Towards Autonomous Drone-Based Dynamic and Seismic Response Monitoring of Bridges

Quarterly Progress Report
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1. PROJECT ABSTRACT

There has been increasing interest and use of unmanned aerial vehicles (UAVs), especially in the past decade, for infrastructure inspection. The goal of this study is to extend the use of UAVs to a new application in the area of infrastructures rapid assessment under service conditions and extreme events such as earthquakes. The project will leverage several well-established technologies such as autonomous UAVs systems along with extensive expertise in vision-based monitoring of infrastructure systems like bridges. Our objective is two-fold: (1) extend the use of video cameras and principles of digital image correlation and target-tracking to UAV systems for dynamic displacement measurements and monitoring; and (2) provide foundational work towards establishing a framework that benefits from early warning systems to launch UAVs and collect vibration videos to use for near real-time post-disaster assessment of infrastructure systems and rapid decision making. We will focus on earthquakes, but the results from the project could be generalized in the future and extended to other extreme events. This project will provide unique testbeds in the Earthquake Engineering Laboratory at the University of Nevada, Reno where UAVs will be used to monitor online shake table tests, and results from the monitoring will be used in establishing the future infrastructure assessment framework.

2. RESEARCH PLAN

2.1. STATEMENT OF PROBLEM

The status of our aging infrastructure in the US or elsewhere around the world has been recently one of the biggest challenges facing governments and decision-makers. Maintaining, repairing, or replacing existing infrastructure systems is a major undertaken activity in the US and around the world. Nonetheless, there is a dire need to have a forward look at future and next-generation infrastructure systems. In the US, the ASCE has laid three pillars for solving the nation's infrastructure problems, i.e. (a) strategic and sustained investment, (b) bold leadership and thoughtful planning, and (c) careful preparation for the needs of the future. A major component of the ASCE's "Preparing for the Future" vision is to utilize emerging technologies to ensure infrastructure resilience in the face of extreme events and develop processes that modernize and extend the life of infrastructure, expedite repairs or replacement, and promote cost savings. The innovative applications of emerging technologies in infrastructure assessment and structural health monitoring has shaped several research thrusts among the civil and structural engineering communities and is one of the key motives of this proposed study.

Several global technologies are on the rise such as aerial robotics, which are commonly referred to as unmanned aerial systems (UAS) or unmanned aerial vehicles (UAVs), or simply "drones". Many of the critical lifelines and infrastructure systems such as bridge networks or power grids and transmission lines have taken serious steps towards adopting UAVs for regular maintenance and inspection. In fact, the federal National Cooperative Highway Research Program (NCHRP) has recently solicited research proposals for "Evaluating and Implementing UAS into Bridge Management Methods Through Element-Level Data Collection". Further using bridges as one example of critical infrastructure systems, we find that a large deal of research studies has been sponsored, mostly through various Departments of Transportation (DOTs), to use UAVs for visual bridge inspections. However, none of the ongoing or emerging efforts have properly considered the use of UAVs for dynamic vibration and structural system identification of bridges or other infrastructure systems, nor considered real-time or near real-time structural assessment in the case

of extreme events such as earthquakes. Future applications of UAVs to rapidly inform post-disaster decisions such as assessing a bridge condition to open it for traffic or not would be of great importance, which is the specific motivation of this proposal.

2.2. RESEARCH APPROACH AND OBJECTIVES

Our specific objectives are: (1) validate and verify (V&V) the use of UAVs videos along with principles of digital image correlation (DIC) and target-tracking for dynamic displacement measurements and structural health monitoring (SHM); and (2) provide foundational work, towards establishing a future autonomous assessment framework, such as exploring target-based and targetless UAVs vibration monitoring, or exploring feasibility of two- vs. three-dimensional (2D vs. 3D) and one vs. two UAVs-based measurements if budget and time allows. Thus, it is important to note that the main developments sought in this study will be in the algorithms and methods in video processing and structural assessment. Developing new algorithms for UAVs path finding or seismically-triggered launch systems is not part of the scope for instance, but rather commercial auto-pilot or autonomous navigation systems will be used to prove or demonstrate the concept. Once the viability of UAVs dynamic and seismic monitoring solutions is demonstrated through this project and further knowledge gaps are identified from the synthesis of available technologies, future multi-disciplinary efforts, through a second year extension of this project for instance, could leverage expertise from computer science, robotics, civil engineering, etc. to optimize or enhance the UAVs triggering, launching, navigation, and data transfer within the envisioned framework.

To accomplish the above objectives, the PI will leverage extensive expertise in vision-based dynamic response and seismic monitoring of infrastructure systems like bridges. We will provide unique testbeds in the Earthquake Engineering Laboratory at the University of Nevada, Reno where UAVs will be used to monitor online shake table tests, and results from the monitoring will be used in establishing the future infrastructure assessment framework as explained in the work plan section. Examples of our previous work that will be further extended in this study focused on vision-based target-tracking measurement errors, demonstrating large-scale and field monitoring of bridges, and tackling image and signal processing challenges. Figure 1 provides some of the vision-based monitoring applications conducted by our team including a recent unique full-scale building test at world largest shake table in Japan through an NSF-funded US-Japan collaboration (Figure 1b). Most of the work so far has used stationary cameras, but we are recently extending many of our established concepts and developed tools to UAV-based video monitoring (Figure 1d).

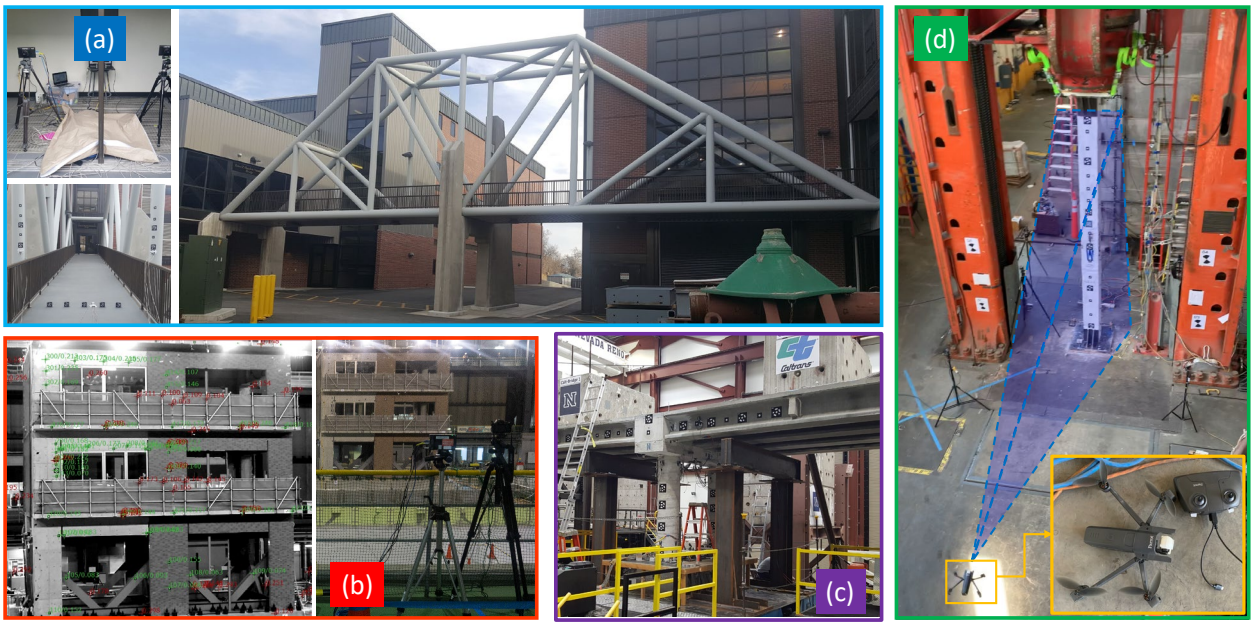

Fig. 1 Sample of vision-based monitoring of large-scale seismic tests and SHM field applications

2.2.1. Summary of Project Activities

An experimental approach will be used and several research activities will be executed to accomplish the objective of this study. A summary of the proposed research tasks is as follows:

- Task 1 – Synthesis of existing methods and technologies towards building a fully or semi-autonomous UAV-based infrastructure dynamic response monitoring and assessment framework
- Task 2 – UAV-based displacement measurement accuracy (V&V tests)
- Task 3 – Large-scale seismic monitoring test framework validation
- Task 4 – Summarize the results in a final report

2.2.2. Progress of Research Tasks

An overview of each research task and progress-to-date is presented in this section.

