A Comparative Study of UAV 3D Path Planning Algorithms

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***Abstract*- UAV 3D path planning aims at finding an optimal and an obstacle free path in a 3d environment while considering the geometric and the environmental constraints. There has been a lot of work done for solving the path planning problem of UAVs. But very less study is available which compares the different path planning algorithms of UAVs. This paper compares different studies regarding the topic and classifies them into five different categories. These five categories are described and the works which belong to each category is mentioned. Then a few interesting works from each category are summarized. The planning algorithms for single UAVs have been taken into consideration. Various parameters have been used to compare these works and determine the best aspect of each work.**

Keywords*- *UAV 3D Path Planning, classification, experience based, node based, computational models, nature inspired, hybrid approach

I. INTRODUCTION:

Unmanned Aerial Vehicles have the capability to navigate through a 3d environment and thus can be used for many purposes such as surveying, military, photo and videography, search and rescue, surveillance, agriculture, and many more. Path planning is the task of finding a route to reach a goal through a continuous free space in an optimal manner under kinodynamic constraints. Simple 2d path planning algorithms cannot deal with complex 3d environments where there are more obstacles, constraints and other uncertainties. It is a crucial element in UAV's goal as the UAV needs to maneuver through environments such as forests, caves, mountains, urban areas, etc. depending upon the mission.

Path planning in 3d environments is much needed nowadays since the use of aerial vehicles has increased on a commercial level as well as research purpose. It has a high potential albeit a higher level of difficulty owing to complex kinematic, dynamic and environmental constraints. In computational complexity theory, it is the NP-hardness [31] (non-deterministic polynomial time hardness) class of decision problem and thus does not have a common solution. While path planning through a 3D cluttered environment it is important to not only find an obstacle free path but also to reduce the time required and optimize a given cost function. Since there are more uncertainties, all the factors should be considered to get a path that can adapt to different 3D environments. A lot of research has been done over the years to find solution to these problems but there is less research which compares the various algorithms. There is even lesser literature on comparison of various algorithms from the point of view of applications of UAVs.

II. METHODOLOGY:

This paper discusses the different methods proposed over the years to solve the path planning problem for single UAVs. Some of the algorithms that are considered are: Adaptive vortex search, Ant colony, Bidirectional sparse A*, Bilateral search, Genetic algorithm, Improved RRT, Improved heuristic A*, K-means and Simulated Annealing, Partially Observable Markov Decision Process, and Receding horizon control with adaptive strategy, etc. The focus of the paper is path planning for single UAVs. Multiple UAV path planning is not considered. Other algorithms which may generate a smooth path for rigid body robots but are not applicable to UAVs are ignored.

The paper is organized as follows. The third section is the preliminary study in which various terms are summarized and the problem statement is formulated. Next section tells the classification of the algorithms and its implications. Further, a brief overview of the papers selected for comparison is given. In this section, two papers from path planning algorithms based on experience, based on nodes and hybrid approach, one paper from nature inspired algorithms and three papers from computational based algorithms has been summarized. Computational model based algorithms are more complex to understand and hence has the greatest number of summarized papers. This will help the reader understand the concepts easily rather than just the taxonomy. Furthermore, a comparison of the applicability is done. This is done to understand the applications of UAVs for which certain path planning methods are better suited. For example, algorithm A might be better than algorithm B in an environment X. But its vice versa in environment Y. This implies that in the real world, A is suited for a certain application better than B and vice versa regardless of their general execution time. Finally, a comparison of all the advantages and novel methods used in different works is shown and future work is framed.

III. PRELIMINARY STUDY:

This section will outline some important concepts and differences which are usually not defined explicitly in literature. Then, the problem statement common to all algorithms is stated.

3.1 Path Planning and Trajectory planning

Both Trajectory and Path planning are very crucial elements in not only UAV designs but also in the design of any robot. Path planning refers to the generation of an optimal collision free path from start point to the goal. Trajectory planning is the generation of the potential trajectories of the system considering the position of the robot at rest is zero. It can be said that trajectory planning is a subset of path planning. In other words, a trajectory is the way on which the robot will move and the information on how it will move. Path planning is making a motion profile and trajectory planning is making a velocity profile.

3.2 3D and 2D Path Planning

The basic difference between 2d and 3d path planning is that in 2d path planning algorithms, it is assumed that at least one of the axes of the co-ordinate space in which the robot is moving is constant. That is, in 2d path planning, the robot will only be able to move through a plain space. Fox example, robots moving on ground, wall climbing robots, surface robots, etc. 3D path planning further extends 2D planning in a way that the robot can move through all three axes. 3D traversing not only requires the basic considerations of 2D traversing but also the environmental considerations. For example, UAVs, ornithopters, under water robots, etc.

3.3 Path Planning for single robots and for multiple robots

There is a difference between path planning methods for a single robot and multiple robots. Multiple robots have the added complexity of avoiding collisions among each other in addition to obstacle avoidance. Each UAV needs to communicate with each other and share information to coordinate activities. The success of the mission depends largely on how effective the networking is.

