSs). Based on the potential field, an improved artificial potential field (APF) UAV path planning technique was introduced and it is more effective in finding the shortest path [21]. Another potential field technique uses the kinematics of a six wheel rover for motion on rough 3D terrain where relative significance of the paths is obtained from four different cost functions with respect to energy, traction force, slip and deviation from a straight line. Extensive experiments and simulations proved that this method is better in obtaining paths [22].

3 Sampling-Based Path Planning

Sampling-based motion planning methods are used during the search within configuration space when information is obtained from a collision detector. The geometric model, a sequence of sampling-based algorithm, depends on potential configuration and checks collision so that the validity of the configuration can be verified and it ends with the matching of a configuration with the goal configuration. Since the collision checking is done as required, thus this algorithm lacks the knowledge about the presence of the object in the configuration space. There are two popular methods in sampling based path planning, namely Rapidly–exploring Random Tree (RRT) and Probabilistic Roadmap (PRM) which are elaborated below [5].

Rapidly-exploring Random Tree (RRT). This algorithm efficiently searches in increment without the outline of high-dimensional spaces by constructing a space-filling tree from randomly drawn samples within the workspace. It is fundamentally influenced to grow towards the large areas of problems that are not searched. This was proposed by LaValle and Kuffner Jr in [24, 25] as an easy solution to handle problems with obstacles and differential constraints for autonomous robotic motion planning. The computation time increases depending on the size of the generated tree. The resulting path from RRT is always not optimal. But it is quite easy to find a path for a vehicle with dynamic and physical constraints, and produces minimum number of edges. A RRT based path planning algorithm generates a cost-efficient path to satisfy the requirements of the mission stated in linear temporal logic (LTL) [26] where the cost function comprises the hazard levels, the energy consumption and the wireless connectivity. Kamarry et al. used a compact RRT illustration by decreasing the redundancy of the nodes and the number of discarded samples. The processing time of the tree growth and the computation cost were also reduced for which the path length was shortened and the energy was saved [27].

Probabilistic Roadmap (PRM). It is a motion planning algorithm that takes random samples from the configuration space by checking the available free space and avoiding the collisions to determine a path. A local planner is used to join these configurations with nearby configurations. A graph search algorithm is applied after adding the initial and goal configurations to determine a path. It has two phases, i.e., construction and query phase. Approximating the motions, a roadmap (graph) is built in the construction phase. Whereas, the start and goal configurations are connected to the graph in the query phase, and then the path is produced by a graph search algorithm. The obtained path often has poor quality and as a result of randomness, it represents the free space connectivity. This method may also be incomplete, i.e., it is unable to figure out a path between two locations although the path exists connecting these locations in the presence of narrow passage. Moreover, it is tough to know about any existing path unless it is found [28, 29]. On the other hand, PRM is probabilistically optimal and complete with reasonable computation time. Chung et al. [30] presented a PRM based method for low-cost path planning of a UAV in a spatially varying wind field using a biased sampling-based path search technique. They minimised its energy consumption by finding time efficient path planning through the available flight region.

4 Biological-Based Path Planning

Biologically inspired method is based on biology, computer science, mathematics and artificial intelligence, mainly on machine learning, and is a major subset of natural computation. It can also be stated as the combination of connectionism, social behavior and emergence. In this technique, the living phenomenon is modelled by using computers and concurrently it tries to make the improved use of computer for a better life [31]. There are numerous methods for an energy efficient path planning of a UAV among which a few are discussed below:

Genetic Algorithm (GA). Constrained and unconstrained, both of these optimization problems can be resolved by using the natural selection process of driving biological evolution and it continuously changes a population of individual results [32]. But it cannot guarantee any optimal path. Local minima might occur in narrow environments and thus, it gives less safety and narrow corridor problem. GA is computationally expensive and practically not complete. Li et al. utilised GA for traversing the energy map in outdoor environment with 3D to avoid local optimisation. The model was incorporated with an estimated energy consumption formula that was served as an input of the energy consumption map and as a result the energy-optimal paths were obtained by GA [33]. Dogru et al. optimised the Coverage Path Planning (CPP) using GA in terms of energy consumption by considering the limitations of natural terrains such as obstacles and relief. This method seems to be effective for a mobile robot performing CPP as per the simulation result to reduce the energy consumption [34].