Task 1 – Synthesis of existing methods and technologies towards building a fully or semi-autonomous UAV-based infrastructure dynamic response monitoring and assessment framework

Our ultimate goal from this project is to provide foundational work and outline future needs towards establishing a successful fully or semi-autonomous UAV-based infrastructure dynamic response monitoring and assessment or inspection framework, which can be employed under service conditions or extreme events such as earthquakes. The objective of the first task of this project, which emerged to be the main task of this project because of the challenges faced in testing in tasks 2 and 3, is to identify the pieces and components that need to be integrated to achieve such framework. An overview of the work underway is presented in Appendix A.

Task 2 – UAV-based displacement measurement accuracy (V&V tests)

A wide-range of methods will be surveyed and synthesized for the various components of the envisioned assessment framework. In this task, we will conduct two sets of V&V tests for UAV static and dynamic displacement measurement accuracy to understand the limitations and potential of hardware effectiveness and control (e.g. gimbals versus UAV motion correction) and post-processing methods. For the two sets of tests, we will additionally explore target-based and targetless UAVs vibration and displacement monitoring, and ideally if budget and time allows, the feasibility of 2D (using one UAV) versus 3D (using two spatially correlated UAVs) measurements. The first set of tests will use the static V&V test previously devised by our research group to measure tracking points displacements against the standard one-inch block. The second set of tests will be more elaborate and consider both static and dynamic motion of a rigid small-scale tower on a shake table as shown in Figure 2. The sought V&V tests in this task are expected to properly quantify both static and dynamic UAV-based displacement measurements. Preliminary results from this task and tests have been recently processed and shown in Figures 3 and 4. Figure 3 shows how the harmonic excitation applied to a rigid tower has been captured using drone video. A correction method has been applied to correct for the drone shifting while recording test video. Figure 4 shows the frequency-domain analysis of the obtained displacement signal of the tower with and without correction for drone shift. The results show that in the frequency-domain, drone displacements and shifts do not affect the system identification results of vibrating structures.

Fig. 2 – Example of a V&V test for drone-based dynamic response monitoring.

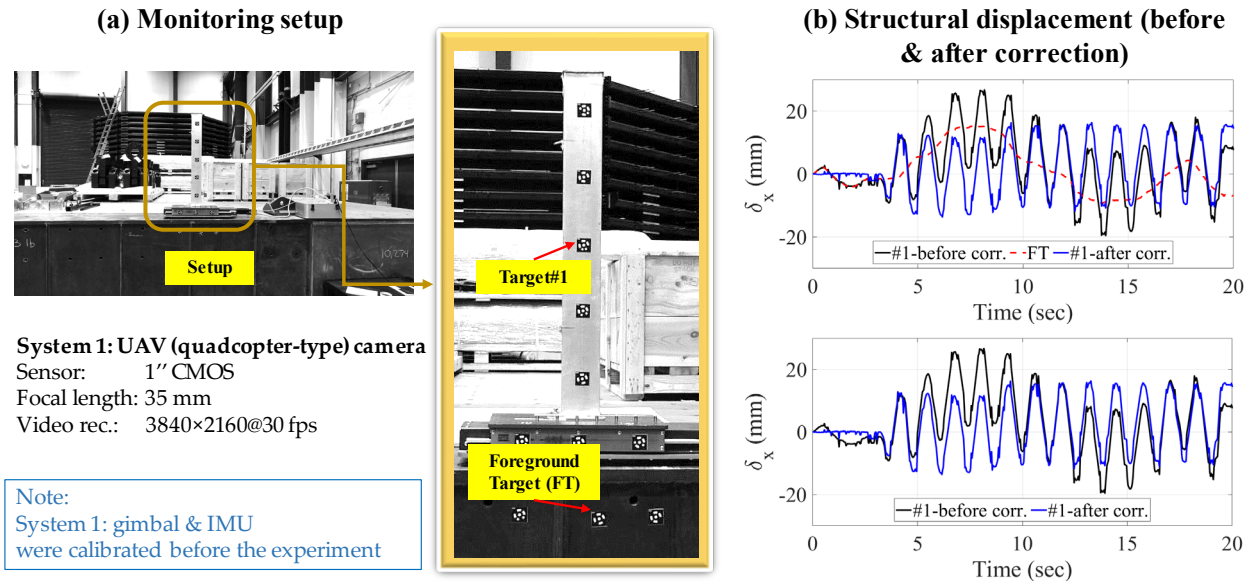

Fig. 3 – Monitoring setup and details (left) along with preliminary displacement results obtained from drone vide (right).

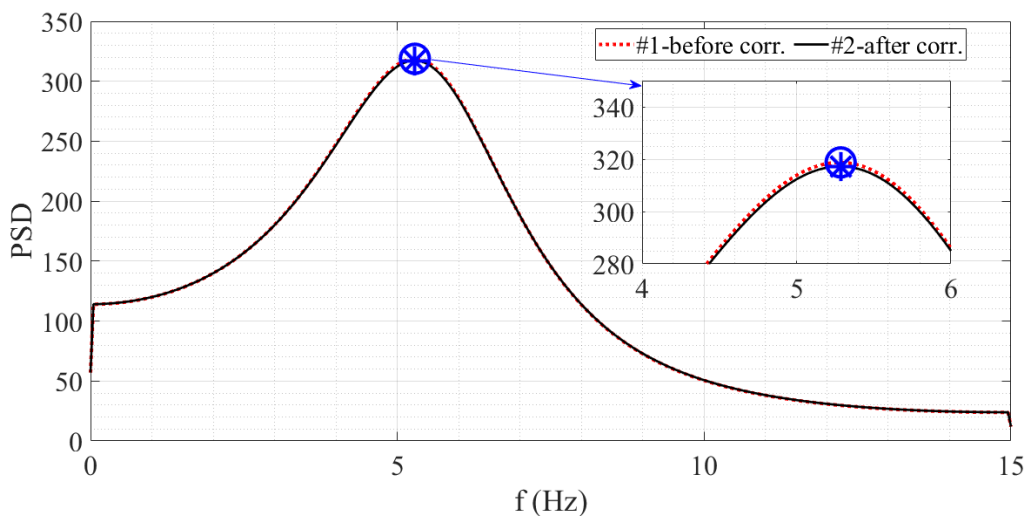

Fig. 4 – Frequency-domain analysis of the obtained displacement signal from the drone with and without correction.

Task 3 – Large-scale seismic monitoring test framework validation.

The objective of this task is to investigate the viability and/or demonstrate UAV-monitoring as part of a full integrated system using at least one large-scale shake table test to be conducted at the Earthquake Engineering Laboratory at UNR. As mentioned before, the PI has been conducting and monitoring several large-scale single or multiple shake table tests over the past few years. In this task, we have already "piggybacked" a full-scale test in late summer 2021 for a natural gas pipeline system (representative large-scale infrastructure system) that was tested using two shake tables at UNR. Figure 5 shows the test setup and Figure 6 shows sample picture collected by the drone for the vibrating system. It is again noted that the purpose of these tests is to validate for the first time the tracking algorithms used in UAV-based dynamic response monitoring systems. Thus, only

exploratory results are expected from this major task and unique test to conclude this phase of the project. However, and similar to Task 3, preliminary results have been now generated from this test and an exclusive sample is shown in Figure 7.

Fig. 5 – Multiple shake table test setup for an infrastructure system monitored by drone at UNR.