3.4 Problem statement for UAV path planning

UAVs can navigate autonomously without human interference, but they need to be given a method to fly optimally. They need to have a path planner which will help them navigate through a complex 3d environment which has obstacles. Based on the different works on path planning algorithms for UAVs, we define a problem statement for which the different algorithms of this paper are applied.

We assume that the UAVs fly in x, y and z direction of the world coordinate frame. This 3D (R^3) workspace is the workspace w. There are obstacles in this workspace which the UAV works to avoid. Let O_i be the i^{th} obstacle. The area in the workspace which the UAV maneuvers while avoiding the obstacles is given as $w_{free} = w - \sum_i^n O$. The start point is given by P_{init} and goal point is given by P_{goal}. Both these points lie in w_{free}. Now, path planning is defined as a process φ for a function $\delta: [0, T] \rightarrow R^3$ with bounds $\delta(0) = P_{init}$ and $\delta(T) = P_{goal}$, which guarantees that $\delta(\tau) \in w_{free}$ for all $\tau \in [0, T]$

IV. CLASSIFICATION OF UAV PATH PLANNING ALGORITHMS:

Several papers based on UAV path planning were referred while writing this paper. Different works made use of different novel approaches to solve the path planning problem. It is easier to look at these approaches and compare them efficiently when they are categorized. Hence this paper makes a taxonomy of the papers based on the type of approach and then summarizes two papers from each category. Fig1. shows the categorization of different approaches.

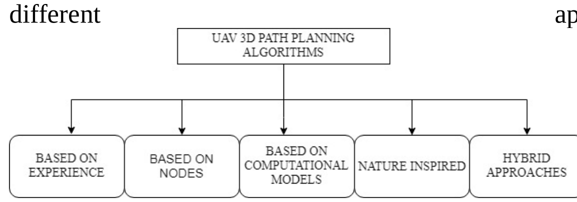

Fig. 1 UAV 3D Path Planning algorithms classification

It should be noted that a lot of works might belong to one or more categories. But for simplicity, the works are only classified into only one of the five categories.

A description of the categories and a reference to all the papers belonging to that category is given below. A total of twenty-eight papers have been classified into five categories as follows.

a) Algorithms based on experience.

Sampling based algorithms, in which the start and the goal point is known, fall into this category. This type of algorithms can be further categorized as single query based and multi query based. Multi-query based algorithms are like passive algorithms in which a set of paths from the start point to the goal point already exists and the algorithm must perform a search to find the best path. Single-query based algorithms are like active algorithms. They work on generating a skeleton path to the goal by their own processing procedure. This type of method can deal with dynamic obstacles but not dynamic goal points. Also, they hold no memory of the previous points that were explored.

The works that are categorized into section are Bilateral search new model [3], Improved RRT [5], Contour based approach [13], RRT connect [23], Spline RRT based approaches [24] and [28], Probabilistic method [29]. Shijian et al [3] introduced a new bilateral search model in which the sampling algorithms could be used from both the start point and the goal point simultaneously. It is shown in the work how this bilateral method is more advantageous over the usual unilateral method, especially for application such as military attacks wherein the goal point and the angle of attack is fixed. Sun Qinpeng et al [5] have used this bilateral approach in RRT algorithm. In [5], the RRT algorithm is improved by applying it from the start point and the goal point. This work will elucidate [3] and [5] works in further sections.

b) Algorithms based on nodes

As the name suggests, algorithms that fall into this category make use of generation of nodes to find the goal point. The working procedure of node based algorithms is that they search through a set of nodes from start point to end point on a graph or a map for an optimal path. When the set of nodes is already generated on a map or a graph, the algorithms start defining a cost function and then search through each node for a path that minimizes the cost function.

Bidirectional sparse A* [2], Improved heuristic A* [6] and [27], Visibility line based method [25], are the works which belong to this category. [2], [6] and [27] improvise the A* algorithm to optimize it for UAV 3D path planning. The further sections in this work elaborates the work by Meng Bo-Bo et al [2] and LiXia et al [6].

c) Algorithms based on Computational models.

These algorithms can really be categorized into the first category, but since the programming complexity of these models is higher, this work classifies them into a separate category. In mathematical modelling, all the factors are considered before generating an optimal path. Both model as well as environment is created while working with algorithms of this type.

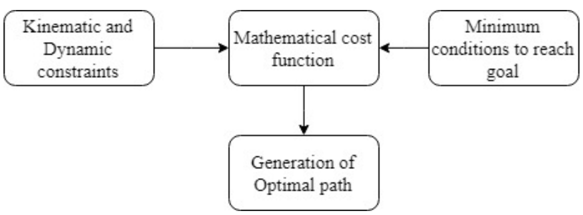

Fig. 2 Representation of Computational models in UAV 3D Path planning.