Particle Swarm Optimization (PSO). This is a classical meta-heuristic population-based algorithm, originally introduced by Kenney and Eberhart in 1995, to resolve global optimization issues based on swarming or collaborative behavior of biological populations. A PSO based path planning algorithm tested the problems of multi-objective path planning models verified with the focus on robot's energy consumption and path's safety [17]. Another PSO based method, known as improved particle swarm optimization (IPSO) with an improved gravitational search algorithm (IGSA), was proposed to reduce the maximum length of the path which in turn should minimize the travel time for all robots to reach their respective destination within the environment along with the optimization of the energy with respect to the turn’s number and arrival time [3].

Ant Colony Optimisation (ACO). This is meta-heuristic and probabilistic technique, developed by Dorigo in 1992 [23] based on the behavior of the ants to search their food and create the paths after locating its source. However, it suffers inherent parallelism. At the same time, positive feedback stimulates the quick discovery for good results. Lee et al. proposed an energy-based ant colony optimisation algorithm for battery-powered electric automobiles to attain the optimised energy-conserving path [10]. Zaza et al. presented an improved Ant ACO to resolve various Vehicle Routing Problems (VRPs) by utilising the task allocation and route planning methods for a UAV. This new algorithm can be used for collision avoidance penalties and it can change the travelling time of each task [8].

Simulated Annealing (SA). This is a probabilistic meta-heuristic technique to approximate the global optimum of a given function within a discrete space for a large search. It is preferable for the alternatives, such as gradient descent, where it is problematic and as well important to find an approximate global optimum than obtaining a precise local optimum within a given time. The enhanced SA is capable of giving a near-optimal or optimal path solution for various dynamic workspaces with less processing time and can also improve the real-time computational efficiency [13]. Turker et al. solved the multiple UAVs' path planning issues using parallel SA algorithms and it was executed on parallel computers [20].

5 Discussion

The information in previous section reveals that VG is more energy efficient than VD in combinatorial method under roadmap technique. It is necessary for CD to adjust with the situation as required; e.g., in exact CD, the cells are not predefined, but they are selected based on the location and shape of the obstacles within the C-space [16].

Table 1 tabulates all the path planning methods versus their properties in terms of path optimality, computation time, real time capability, memory usage and completeness. Sometime PF could not find the goal because of local minima issue. In sampling based method, RRT does not always provide optimal result and PRM is expensive without any guarantee of finding the path. GA is currently used for energy efficient path planning but it also cannot guarantee to produce optimal path because local minima may occur in narrow environments. Moreover, GA is computationally expensive and practically not complete. PSO has real time effect but it can easily falls into local optima in many optimization problems. Furthermore, there is no general convergence theory applicable to PSO in practice and for multidimensional problems, its convergence time is also uncertain. ACO does a blind search and thus, is not optimistic and suitable for energy saving path planning. Apart from very slow and very high cost functions, SA is also not capable of finding optimal path.

6 Conclusion

Researchers used a number of path planning algorithms. Efficient path planning algorithm (i) can find an optimal collision-free path, (ii) is complete, (iii) has minimal computation time, and (iv) produces energy efficient path. Currently path planning approach is multi-dimensional. This paper focuses on the classification of path planning algorithms that consider energy efficiency and their nature of motion, advantages and drawback. Based on the objective of the UAV's mission and considering the outcome of the available path planning algorithms, such as computation time, completeness and safety [16], they can be optimised to produce the energy efficient path planning algorithm.

Acknowledgments. This work was supported by UTHM and funded by GPPS and Fundamental Research Grant Scheme (FRGS) with vot numbers of U457 and 1489 respectively.

Table 1. Comparison of Different Path Planning Methods Properties

C-Space Representation Techniques		COMBINATORIAL METHOD			
		Method	**Optimal Path**	**Computation Time**	**Completeness**
	Road map	Visibility Graph	√	×	√
		Voronoi Diagram	×	√	√
	CD	Regular Grid	×	×	×
		Adaptive Cell Decomposition	×	√	√
		Exact Cell Decomposition	×	×	√
	PF	Potential Field	×	√	×
SAMPLING BASED METHOD					
RRT			×	×	√
PRM			×	√	×
BIOLOGICALLY INSPIRED METHOD					
GA			×	√	×
PSO			×	×	√
ACO			×	×	√
SA			×	√	√

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