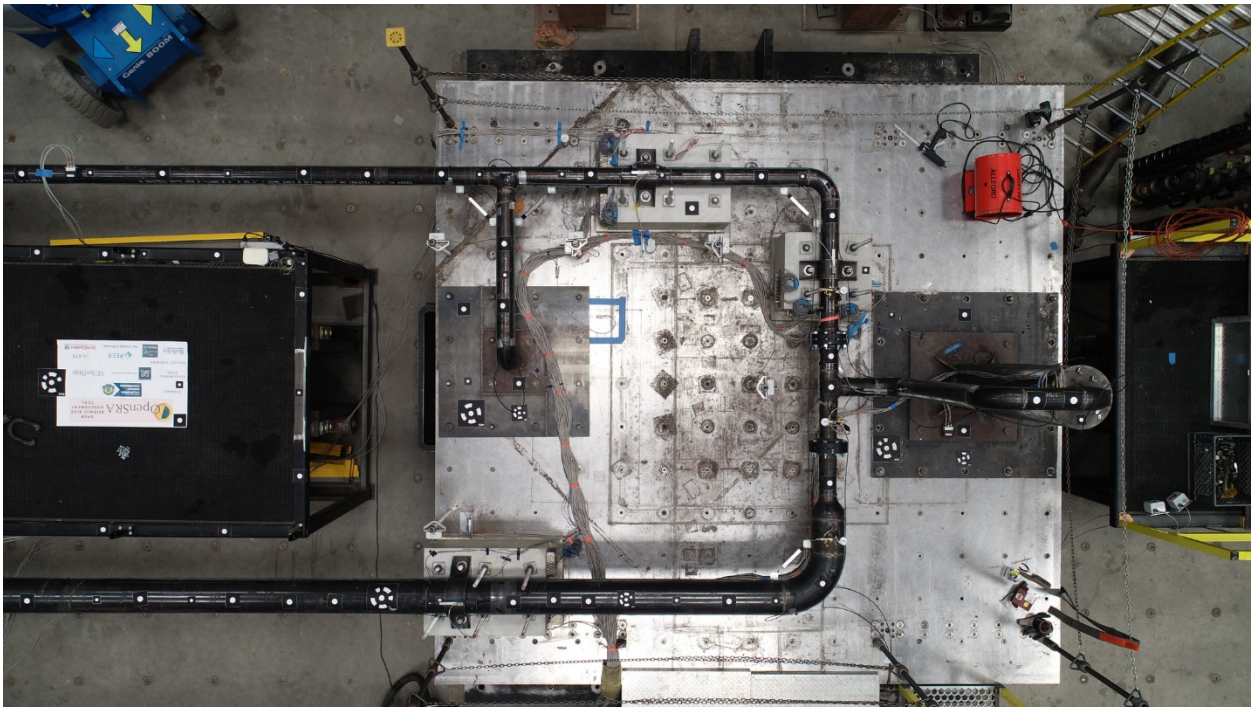

Fig. 6 – Sample picture collected by hoovering drone for the tested infrastructure system.

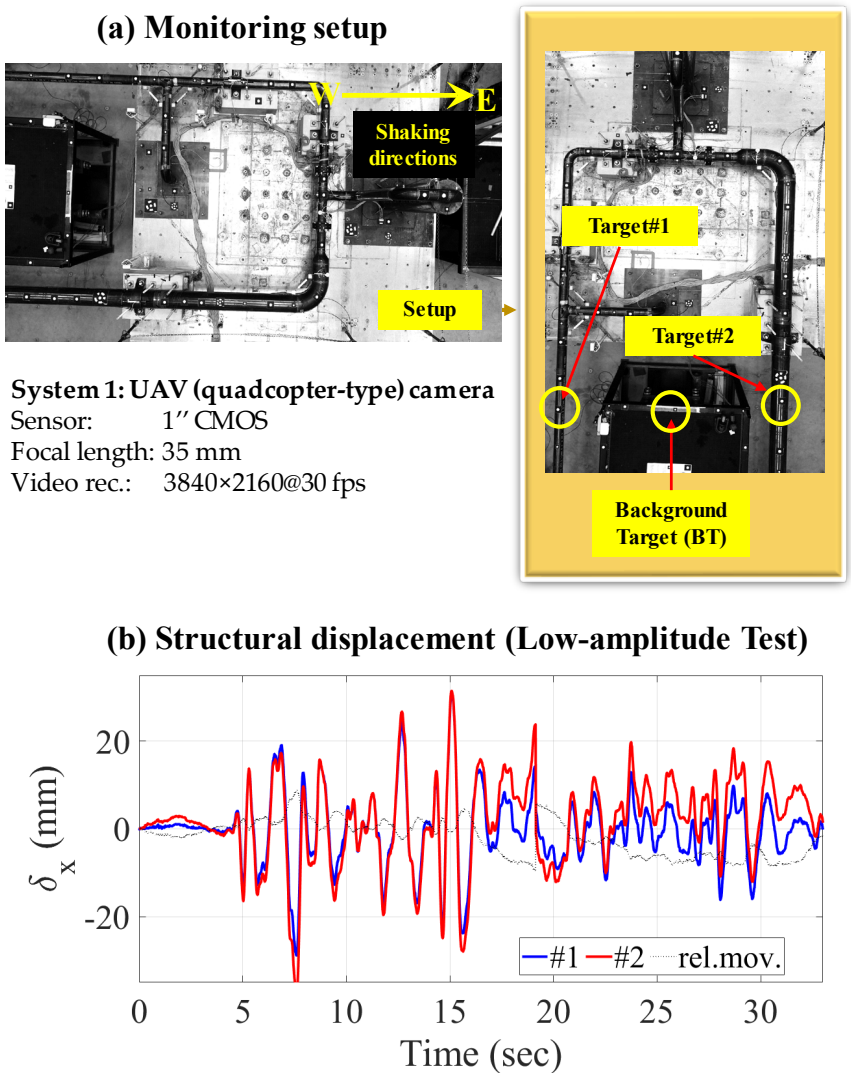

Fig. 7 – Monitoring setup details and sample dynamic displacement response history as captured from the drone video for the two targets identified on the tested system.

TASK 4 – Results dissemination and Final report

A final report will be prepared and submitted for wide dissemination through the ABC-UTC. The report will be complemented with ABC-UTC guide for the roadmap of future implementation of UAV-based dynamic response assessment of bridges. At least one journal paper will be produced from this project and will be submitted for potential publication in a peer-reviewed journal.

2.3. ANTICIPATED RESEARCH RESULTS AND DELIVERABLES

- Final Report and ABC-UTC guide on UAV-based dynamic response assessment of bridges
- One comprehensive manuscript that lay the foundation for future-implementation of drones for dynamic and seismic response monitoring of bridges
- Five-minute video summarizing research study and findings

2.4. APPLICABILITY OF RESULTS TO PRACTICE

The results from this project are expected to benefit different states DOTs in the future, but an immediate impact is not expected from this fundamental research project.

3. TIME REQUIREMENTS (GANT CHART)

To allow for the completion of all the project tasks, the study will be conducted over a period of 15 months (5 quarters) following the schedule in Table 1.

Table 1 – Gantt schedule of major project tasks

Task	2021				2022			
	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8
1. Synthesis of available methods								
2. V&V drone-based monitoring tests								
3. Large-scale drone-based monitoring tests								
4. Final report & dissemination								

	Completed or work in progress		Remaining

Percentage of completed work: 65%

Percentage of remaining work: 35%

Appendix A: Synthesis of Autonomous UAV Navigation and Trajectory Planning for Civil Infrastructures

1. INTRODUCTION

Due to the climate change and global warming, disasters – whether it is artificial or natural, are nowadays more frequently disrupting our world even costing human lives. This is more of a concern for the urban areas as the trend of population here is in a rise. In dense urban environments, these disasters can cause extensive structural damage to the civil infrastructures not only making recovery efforts slow and painstaking work but also putting responders in harm's way because of the uncertain knowledge of structure's stability. Therefore, post-disaster structural assessment has been placed in the spotlight of the research community (Rastiveis et al., 2013). Now, if the data required to assess the damages could be gathered and processed remotely, early responders and engineers could more effectively respond, perform detailed assessments, and better plan for rescue, recovery and reconstruction of the affected areas (Torok et al., 2013). In this case, significant research attention in civil engineering discipline have been focused on the aerial robot or more famously known as Unmanned aerial vehicle (UAV) in the past decade due to their cost-effectiveness and convenience for imagery data collection (Meyer, 2015).

Previously UAVs are mostly controlled by Pilots however, with the advent of modern technologies such as AI, accomplish different level of autonomy for UAVs. According to the National Highway Traffic Safety Administration (NHTSA and SEA, 2014) six levels of autonomous vehicle navigation are defined which are also applicable to UAV navigation. Where Level 0 is completely manual control of navigation by pilots. Level 1 is UAV navigation performed by pilots but with some automation applied to specific flight modes, such as holding altitude and hovering. In Level 2 automation, users can define multiple flight modes for automation, and the UAV then navigates based on the scheduled flight modes if there is no unexpected change in the flying environment. In Level 3, a UAV understands changing flying environments and controls flight modes itself to navigate the new environments. In Level 4 navigation, a UAV can adaptively react when there is any system anomaly or a sudden accident, such as a collision with other objects. In Level 5, a UAV can autonomously navigate in all environments and situations.