Adaptive vortex search [1], Partially Observable Markov Decision process [8], Receding horizon [10], Contour based path planning [13] are the works which go into this category. Chunying Wang et al [1] showed a method to optimize the vortex search algorithm to solve the path planning problem. The environment is created using cubic interpolation method. Qiming Yang et al [8] uses the Partially observable markov decision process model to improve the UAV's autonomous target tracking ability under the condition of passive detection. For optimization, this method is combined with Unscented Kalman Filter (UKF). Zhe Zhang et al [10] provides a method to increase the efficiency of path planning algorithms which are large and usually take time to converge. [1], [8] and [10] are discussed in detail further.

d) Nature inspired Path planning algorithms

The ways of nature have always caught attention of the scientists and has given rise to several biologically inspired algorithms. These algorithms imitate methods from nature to achieve the targets. For example, the ant colony algorithm mimics the ant's behavior of pheromone based communication to find food. Many nature inspired algorithms are applied to swarm or multi robots path planning algorithms as the nature has excellent ways of organization.

Genetic Algorithm [4, 26], Ant Colony optimization [9, 18, 19], Particle swarm optimization [17, 21], Parallel evolutionary [20] are classified into this category. Nature inspired algorithms could rather be further classified into the above four categories itself, owning to the burgeoning works in this field. The works by Abdurrahim Somnez et al [4] and Chao Zhang et al [9] have been summarized in further section.

e) Hybrid approaches to 3D path planning algorithms

A lot of path planning algorithms make use of more than one algorithm to get an optimized output. They make use of best practice in different algorithms to generate a method to solve the path planning problem. In some cases, one method is used to generate a path, and another is used to optimize it. The algorithms may belong to the same or different category individually. S. Aditya Gautam et al [15] used a combination of Genetic Algorithm and Artificial neural networks for UAV 3D Path planning. Here, the genetic algorithm is used to solve the optimization problem and artificial neural networks are used for function fitting. This work will elaborate [15] further. GSO-DE [12], Virtual force and A* [16], Potential Field and modified receding A* [22] are some other works which come into this category.

These hybrid algorithms manage to solve problems which the algorithms would not have been able to solve independently. They integrate several algorithms advantages to achieve global optima and cost minima. These are often considered to be the most time saving methods, although in some cases or for some specific applications, singular methods might be more advantageous.

To summarize, this table provides the overview of classification. Reference papers are the papers categorized in the respective category. Further sections explain

Table: 1 Reference papers for each category

Type	Reference papers
Based on experience	Bilateral search new model [3], Improved RRT [5], Contour based approach [13], RRT connect [23], Spline RRT based approaches [24] and [28], Probabilistic method [29]
Node based methods	Bidirectional sparse A* [2], Improved heuristic A* [6] and

	[27], Visibility line based method [25]
Computational model based methods	Adaptive vortex search [1], Partially Observable Markov Decision process [8], Receding horizon [10], Contour based path planning [13]
Nature inspired algorithms	Genetic Algorithm [4, 26], Ant Colony optimization [9, 18, 19], Particle swarm optimization [17, 21], Parallel evolutionary [20]
Hybrid approaches	Genetic Algorithm and Artificial neural networks [15], GSO-DE [12], Virtual force and A* [16], Potential Field and modified receding A* [22]

Experience based algorithms, node based algorithms and computational model based algorithms are applied in static as well as dynamic environments depending on the work. Nature inspired algorithms are applied in static environments and the environment of hybrid approaches depend upon the types of algorithm involved in it. The next section summarizes a few works from each category.

V. SUMMARY OF A FEW WORKS FROM EACH CATEGORY

a) Experience based algorithms.

From this category, Bilateral search new model [3] and Improved RRT [5] is summarized below.

1. UAV Path Planning Based on Bilateral Search New Model [3]

In this paper, Yue Wang [3] has given a search model in which the path planning is carried out by searching for an optimal bath from both the start point and the goal, provided the angle of attack is specified. The specific application mentioned in this paper is that of a self-destruct UAV finding the best way to attack the weakest part of the enemy target on a battlefield while avoiding the enemy bunkers. Since it is a battlefield environment, it is obviously dynamic. The simulation in this work is done in MATLAB software.

The first section of this paper points out the problems with using unilateral search. It takes A* algorithm into consideration to point out the ambiguity between the expected result and the practical result. A constraint that is added here is that of final angle of attack. It is defined as the final enter degree when UAV approaches the target along the positive y axis. The simulations for the algorithm are done for different angles of attacks based on this definition.

The steps for bilateral searching model are given in the next section of the paper. This is a six step process. The first step is to determine whether the condition meets the planning requirement using Gaussian of initial parameters. The next step is to set the start point and the goal point as the first node to start searching from both directions. Third step is to find minimum cost from both the points by setting up temporary nodes on the graph. The fourth step is to determine whether the temporary nodes meet the requirement of joining together. If it is met, then generate the path and if not repeat third step. Next step is to convert rectangular coordinate to latitude and longitude and then exit planning.