For post-disaster data collection of civil structures, the navigation space can be considered as a known space with no sudden change of environment, where autonomy of a UAV with scheduled flight plan and some specific flight modes can be accepted to be adequate. Thus, in most cases, as the flying environment is known previously, Level 2 or semi-automated UAV automation is of interest for emergency data collection. (Kang, 2018).

UAV is one of the emerging and most used technologies nowadays. They are rapidly being deployed in every field of life and are performing daily chores efficiently making life easy. The main concern related to UAV is to plan an optimum and feasible path for UAV to perform any task efficiently and in a minimum possible time. Many researchers have explored path planning of UAVs from different perspectives. Recent studies on path planning in UAVs have made a great advancement. Still there is a lot more to know about path planning in UAVs.

The reason behind writing this paper is to gather all the information related to path planning in UAVs in one hand. Comparative to the existing literature, the paper focuses on the need

of path planning, aspects of path planning, optimization techniques, and so forth. The purpose of this paper is to provide a comprehensive overview of path planning to the newcomers. So that the new researchers have a quick knowledge about the path planning. Our goal is to discuss all the related details and highlight important aspects of path planning in UAVs.

2. UAV COMPONENTS & SYSTEM ARCHITECTURE

The layered structure consists of data collection, data processing, and actuation. The data collection layer having hardware components such as-on-board sensors, light detection and ranging (LIDAR) path planning track, back and front cameras and communication smart devices, i.e., transceivers. The data is collected by these hardware components of the UAVs and is processed by the UAV's central control system, which is then used in mapping, localization, and decision-making system. The central control system actuates the UAVs and is used for the real-world environment. The area covered by the above-mentioned hardware components. For instance, the infrared devices avoid front and rear UAVs collision by detecting the obstacles during UAVs path planning. These infrared devices provide the solution from avoiding collisions such as—path change warning by detecting the extra object and traffic view in the path. UAVs are equipped with a series of video and photograph cameras to locate the surrounding and back view of the path. LIDAR is used for avoiding collisions in UAVs path planning. UAVs consist of major components such as—electronic speed controller (ESC), GPS module, sensors, gimbal, flight control, battery. All the aforementioned components are inter-connected and work closely with each other. The detail description of the components of the UAVs is as follows.

2.1 ELECTRONIC SPEED CONTROLLER

ESC is an electronic circuit, which is an essential part of the UAVs that offers high frequency and power to the UAVs motors. It is used for varying the electronics' motor speed and to convert the direct current (DC) power to 3-phase alternate current (AC) power.

2.2 UAV NAVIGATION SENSOR

Normally, UAVs obtain states of their own and information of surroundings from both exteroceptive and proprioceptive sensors. Multiple types of sensors are available for a UAV to determine its position. These sensors provide vehicle position data for the UAV to conduct its scheduled mission.

The traditional sensors used for navigation are mainly- GPS, Axis Accelerometers, Gyroscope, Vision Camera (Monocular Camera, Stereo Camera, RGB-D Camera, Fisheye Camera etc.), Laser lighting, Ultrasonic Sensors (such as: Ultra-wideband bacon, Ultrasonic bacon sensor), Inertial Navigation System, 3D Volumetric Sensors etc.

GPS is the most popular option for position sensors, as GPS sensors are cheaper and easier to use than other types of position sensors. A simple autonomous outdoor navigation by waypoints has been demonstrated using the GPS for localization of the UAV (Carvalho et al., 2017). Unfortunately, GPS cannot be used by a UAV for autonomous flight near some parts of certain structures (e.g., beneath a bridge). The usage of a UAV is often limited to outdoor environments only and complex topographic environments of the navigation space for data collection require higher accuracy in UAV localization than commercial GPS can provide.

Numerous researcher have worked with ultra-wideband beacon system to provide high precision positioning to enable a new range of applications in GPS-denied environments (Vossiek et al.,

2003; Zwirello et al., 2012; Sunget al., 2016). However, some experiments have shown millimeter-level accuracy of ultra-wideband beacon positioning systems, but the direct application is not practical in UAV systems due to high cost and a lack of integration (Zhang et al., 2006). An ultrasonic beacon system (UBS) can be an alternative for a practical mapping and localization system using low-cost hardware. It is cheaper and easier to integrate into and provides centimeter-level accuracy with proper parameter tuning (Dıaz et al., 2017). A UBS has multiple mobile and stationary beacons. Where mobile beacons provide 3-dimensional (3-D) position data (x,y,z) of a UAV, and the stationary beacons define the border lines of the map. The stationary beacons are similar to a GPS, sending ultrasonic signals and calculating distances to the mobile beacon installed in the UAV through a router.

Visual sensors are another source to acquire rich information of surroundings based on color, texture, feature, and other visual information. As they are cheaper and easier to deploy, vision-based navigation has becoming a hot spot in the field of UAV research. Different types of cameras are used as visual sensors based on their compactness, weight, cost, flexibility to deployment and visual capacity. However, the performance of visual sensors are dependent on the environment. For example, if the vision sensors cannot obtain features adequate to identify a UAV's location, they incur a high computational cost and accumulate localization errors (Hesset al., 2016).

2.2.1 GIMBAL

Gimbal is the pivoting point of the UAVs that rotates about x, y, and z-axis. It provides stabilization to the UAVs. It is important for clicking good photographs and videos.

2.2.2 FLIGHT CONTROLLER

Flight controller takes input from the GPS module, light amplification by stimulated emission of radiation (LASER) monitors and other sensors. It is the central part of the UAVs and controls the whole functioning of the UAVs network communication.

2.2.3 MISSION PLANER

A Mission Planner is a software that provides a graphical user interface (GUI) to manage and monitor the navigation of the UAV. Mission Planner has many roles. It displays the status of a UAV through different protocol (Meier et al., 2011).The Mission Planner can record and replay the log data of a UAV flight. A user can review error messages associated with the status and navigation plan, including environmental noise such as magnetic interference.

2.2.4 BATTERY

The battery in UAVs is made from the lithium polymer (LiPo) for power, energy and lifetime density of the UAVs. They always carry an extra battery for the emergence of long duration target operations.

3. NEED FOR PATH PLANNING

With the rapid increase in the construction of tall buildings, towers, and trees, chances of UAV collision are also increased. For success full completion of UAV mission, proper planning of UAV track is necessary. The planned path must be collision free, path length from source to destination should be optimal, mission completion time should be minimum, UAV should consume less energy, and total cost of path planning should also be minimum. The path planning techniques must satisfy the completion, convergence, and robustness criteria. An optimal or feasible UAV

path must be cost, time, and energy efficient. A comparison of time, energy, and cost efficient path planning is shown. To optimize the UAV path, cost, energy, and time should be minimized. Path planning optimization is always a balancing act of minimizing cost, time, and energy. Although the optimization of cost, time, and energy are directly or indirectly related to each other. Optimizing the time of UAV mission will require less fuel to complete the mission which in turn reduces the cost of path planning. Similarly, optimizing the fuel will require UAV to complete the mission in minimum possible time, which will also result in reduced cost of path planning. A brief description of cost, time, and energy efficient path planning is discussed below.

3.1 COST EFFICIENT

UAV path planning includes the battery cost, fuel cost, hardware cost, and software cost. Total path planning cost may also include the cost of cameras used for capturing the images, sensors for sensing the environment, and GPS for locating the position. The initial manufacturing and maintenance cost is also included. For optimizing the path of UAV, the total cost of the UAV flight should me minimum. The authors in reference2 discussed the cost efficient path planning by reducing the fuel cost while in reference,49 cost was optimized by reducing the number of drones used to monitor an area while increasing the coverage area.

3.2 TIME EFFICIENT

Time efficient UAV path planning is defined as the completion of UAV entire mission in minimum possible time. This is done by choosing the shortest collision free optimal path from source to destination. In some applications, completing the task in the minimum time is crucial such as rescuing the tourists and providing aid to disaster areas. In the authors minimized the information transmission time for fixed wing UAV communication by planning optimal UAV paths. The authors discussed the problem of cooperative timing of multiple UAVs. The authors compared the A*(star) algorithm and probabilistic road map algorithms on the basis of time taken. In case of multiple UAVs, the delay between the arrival of UAVs need to be optimized.