The paper further presents the evaluation function of the search model. The equations for evaluation factors are as follows:

$$Threaten\ value\ (W) = Threatenvalue\ from\ starting\ side\ (W_{S)} + Threaten\ value\ from\ ending\ side\ (W_{M)}$$

$$Route\ distance\ (L) = Route\ searched\ (L_y) + 2 * Step\ length\ (L_{bc}) + Linear\ distance\ between\ two\ navigation\ sides\ (L_z)$$

$$Time\ (T) = Otherimpact\ factors\ (\theta) * Distance\ between\ two\ navigation\ points\ (L_g)$$

$$Deviation\ of\ directivity\ (Z) = (180 - \alpha) + \beta$$

And the evaluation function is given as:

$C = a * W + b * L + c * T + d * Z$. Here, a, b, c, d represent the weights of individual cost.

The next section of the work shows the simulation results for 90^o and 270^o angle of attack. There are two threats (obstacles) to be avoided by the UAV in the simulation. From the simulation results, it is seen that the result for 270 degrees angle of attack are very effective. It is concluded that the planning path for UAV attacking the target with a specified angle in the target space is very effective using this method. Search method and the dealing with constraints are the major innovative concepts of this work.

2. UAV Path planning based on Improved Rapidly-exploring Random Tree [5]

SUN-Qinpeng et al [5] have followed a similar approach as the above work, difference being that, here the RRT algorithm is applied from both sides. RRT algorithm is improvised by applying it from both the start point and the goal point and using a dynamic probability value and dynamic step value. The problem is framed out that the traditional RRT method does not consider the comprehensive cost of the path while searching. The second section explains the basic RRT algorithm and the third section explains the improved method. The simulation results and the conclusion are presented in the last section.

In Bi-RRT method, P_{init} and P_{goal} is used to generate tree1 and tree2 from both sides simultaneously till they converge. The dynamic probability value (ρ_g) is reduced to increase the randomness of the search which resulted in increased success rate. This value is given by:

$$\rho_g = \rho_{gmin} + \left(\rho_{gmax} - \rho_{gmin}\right) * \left[\frac{1}{1 + INT\ \left(\frac{N_r}{N_0}\right)}\right]$$

Here, ρ_{gmin} and ρ_{gmax} are the lower and upper limits of ρ_g respectively. N_r is the number of random generated nodes and INT is the downward integer valued function. The change in ρ_g with respect to N_r value is shown further in table 1 of [5].

The distance between the temporary node and the next node is the step length value which influences the success rate of the algorithm. A dynamic step length is used in [5] to improve efficiency and increase success rate. The dynamic step length design is given as:

$$\begin{cases} d = d_{min};\ \alpha > 90 \\ d = d_{min} + (d_{max} - d_{min}) * \cos\alpha\ ;\ \alpha \le 90 \end{cases}$$

The further rule to this is that the extension of the new node cannot collide with the obstacles.

Both tree1 and tree2 are constructed in the same way and the construction of a single tree is described in the paper. The simulation is done in MATLAB with about 25, 75 and 100 obstacles in the simulation space. It was observed that the improved RRT worked best when the obstacle density is more. Significant increase in the path length and decrease in the number of nodes is seen using improved RRT which is better for a UAV since the UAV has a limited range. However, the testing is conducted and is based only on computer simulations and further verification is necessary to check the practicability of the improved algorithm

b) Node based methods

From this category, Bidirectional sparse A* [2], Improved heuristic A* [6] is summarized below.

1. UAV Path Planning based on Bidirectional Sparse A* Search Algorithm. [2]

A* is a best first search heuristic function which computes a cost function for various locations in the given environment. A* algorithm has been widely used in path planning literature and there are many works which improve A* algorithm to optimize it. This work is one of them. In sparse A* algorithm, constraints such as minimum route leg length, maximum route turning angles, route distance and fixed approach vector constraint are introduced to reduce the search space and search time of A* algorithm. This makes sparse A* more conducive for 3D environments. [2] describes this path planning based on sparse A* algorithm initially and then proposes improvement to it by applying it from both the P_{init} and $P_{goal.}$

The problem of SAS algorithm is identified to be an increase in risks associated with quick search. It is seen how a flyable path in searching space is not identified in SAS algorithm because all the nodes were lying in threat areas. BSAS introduces the concept of Line of Sight (LOS) between a path node and the goal node. It is assumed that the UAV has a global vision and when it sees the goal point, it jumps out of the current point directly to the goal point. Adding LOS makes the SAS algorithm more robust. However, it is seen that this does not always work as not all points are globally visible. Figure 3 in [2] shows such a condition.