3.3 ENERGY EFFICIENT

Energy efficient path planning is defined as the minimum use of fuel, power, and energy consumed by the UAVs during their mission from initial point to final point and back to initial point. The energy used by the UAVs need to be optimized because the UAVs have to complete the entire mission and return to the destination by utilizing the given fuel. If the total fuel is consumed before the mission completes, UAV may fall down which results in a huge loss. Energy optimization includes all aspects of energy consumed by the UAVs during flight. There are three components of the consumed energy: (1) flying energy: energy used by the UAV to fly from source to destination; (2) hovering energy: energy used by the UAV to stay in the air for performing the task, that is, inspection; and (3) transmission energy: energy used by the UAV to send the data to the source. Multiple UAVs were used to minimize the energy consumption by proper planning of the UAVs trajectories.

4 ASPECTS OF PATH PLANNING IMPLEMENTATION

Suppose a UAV has to fly in a smart city performing daily chores shown. Before UAV start its flight, certain factors must be known for the successful completion of the mission. There are different aspects which need to be considered while planning a path for UAV. The UAV should know about the environment of the smart city, dimensions of the area, the obstacles present during

the flight, number of UAVs used to complete the mission, and the mode in which UAV plans path. These aspects play a vital role in planning a feasible and optimum path for a UAV flight. A brief description of these aspects is discussed below.

4.1 ENVIRONMENT

Before planning the path of UAV, it is important to know about the environment in which the UAV has to fly. The environment may be static or dynamic. Different authors discussed path planning in different habitats wind field, static environment, and low dangerous altitude. The nature of the terrain plays vital role in path planning. The terrain may be urban or there may be wind, sunlight, or rain in an area. The environment may be uncertain; that is, it may continuously change from static to dynamic. The authors in implement firefly algorithm for the path planning in uncertain environment. The implemented algorithm gives the effective obstacle avoidance and low cost optimal path. Path planning of UAVs with engine failure in the presence of wind was discussed in In the presence of jamming signal, the path planning of UAV was studied by. A multi-objective approach for the path planning in urban environment was explored in The authors in discussed the dynamic path planning in complex environment. Evolutionary algorithm was used to track the UAV path in unknown geographic area.

4.2 DIMENSIONS

It is either two-dimensional (2D) or three-dimensional (3D). Path planning in 2D is comparatively easy. In 2D, the UAV will fly at a fixed altitude with constant speed and the direction is not changed periodically, while path planning in 3D is a complex task as there is a changing altitude, UAV changes its speed according to the height, and the direction can be changed at any moment. Commonly used path planning methods focus on, which is easy to accomplish. However, with the advancement in UAV maneuverability and the demands for low-altitude and terrain following flight, path planning in 3D terrain is gaining more attention.

4.3 OBSTACLES

The main purpose of planning a UAV path is to provide UAV a collision free path and to ensure the safe flight of UAV from source to destination. Anything that interrupts the UAV flight is regarded as an obstacle. The objective of the path planning is to detect obstacles, to avoid obstacles, and to follow an optimum path to the destination. During its flight, UAV may encounter two types of obstacles. Obstacles may be technical or non-technical.

4.3.1 TECHNICAL OBSTACLES

Technical obstacles are also known as constraints. Constraints are the limitations and restrictions which are implemented for economical and successful completion of any task. For favorable outcome of the path planning of UAVs, number of constraints or technical obstacles are considered. The UAVs must follow these constraints in order to complete its mission successfully. A few constraints are discussed below.

Track segment length constraint: Track segment length is the minimum length of path that UAV should cover before changing its direction. If the minimum track segment length is lmin, then UAV

Mission constraint: Mission constraint is defined as the length of UAV entire journey from source to destination and in some cases back to source. UAV has limited fuel capacity and the entire

journey should be completed in the given fuel and time. If the maximum mission length is L_{max}, then path needs to satisfy the following equation:

Turning angle constraint: Turning angle is the angle generated by UAV before turning in the horizontal direction. It depends on the terrain and performance of UAV. The turning angle should be less than the maximum turning angle. If the turning angle is θ and maximum turning angle is θ_{max}, then the following equation should be satisfied:

Dive/climb angle constraint: Dive/climb angle is the angle generated by UAV before turning in the vertical direction. The angle is decided by the maneuver performance of UAV.

Flight height constraint: To ensure the safety of UAV during flight, UAV should maintain a minimum height from the ground. Suppose H_{min} is the minimum height from the ground, then the flight height of each path segment H_j should satisfy the following equation:

In applications where UAV has to capture images from a height, a combination of image size and flying height is decided to maintain the accuracy and to reduce the storage capacity.

Timing constraint: Timing constraint is defined as the time interval in which the UAV has to complete its mission. Timing constraint is particularly more important when multiple UAVs are used. It guarantees the sequential arrival of multiple UAVs at the target with specific time interval, simultaneous arrival of all UAVs at the same time, and the arrival of the UAVs at the target in the same order and in the given time limit [t_{min}, t_{max}].

4.3.2 NON-TECHNICAL OBSTACLES

Non-technical obstacles include static or dynamic obstacles.

Static obstacles: Static obstacles include buildings, mountains, trees, and poles. In a static environment, obstacles are assumed to be stationary; that is, the UAV knows the exact location and size of the obstacles. UAV has to fly from initial point to final point avoiding these obstacles. An offline path planning approach will guide UAV to avoid the obstacles and reach the destination safely.

Dynamic obstacles: Dynamic obstacles include birds, other flying objects, and unexpected threats. Dynamic environment consists of both static and unexpected obstacles. The obstacles may be of any shape, size, and dimensions. UAVs are equipped with sensors which provide information about the surroundings and position of the obstacles. An online path planning method is proposed to direct the UAV to destination in a dynamic environment.

There are also some restricted areas or no-fly zones which UAV has to avoid during flight. UAV was required to avoid no-fly zones. Modeling of the obstacles plays an important role in planning the trajectory of UAV. The authors modeled the hill as cone, buildings as parallelepiped, radar as hemisphere, and antiaircraft as cylinder. Obstacles were also modeled as cuboid or cylinder. If the environment is obstacle free, the flight of UAV is usually in straight paths from source to the destination. While flying in a region near radar detection, UAV is required to maintain larger distance from radar so that the probability of being detected is minimum.

4.4 NO OF UAVS

Depending upon the application, number of UAVs are decided. A single or multiple UAVs may be used according to the application, terrain, and so on. Multiple UAVs are preferred over signal

UAVs because they have improved efficiency and robustness. Many tasks such as surveillance and inspection require multiple UAVs to have more information in less time.

4.5 MODE

It includes the time at which the path planning is being done. The path planning of UAVs is done either offline or online. Offline path planning includes the planning of UAV track before the flight of UAV begins while online path planning is planned in real times while heading towards the goal, keeping in view the environmental changes. Offline path planning is used for static environment where the information about the terrain, obstacles, dimensions, and so on are known and is planned before the flight begins. For dynamic environment, where the obstacles and threats are unexpected, online path planning must be used to update the path according to the environmental changes. According to a survey, 29.9% of methods are online, while 70.1% of the methods are offline. Online path planning algorithm in a low dangerous environment with static obstacles and dynamic threats was presented. Online path planning approach in 3D was used by researchers in previous works, while offline approach in 2D was discussed by authors. Some authors also explored the offline path planning method in 3D. The authors in studied the offline method in 3D environment while keeping the obstacles static. For a multi-objective path planning, both offline and online search methods.

5. PATH PLANNING

Path planning is a problem of determining a path for the UAVs from an initial point to the goal point. The path determination f or the UAVs should be free from all collisions from the surrounding obstacles. Their planned motion satisfies the UAVs physical/kinematic constraints such as-electrical energy and kinetic energy. UAVs path planning consists of following key terms, which are discussed below.

Motion planning: Motion planning is concerned with robotics. This planning satisfies the constraints such as-flight path, turning a crank in path planning motion. It optimizes the path in terms of short path length and minimum turning angle.

Trajectory planning: Trajectory planning is about the motion planning. It encloses the path planning having velocity, time, and kinematics of UAVs motion.

Navigation: Navigation is a part of motion planning, trajectory planning, collision avoidance, and localization. It is a general term in which controlling and monitoring of the UAVs movement is from one place to another.

In order to successfully complete a scheduled mission, planning and control of UAV navigation can be accomplished through the steps as shown as Figure 1.