To solve this problem, start point and the goal point are both expanded, and it is checked whether there is a LOS between every two different expansion nodes produced by both the expansion processes. This is the basic concept of BSAS algorithm which is further explained to be an eight step process. The first step is to find the LOS and if its easily found here, jump to eighth step. Next step is to insert P_{init} and P_{goal} into an empty list S and list T. Remove node x from S and expand *x* using SAS till a suitable expansion *x** is found. Check for LOS. If it is not found, perform fifth step. Fifth step is to expand node y in list T similar to the previous step. If LOS is still not found, it can be judged that there is no suitable path. The eighth step is to find the final route and exit planning. Through this analysis, it is observed that the BSAS algorithm has even more robustness than the SAS algorithm.

The simulation is done in a search space with six obstacles and SAS and BSAS algorithms are compared through this simulation. The simulation results are obtained for three variations of parameters and comparison shows that BSAS is significantly better than SAS in terms of reduced time and number of nodes visited.

2. Path Planning for UAV Based on Improved Heuristic A* algorithm [6]

In this work, a UAV path planning method based on A* algorithm is proposed which makes the UAV's path planning for low altitude penetration more real time, effective and engineering oriented. In this work, a 3D space is specifically created for better simulation. Section 2 of this paper describes the mathematical model including the threats of the 3d search space. The next section describes the path planning algorithm starting with traditional A* algorithm, description of cost function, improvement of search strategy, steps of the algorithm and optimizing and smoothing of the planning graphs. The last section shows the simulation results.

This paper follows the below formula to translate the threat quantitative information into the data which can be compared with terrain data:

$$T(x, y) = \sum_{i=1}^{M} T_i exp\left[-\left(\frac{x - c}{x_{si}}\right)^2 - \left(\frac{y - y_{oi}}{y_{si}}\right)^2\right]$$

Here, T(x,y) is the threat danger index of every point on the terrain grid; $T_{i,}$ i ε [1,M] is the magnitude of the threat i, x_{oi}, y_{oi} is the threat i's center coordinate; x_{si}, y_{si} is the threat i's corelative attenuation magnitude along x and y axis. The actual cost function is described as

$$g(n_i, n_j) = \omega_1 T(n_i, n_j) + \omega_2 D(n_i, n_j) + \omega_3 H(n_i, n_j)$$

Where $T(n_i, n_j)$ is the average threat strength of two nodes; $D(n_i, n_j)$ is the voyage between two nodes; $H(n_i, n_j)$ is the average height, ω_k is the weight coefficient and $\omega_k > 0, \sum_{k=1}^{3} \omega_k = 1$

In the traditional A* method, the node is seen to extend to 8 other nodes. In the improved algorithm, the minimal turning radius and maximal course angle variety rate is considered. 5 child nodes in w_{free} are extended. This improves the extending efficiency and fulfills the maneuverability requirements. The next section in the paper elaborates the 7 step method followed in the improved algorithm.

This improved algorithm creates a path comprising of broken lines with optimal cost without considering the UAV's maneuverability and hence it is necessary to smoothen the path. This is done using the k-path method. The simulation is done in MATLAB. This paper considers the whether conditions during simulations as well which is an added advantage. It is seen that the improved algorithm can make the path much smoother and more feasible for real time engineering application.

c) Computational model based approach.

From this category, Adaptive vortex search [1], Partially Observable Markov Decision process [8], Receding horizon [10] are summarized below.

1. The Adaptive vortex search algorithm of Optimal path planning for forest fire rescue UAV. [1]

In this paper, Chunying Wang et all [1] have proposed a method based on vortex search algorithm for UAV path planning in case of a forest fire, to generate a collision free path from P_{init} to the fire sight. The terrain is created using the cubic interpolation method. The second section of the paper describes this method and how the terrain was generated for the work. The next section explains the vortex search algorithm and the proposed improvement in it to use it for 3D path planning. The last section shows the simulation results.

The terrain generated using the cubic interpolation method by the feature point matrix M ($M = [X_m, Y_m, Z_m]$ is shown below. The change in colour represents change in altitude, highest being orange and lowest being dark blue.

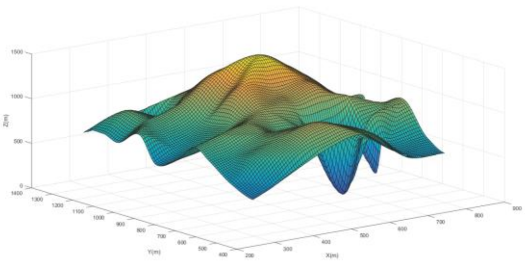

Fig. 3 Terrain of a forest simulated in Matlab

M is the matrix decomposed by terrain and m is the number of points. UAV path planning problem is established in the paper as

min f = min ($f_{path} + f_{height} + f_{corner}$) where f_{path}, f_{height} , f_{corner} are the cost functions of length of path, sum of height deviations sum of corner deviations respectively.