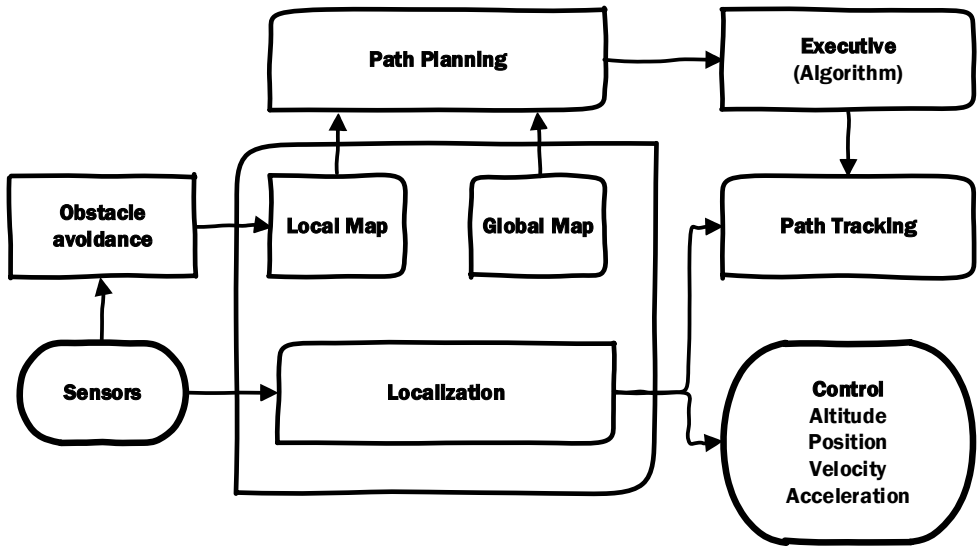

Figure 1: The steps of path planning of UAV

5.1 PATH PLANNING PROBLEM DEFINITION

To define the problem of path planning and obstacles avoidance, a number of main concepts must be reviewed. A workspace defined as $W = R^3$ can be divided into a finite series of spaces occupied by different obstacles C_{obs} and a series of different free spaces C_{free} inside a set of C_{spaces}.The path planning task is defined as the ability to travel from an initial point p_{Init} to a goal point p_{Goal}, passing through a path constructed by free spaces in C_{free}. In UAV context,the aircraft must be defined as a 3D solid object that can be translated and rotated in space and its configuration requires of six variables:(x, y, z) for translations and (α, β, σ) for Euler angles. Search space can be defined as a continuous or discrete space. Depending on this definition a type of path planning algorithm can be used. These methodologies have a computational complexity NP(Nondeterministic Polynomial Time) and the data assignments to a connectivity graph G are built along the algorithm iterations. The graph G(V,E) is constructed by a non-empty set of vertices V and edges E. Where V is the set of collision-free vertices belonging to C_{free} and E is the set of neighboring pairs corresponding to V. The consecutive sequence of collision-free spaces P resulting from the path planning algorithm, defines the trajectory that the UAV follows.

For path planning, there is a requirement of 3-D (three-dimensional) view in complex environments. The simple 2-D (two-dimensional) path planning methods are not able to find the obstacles and objects in comparison to the complex 3-D environment. So, 3-D path planning techniques are on demand for UAVs surveillance and navigation in a cluttered and complex environment. The scenario of a 3-D environment is as shown below:

A path planning for 3-D (D^3) environment with stationary obstacles $O = \{O_1, O_2, \ldots\ldots O_n\} \subset D^3$, from P_s to P_t is as shown. Assume that the free workspace without obstacles/problems is represented by W_{free}. Then, the path planning problem for D^3 environment is (P_s, P_t) for which various functions is defined as follows. Let a function $[0,T] \rightarrow D^3$ is defined in the bounded region where, T is represented as a time. Then, following holds:

$$(0) = P_s \rightarrow \text{at starting time}$$

$$(T\ ) = P_t \rightarrow \text{at target time, and}$$

$$\emptyset = (\beta) \in W_{free} \text{ for all, } \beta \text{ in [0,T]}$$

Then, $\emptyset$ is called path planning of UAVs. For an optimal path planning, cost (c), time (t), energy (e) should be minimized. So, it can be defined as follows.

$$\delta'(c, t, e) = \text{minimum of } \delta(c, t, e)$$

where, δ is the function of all set of feasible path and δ' is an optimal path computation function. The communication energy of UAVs base-station can be reduced by minimizing the transmission power. Similarly, minimizing the mechanical energy of UAVs, there is a need for consumption model in UAVs communication system. The energy-efficiency in UAVs communication system can be modeled as follows.

$$E = (P_{min} + \alpha \text{h})\text{t} + (P_{max})\ (\text{h/s})$$

where as, t represents the operating time, h represents the height, and s represents the speed of the UAVs. P_{min} and α depends on weight and motor characteristics. We can say that, P_{min} is the minimum power needed to start the UAVs with α as the motor speed multiplier. Hence, the total communication cost (T_{com}) to minimize the time and cost in UAVs communication system is as follows:

$$T_{com} = t_s + (t_o + t_h)\text{l}$$

where as, t_s represents the startup time of UAVs, t_o represents the overhead time, t_h represents per-hop time of the UAVs, and l represents the communication links between the source and destination. With these parameters, robustness, completeness and collision avoidance factors have also been considered in the existing proposals for finding the optimality of UAVs path planning.

5.2 PATH PLANNING TECHNIQUES

Path planning of the UAVs is represented as 'U' consists of two phases as follows. The first phase is the pre-processing phase. In this phase, nodes (points) and edges (lines) are drawn on the workspace 'W' with obstacles 'O'. Then, the concept of the configuration space (c-space) to describe U and O on W is applied. Next, representation techniques are applied for generating the graph maps. Each path planning technique defines the path for UAVs having points and lines in a different way. The second phase is the query phase in which search and rescue operations are performed from the starting point of the path to the target point. For the query phase, the graph search based algorithms such as-ant colony algorithm, flood-fill algorithm, Floyd algorithm are used. There are a number of path planning methods such as-probabilistic models, mixed integer linear programming, bio-inspired models, evolutionary models, which can also be used for an optimal UAVs path planning.

5.2.1 LOCALIZATION AND MAPPING

Mapping and localization are critical to realization of Level 2 autonomous navigation. To develop autonomous navigation for a UAV, positioning sensors are used for local mapping and a ground station including a mission planner is used to assign a navigation plan. Where a commodity computer can serve as a ground station and the role of mission planner is to assign a navigation plan and monitor the UAV.

Considering the environment and prior information used in navigation, localization, and mapping systems can be roughly classified into following categories:

I. RANDOM GEOMETRIC GRAPH

Random geometric graphs are in general defined as stochastic collections of waypoints in a metric space, connected pairwise by edges if certain conditions (e.g. on the distance between the points) are satisfied. From the theoretical point of view, the study of random geometric graphs makes a connection between random graphs and percolation theory. Much of the literature on random geometric graphs deals with infinite graphs defined on unbounded domains, with vertices generated as a homogeneous Poisson point process. The most studied model of random geo-metric graphs are the following-

1. **Infinite Random geometric graph**
   a. Gilbert's disc model
   b. Boolean model
2. **Random finite geometric r-disc graph** – models of finite graphs on a bounded domain such Penrose model.
3. **Infinite random K-nearest neighbor graph**
4. **Finite random K-nearest neighbor graph** – considers the edges between K-nearest neighbors
5. **Online nearest neighbor graph** – connected by construction and trivially percolates.

II. VISUAL LOCALIZATION AND MAPPING

1. Mapless system

Mapless system performs navigation without a known map, and UAVs navigate only by extracting distinct features in the environment that has been observed. Currently, the most commonly used methods in maples system are-

a. **Optical flow methods**

Generally, the optical flow techniques are divided into two categories: global methods and local methods. It is based on the method imitating the bee's flight behavior by estimating the object movement through cameras on both sides of a UAV. It calculates the optical velocity of two cameras relative to the next waypoint. If they are same, the UAV moves along the central line; otherwise, it moves along the speed of small places forward. It is prone to have a poor performance when navigating in texture-less environment.

b. **Feature tracking methods**

It primarily tracks invariant features of moving elements, including lines, corners, and so on and determines the movement of an object by detecting the features and their relative movement in sequential images. During the process of UAV navigation, invariant features that have been previously observed in the environment are likely to be reobserved from different perspectives, distances, and different illumination conditions. Traditionally, natural features used in localization and mapping are not dense enough to avoid obstacles. Li and Yang (2003) proposed a behavioral navigation method, which utilized a robust visual landmark recognition system combining with a fuzzy-based system for obstacle avoidance.