The vortex search algorithm is based on the vortex flow pattern created by vorticial flow of stirred fluids. The first step here is to generate the initial solution from starting point S to target point P. Then the largest circle of the vortex is first centered on S, while the initial center μ_0 and target v are defined as follows:

$$\begin{cases} \mu_0 = S; \\ S = [S_x, S_y, S_z]; \\ v = P; \\ P = [P_x, P_y, P_z]; \end{cases}$$

The next step is to replace the current solution. This is done by generating several neighbor solutions randomly around the center μ_t (t is the iteration index with initial value 0) by using a Gaussian distribution. Then calculate the objective function value of these alternate solutions. Take the alternate solution position with minimum fitness value in the iteration to be the best one.

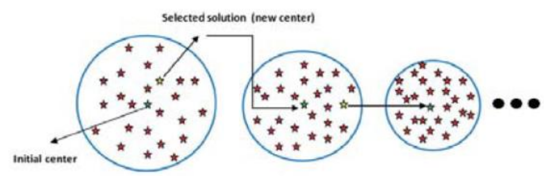

Fig. 4 Generating new solutions around initial centers iteratively

Further, the inverse incomplete gamma function given by

$$\gamma(x, a) = \int_0^x e^{-t} t^{a-1} dt, a > 0$$

is used to decrease the value of the radius during each iteration. This is also a type of adaptive step size adjustment process.

The simulation is conducted in MATLAB and every experiment is carried out 30 times. The algorithm is compared to PSO algorithm. The proposed solution produces a smooth, short path which passes over low altitude.

2. Path planning for Unmanned Aerial Vehicle Passive Detection under the framework of Partially Observable Markov Decision Process. [8]

This works solves the path planning problem using a passive detection system unlike others. This is very beneficial for UAVs which are going to be used for military purposes since the UAV itself will not emit any high power electromagnetic waves. This will make the system more secure from enemy attacks. The first section of this work introduces us to the military UAV problems and the POMDP model. The next section describes the elements of path planning POMDP model – state space, action space, observation, state transfer law, cost function, belief state. The next section establishes the POMDP framework for path planning and then the POMDP model for path planning. The next section describes the path planning model solving and approximation and hypothesis of algorithm. The optimal operation is carried out by combining the method and unscented Kalman filter (UKF). The last section shows the simulation results for single target with long range and dual target with close range.

The framework for POMDP model is shown in the diagram below.

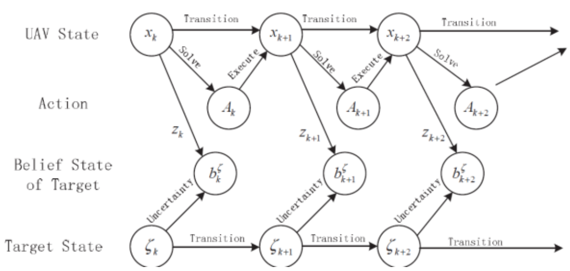

Fig. 5 POMDP Path planning model framework

It is a sequential decision making process which updates the target belief state according to the observation and solves the optimal action policy according to the state. The aim of POMDP path planning model is to find a series of optimal action values, to minimize the cost of accumulated value of future action. Equation (28) of [8] defines this cost function. It is difficult to solve the exact solution of POMDP model in time due to the randomness of the state. For this, Monte Carlo method [7] and particle filter method are used. POMDP path planning model calculates optimal policy based on the future prediction which are the states and costs after a period of time from decision point.

The simulation is done in MATLAB based on the initial assumptions and hypothesis made in the previous section. The advantage of this algorithm is the predictive ability albeit the higher number of calculations pose a difficulty.

3. UAV Path planning based on Receding Horizon control with adaptive strategy. [10]

In this work, Zhe Zhang et al [10] have developed a method to converge large scale path planning problems. Earlier works model path planning to be a linear optimal control problem to ensure convergence. But this increases the time complexity as the problem grows. Receding horizon control is an adaptive strategy which ensures convergence of path planning problems. The second section of the paper describes the system model- the cost function, state equation, the feasible region, and problem modelling. Further, the receding horizon control is explained and then the application of an adaptive strategy to it. The adaptive strategy consists of six steps and the simulation is done for two scenarios.

Receding horizon control is defined to be an algorithm to solve a finite horizon open loop optimal control problem using current system state as initial state to repeat this process at each sampling state. The horizon span N is the input needed in advance. This N needs to be small to meet the real time requirement, but it may trap into the local optimal. Bigger N means less cost value but higher computing burden. Hence, an adaptive strategy is proposed to choose this value of N.

The figure 6 shows the algorithm for UAV path planning based on receding horizon control with adaptive strategy.

Initialization:
Input: initial position x_0, final position x_f

Set $x_{0|ini} = x_0^* = x_0$, $u_{0|ini} = u_0^* = 0$, receding horizon span $N = \omega_{ini} * M^*$

for $k = 0$ *until meeting terminal condition* **do**

  Obtain optimal sequence $\{x_{k+i|k}^*\}_{i=1}^N$, $\{u_{k+i|k}^*\}_{i=1}^N$ by solving $\mathcal{P}(k, N)$

  if $x_{k+N|k}^* = x_f$ **then**

    Set $x_{k+i}^* = x_{k+i|k}^*$, $u_{k+i}^* = u_{k+i|k}^*$, $i = 1, \ldots, N$

    break;

  end

  Update:

  1 Current cover distance $dis(k) = \left\| x_{k|k} - x_{k+N|k} \right\|_2$ and distance ratio $\rho_{dis} = \left\{ \frac{dis(k)}{dis} \right\}^2$

  2 The obstacle number $O_n(k)$ in current region and obstacle ratio $\rho_{obs} = \frac{O_n(k)}{O_n}$

  3 Time span weight $\omega_{env} = \omega_{dis} \cdot \rho_{dis} + \omega_{obs} \cdot \rho_{obs}$

  4 $x_{k+1|ini} = x_{k+1|k}^*$, $u_{k+1|ini} = u_{k+1|k}^*$

  5 $x_{k+1}^* = x_{k+1|k}^*$, $u_{k+1}^* = u_{k+1|k}^*$, $k = k + 1$

  6 Receding horizon span $N = \omega_N \cdot \omega_{env} \cdot M^*$

end

Output: $\{x_i^*\}_{i=0}^{k+N}$, $\{u_i^*\}_{i=0}^{k+N}$

Fig. 6 Algorithm for receding horizon control

The simulation is done for two scenes comprising of seven and eleven cubic obstacles respectively. This work is useful for UAV path planning in city areas. The simulation results showed that the proposed strategy is beneficial for real time applications and fuel consumption.

d) Nature inspired algorithms for UAV path planning.

From this category, Genetic Algorithm [4] and Ant colony algorithm [9] have been summarized.

1. Optimal Path planning for UAVs using Genetic algorithm. [4]

This work makes use of genetic algorithm which is an evolutionary algorithm to find the optimal UAV path. The second section of this paper explains the related work and the third section explains how this work is implemented in MATLAB. The implementation is a six step procedure.

The basic idea of genetic algorithm is that we anticipate the next generation to be better than the previous generation. The first step is to initialize the population, produced randomly. Integer coded chromosome design is used instead of chromosomes composed of binary codes. Each path is a sample chromosome and each control point is assumed as one gene. The total navigation length of the path is the fitness value in this model. Tournament selection method [30] is used to select the parents. After selecting two parents, the offspring is produced using the same method. The fourth step is mutation, which has some disadvantages due to the numerical method. After mutation, cross over takes place in order to transform the genes. The last step is local optimization. As logical structure of GA, each generation should be better than the previous one.

The implementation is done in MATLAB using the views from DTED packages. Number of CP, Crossover rate, mutation rate, elitism rate, parent selection, and crossover type are the parameters which have affected the solution critically. GA is found to be one of the most real algorithms among the evolutionary algorithms. The simulation results show the optimal 3d route generated in the terrain. Although, we should also consider the possibility of comparing the results with that of immunized genetic algorithm for a more optimal output.

2. UAV Path planning method based on Ant Colony optimization. [9]

In this paper, Ant colony algorithm is used to plan the path for UAVs. The main steps for ACO are the calculations of transition probability, visibility and pheromone amount. The work is divided into four sections. The first two sections are introductory. The third section describes the ACO algorithm as used and the last section shows the simulation results.

The ACO algorithm for path planning is a six step process. The first step is to create a grid map of the UAV flying area including the threats as obstacles. Ant should choose the point meeting the yaw angle constraint. Calculate path visibility assuming that the radar poses a constant threat on the path continuously. The threat intensity is considered as the visibility for the ant. Calculate the path probability. Assess the ant searching task. When a path is found from P_{init} to $P_{goal,}$ one searching task is finished. Last step is to update the path pheromone based on evaluation function after one searching task is finished.

The simulation is done on an area of 10km * 10km with 8 threats. The area is divided into a grid of 1km * 1km. Figure below shows the simulation results.

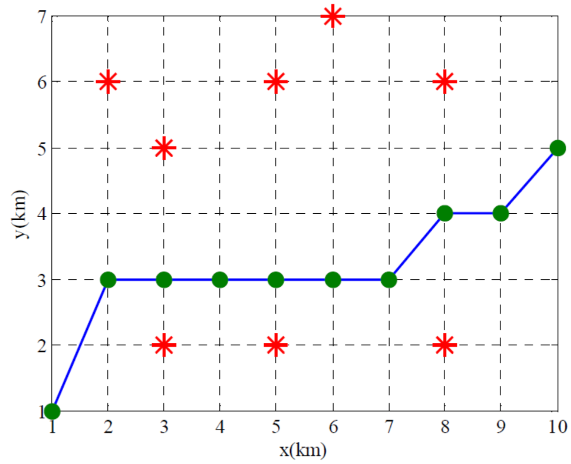

Fig. 7 Path generated using ACO algorithm

This ant colony algorithm inspired from ant's method of looking for food gives good results due to its positive feedback mechanism. Compared to traditional ACO, this gives more optimal path quickly as seen from simulation results. However, the path will have to be smooth in order to be applied for real UAV flying.

e) Hybrid approach to UAV 3D Path planning.