2. Map based system

Map-based system predefines the spatial layout of envi-ronment in a map, which enables the UAV to navigate with detour behavior and movement planning ability. Generally, there are two types of maps:

a. **Octree maps**

Fournier, Ricard, and Laurendeau (2007) used a 3D volumetric sensor to efficiently map and explore urban environments with an autonomous robotic platform. The 3D model of the environment is constructed using a multi-resolution octree. Hornung et al. (2013) devel-oped an open source framework for representation of 3D environment models. The main idea here is to represent the model using octree, not only the occupied space, but also the free and unknown space

b. **Occupancy Grid Maps**

Dryanovski, Morris, and Xiao (2010) used a multi-volume occupancy grid to represent 3D environments, which explicitly stores information about both obstacles and free space.

3. Map-building systems

Sometimes, due to environmental constraints, it is difficult to navigate with a preexisting accurate map of the environment. Moreover, in some emergent cases when known environment is not a priori, it would be impractical to obtain a map of the target area in advance. Thereby under such circumstances, building maps at the same time as flight would be a more attractive and efficient solution. Map-building system has been widely used in both autonomous and semi-autonomous fields, and is becoming more and more popular with the rapid development of visual simultaneous localization and mapping (visual SLAM) techniques. According to its way of visual sensor image processing, visual SLAM algorithms are divided into three types of methods: indirect method, direct method, and hybrid method.

a. **Indirect method**

Instead of using images directly, the indirect method firstly detects and extracts features from images, and then takes them as inputs for motion estimation and localization procedures. Current SLAM algorithms are mostly under the feature-based framework. Some of the indirect SLAM based algorithms are-

i. *Monocular Visual SLAM* - Davison (2003) presented a top-down Bayesian framework for single camera localization with real-time performance via mapping a sparse set of natural features. It is a milestone for monocular visual SLAM and has a great impact on future work.

ii. *Parallel tracking and mapping algorithm (PTAM)* – It is the first one to divide the SLAM system into two parallel independent threads: tracking and map-ping, which was first developed by Klein and Murray (2007). This has almost been the standard of modern feature-based SLAM system.

Some other indirect methods are Spare indirect method, Dance Indirect method etc.

b. **Direct Method**

Though indirect methods prove to perform well in ordinary environment, they are prone to get stuck in texture-less environment. So, direct methods also become a hot spot in the last decade. Different from indirect methods, direct method optimizes geometry parameters using all the intensity information in the image, which can provide robustness to photometric and geometric distortions present in images. Newcombe, Lovegrove, and Davison (2011) presented a real-

time monocular SLAM algorithm, DTAM, which estimates the camera's 6DOF motion using direct methods. Engel, Schöps, and Cremers (2014) employed an efficient probabilistic direct approach to estimate semi-dense maps, which can be used for image alignment.

c. **Hybrid Method**

Hybrid method combines the direct and indirect methods together. First, it initializes feature correspondences using indirect methods, and then continuously refines camera poses by direct methods, which is faster and more accurate. Forster, Pizzoli, and Scaramuzza (2014) innovatively proposed a semi-direct or hybrid algorithm, SVO, to estimate the state of a UAV. Similar to parallel tracking and mapping algorithm, motion estimation and point cloud mapping are implemented in two threads.

III. OBSTACLE DETECTION AND AVOIDANCE

1. Optical flow based methods

The optical flow-based detection method determines the motion speed of the each pixel by analyzing the temporal variation and correlation of the pixel gray levels on the surface of the image and is used for the motion of the target. Literature locates the obstacle by detecting the change of the optical flow in the image sequence, but the depth information of the obtained obstacle is relatively rough. Literature uses optical flow to detect obstacles in video images and demonstrated that fixed-wing aircraft can effectively avoid obstacles in the environment. Literature proposes a pyramid-based LK optical flow method for the detection of accuracy and poor adaptability of traditional optical flow, and set the adaptive threshold by obtaining the relationship between the optical flow size and the object distance. Then compare the size of the optical flow and the threshold to detect and determine the obstacles. The advantage of the optical flow-based obstacle detection method is that it does not require knowing the specific characteristics of the obstacle in advance, and does not apply to the stationary or relatively slow-moving target.

a. Based on change in obstacle size (mechanism of human eye)
b. Based on insect's vision optical flow navigation
    i. Bee's vision – visual nerve structure of insect
    ii. Based on compound structure of flies
    iii. Based on distance between objects by the speed of light or light intensity

2. SLAM based methods

Precise metric maps, simultaneous localization mapping The stereoscopic vision-based detection method uses two or more cameras to capture scene images of different angles at the same time, and uses an image matching algorithm to find and confirm the obstacles information. This is currently used in obstacle detection methods.

Literature uses a binocular stereo vision system to implement drone navigation and obstacle detection. Literature uses a 3D camera to generate depth information and parallax images for the obstacle detection. Literature proposes an obstacle detection algorithm based on sparse stereo vision and clustering. Iacono et al. use the output of RGB-D camera (Microsoft Kinect) sensor to build environment map step by step and generate conflict free path.

a. Artificial potential field – for static and dynamic obstacles
b. PTAM algorithm
c. c. Oriented fast and rotated brief SLAM

5.2.2 PATH PLANNING ALGORITHMS

Path planning is an important task in the UAV navigation, it means finding an optimal path from the starting point to the target point, based on some performance indicators (such as the minimum cost of work, the shortest flying time, the shortest flying route). In addition, during this process, the UAV needs to avoid obstacles. Different types of path planning algorithms are discussed below:

1. Cell decomposition based method

Cell decomposition (CD) is the most used technique especially in outdoor atmosphere. This strategy is based on partitioning the configuration space into a set of simple, discrete, non-overlapping and connected representative areas known as cells. If a cell is consist of obstacle, then it is identified as occupied, otherwise it is obstacle free. The cells may be of rectangular or polygonal shapes in between start and target points producing a continuous connectivity graph, where each node corresponds to an obstacle free cell and each arc links two free adjacent cells. After the decomposition of the cells in c-space, different path planning methods or algorithms can be used to find a minimum cost path, based on the type and size of the cell. It is required for CD to fine-tune with the situation, as necessary, thus pre-known environmental skeletal knowledge is essential for cell-based optimal PPA (e.g combinatorial algorithms).

The pros of CD are that it ensures the identification of a collision-free path if exists and is controllable. Hence, it is a thorough c-space representation for an UAV that can traverse the path without the risk of experiencing local minima. In addition, the CD-based method yields paths that do not cross any obstacle vertices or are dangerously close to obstacles, and computational complexity. Unfortunately, CD has several drawbacks such as limited granularity, combinatorial explosion, and generation of infeasible solutions. In a real-time dynamic state, this approach does not offer satisfactory results. Further, if the defined cell is too trivial, then computation is time-consuming, where if the cell is too rough, it is not feasible to achieve the smallest path.

Based on the shape and achieving detailed information of the cells there are several variants of CD is shown in Figure 2.