From this category, Path planning based on Genetic algorithm and ANN [15] is explained.

1. Path Planning for Unmanned Aerial Vehicle Based on Genetic Algorithm and Artificial Neural Network in 3D [15]

This paper proposes a new approach of combining Genetic algorithm and artificial neural networks for UAV path planning. GA is used to solve the optimization problem and ANNs are used for function fitting. The output generated by genetic algorithm is used to train the artificial neural networks. The second section explains the approach and the third section proves it through simulation.

Initially, a solution to the path planning problem is found using the genetic algorithm. This solution is in the form of a fitness function that needs to be minimized. The concept here is that if this fitness function is made to be the total length of the path, then GA will try to minimize it. The initial population in GA is created randomly based on the given constraints. Then all the paths are evaluated in terms of their fitness values. Then, the selection operator decides which paths in the solution should survive and participate in crossover and mutation to form the next generation. Then, the input and target data from GA are given as input to the ANN. Figure 8 shows the methodology followed in path planning algorithm.

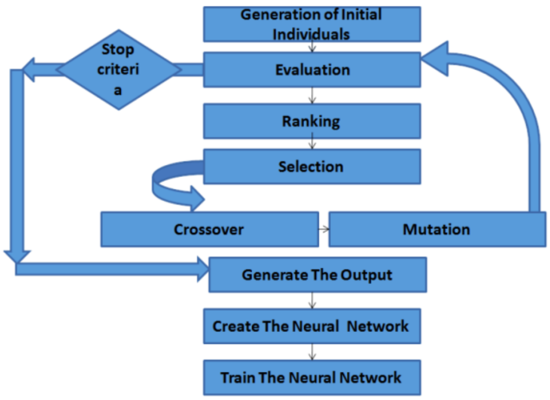

Fig. 8 Path Planning based on GA and ANN

It is a nine step method in which the UAV assumes that the line connecting P_{init} and P_{goal} is minimum in length and so the movement is started along this line. The nine steps consist of generation of initial individuals, evaluation, ranking, selection, crossover, mutation, generation of output, creating and then training the neural network.

The simulation is done in MATLAB for a security application of a military UAV searching for a path. The radar is considered to be an obstacle. The GA is applied generate the dataset which is given as an input to train the ANNs. If the number of waypoints is increased, the algorithm will be better. This is similar to supervised learning. The simulation data shows the percentage up to which the ANN has been successfully trained.

This paper proposes an efficient method based on genetic algorithms and ANNs although the simulation is done in a workspace having only one obstacle. It follows an innovative approach which gives a good scope for future research.

VI. DISCUSSION

Establishing a literature survey of a category of algorithms will help a user select the right algorithm and the environment needed to simulate that algorithm. This paper successfully creates such a literature survey by analyzing a number of UAV path planning algorithms. By categorizing the different methodologies used in papers, it is easier to understand the basic principle used behind all the papers which come in that category.

Experience based algorithms divide the workspace into a set of nodes and then use the best procedure to connect them. Based on this experience, they start searching for the best path. They can be implemented online for static planning.

Node based algorithms do not form a map. Instead, they work upon reducing the distance between two nodes by giving a cost to nodes generated and then finding the best path. It can be seen that most hybrid approaches include a node based algorithm.

Hybrid approaches are those which have more than one algorithm used to tackle the path planning problem. The best aspect of using this kind of approach is that the advantages of different methods are combined together, and the problems are eliminated. This makes it an excellent approach to solve the problem. Hybrid approach is rightly considered to be a time saving method to achieve global optimal and cost minimum. Selection of the right algorithms should be innovative and well thought before using this approach.

The works of mathematical model based approach category can actually come under one of first two categories. But a different category is made in this paper for this approach because this approach is more complex to understand than others. In this approach, all the constraints and the obstacles are considered. The entire workspace is described in the form of a mathematical equation which is an optimization problem. This type of approach requires a high end computer processing capability. Since technology improves day by day, this approach becomes more and more feasible.

Nature inspired algorithms can deal very well with complex constraints. They can also be used in places where the constraints are not structured. Since they make use of mutation process to optimize the path, they take a longer time and can be used only in static environments.

VII. CONCLUSION

Various approaches have their own pros and cons and which approach to follow depends upon the application for which the UAV is to be used. If the environment is completely known and there is no chance of a dynamic approach, then any simple approach will work. But considering the usual applications of UAVs, this will most likely not be the case. Based on the observations we can say that an innovative combination of experience based, node based or nature inspired algorithms, i.e. a hybrid approach simulated using a computational model on a system will most likely yield the best result.

The future work for this study will be to provide sub divisions and generate a hierarchy tree of classifications. For example, nature inspired algorithms can be further categorized as genetic based and evolutionary based. The last division of this tree will be the works which come under that category. The papers which are published in the future can be included in its respective category easily.

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