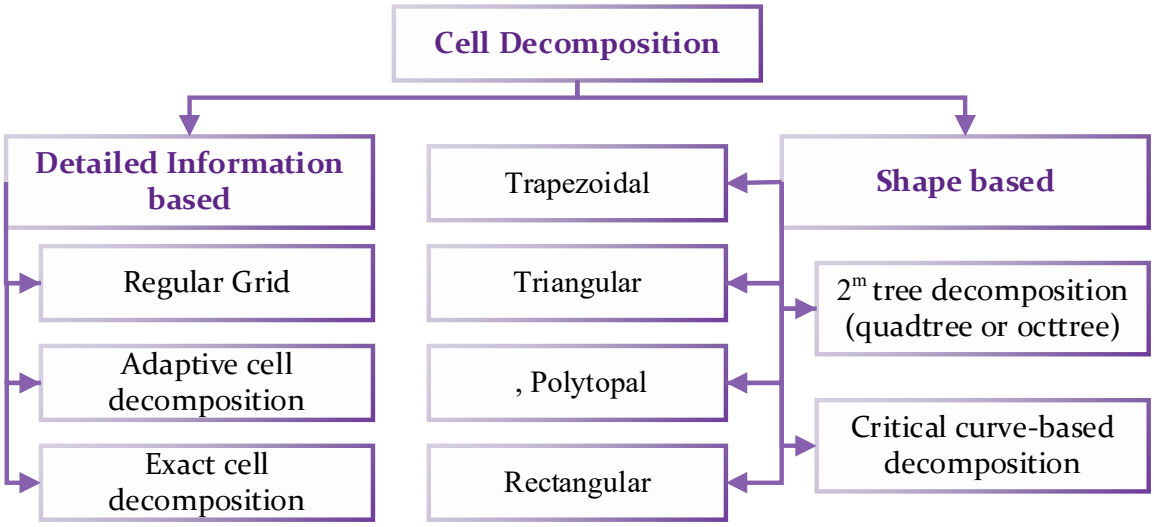

Figure 2: Different variants of cell decomposition method

1.1 Detailed Information Based Cell Decomposition

1.1.1 Regular Grid (RG)

Regular grid (RG) technique was introduced by Brooks and Lozano-Perez to find a collision-free path for an object moving through cluttered obstacles. In general, RG can be constructed by laying a regular grid over the configuration space. As the shape and size of the cells in the grid are predefined, RG is easy to apply. RG basically samples the domain and marks up the graph subsequently to know whether the space is occupied, unoccupied or partially occupied.

A cell is marked as an obstacle if an object or part of it occupies the cell; else it stays as free space. The node is located in the middle of every free space cell within the C_{space}. Connectivity graph is then constructed from all the nodes. Path planning using RG is illustrated in Fig.4. The path connecting starting point and target point is shown by solid yellow line.

RG method is popular because they are very easy to apply to a C-space and also flexible. The computation time can be reduced by increasing the cell size. On the other hand, the cell size can be made smaller to provide more detailed information and completeness.

Although RG is easy to apply, there are some drawbacks with this method. Firstly, it has the digitization bias wherever an obstacle that is too smaller than the cell dimension results in that whole grid square as filled or occupied. Consequently, a traversable space may be considered impenetrable by the planner. This scenario is illustrated in Figure 4 (b). Furthermore, if the cell is too big (hence grid resolution is too coarse), the planner may not be complete.

1.1.2 Adaptive Cell Decomposition (ACD)

The, adaptive cell decomposition (ACD) is built using quad-tree unlike RG. The cells of a quad-tree are identified either as free cells, which contain no obstacles, as obstacles cells, where the cells are occupied or as mixed cells, which represent nodes with both free space and obstacles. The mixed cells should be recursively sub-divided into four identical sub-cells until the resulted smaller cells contain no obstacles' region or the smallest cells are produced.

ACD maintains as much detail as possible while regular shape of the cells is maintained. It also removes the digitization bias of RG. An ACD representation employed for path planning is depicted in Fig.5. The collision-free path that connects starting point (Start) and target point (Goal) is depicted via solid yellow line.

1.1.3 Exact Cell Decomposition

Another variant of CD is Exact Cell Decomposition (ECD) method and it consists of two-dimensional cells to resolve certain dilemma linked with regular grids. The sizes of the cells are not pre-determined; nonetheless they are decided based on the location and shape of obstacles in the C-space. The cell boundaries are determined exactly as the boundaries of the C-space, and the unification of the cells stands the free space. Therefore, ECD is complete that always finds a path if one exists. ECD is shown in Fig.6. The path connecting the starting (Start) and target (Goal) points is shown as solid yellow line. These methods decompose the free configuration space into smaller convex polygons, which are then connected by a graph and searched using a graph search.

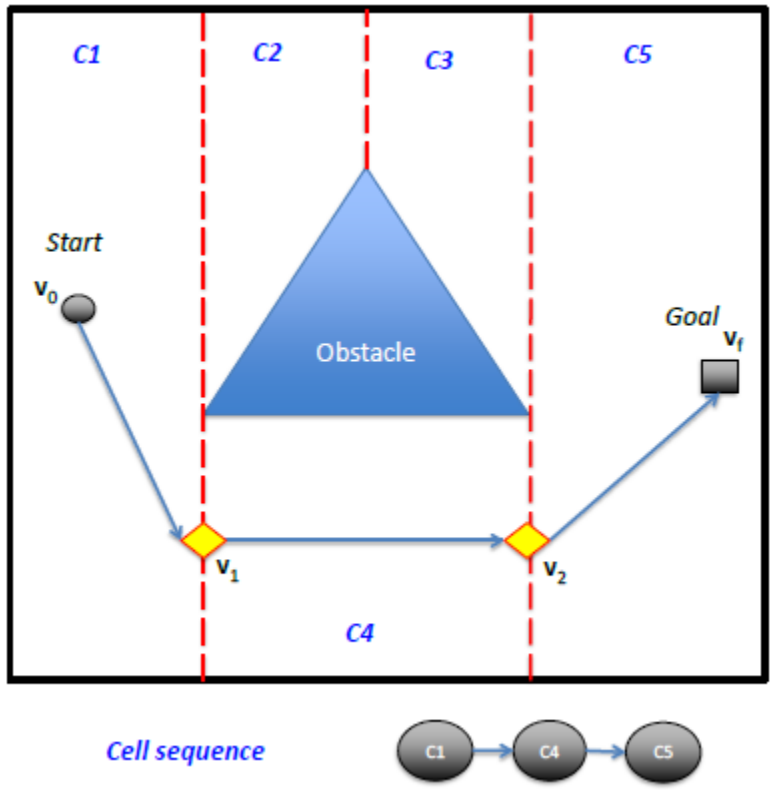

Figure 3: A typical representation of Exact Cell Decomposition

Opposed Angle-Based Exact Cell Decomposition is suggested and it is intended for the mobile robot path-planning issue through curvilinear obstacles for more natural collision-free efficient path.

1.2 Shape Based Cell Decomposition

a. Trapezoidal

Where each cell is a trapezoid (some being reduced to triangles). The decomposition is obtained by a sweeping line algorithm, where from each obstacle vertex a vertical line is extended until it hits another obstacle or the environment bounds, thus solating trapezoids with parallel vertical sides. This approach divides the free space into trapezoidal regions by dividing it with vertical lines from each of the obstacle vertices. The vertical lines are trimmed so that they do not bisect the obstacles themselves. A roadmap is then formed by connecting the midpoints of adjacent trapezoids, and searched using a graph searching algorithm. This approach is complete but not optimal, and runs in O(N log N) time.

b. Triangular

Where each cell is a triangle whose vertices belong to environment corners and obstacle vertices. A cell exactly shares facets with adjacent cells or obstacles, and the decomposition is sometimes called constrained triangulation, for differentiating it from triangulations based on points rather than obstacles.

c. Polytopal

Where each cell is a convex polygon (polytope) with any number of vertices. The cells are obtained by extending the supporting lines of obstacles and by finding non-empty intersections of the isolated half-planes.

d. Rectangular

Where cells are rectangles with same ratio of width and height as the environment. This is an approximate decomposition, where the free space is covered up to a given precision by the union of cells. The algorithmic construction is inspired by image segmentation and computational geometry routines, and it is based on recursively splitting each rectangle that contains both free and occupied space.

For a better understanding, illustrates a trapezoidal decomposition of the environment and a sequence of cells (graph path with smallest number of nodes) that can be traversed by the robot. The piecewise linear trajectory (represented with a thick line) is obtained by linking the waypoints, i.e. the middle points of line segments shared by successive cells from the path. This reference trajectory can be followed by the robot for arriving at the goal position, without colliding with obstacles. Note that in this work we only handle the planning part, the path following part for various robots will be considered in future efforts.

Before detailing the quantitative comparison, we just mention some qualitative aspects of considered decompositions. Thus, the polytopal and rectangular decompositions can be straightforward extended to larger workspace dimensions. The triangular and polytopal decompositions can be easily adapted to decompose regions of interest, and their neighboring cells share an entire facet (bringing advantages for controlling some systems in such partitions).

e. Critical-Curve Based Decomposition

While the trapezoidal decomposition is useful for point vehicle path planning, rigid vehicles with freedom to rotate require a more complex approach. In this algorithm, free space is divided into critical and non-critical regions. The boundaries of these regions are piecewise polynomial curves. The various regions formed by the decomposition process are connected by a graph and this graph is searched for a path. The algorithm is complete but not optimal, and runs in O (N2 log N) time.

f. Cylindrical Algebraic Decomposition

This more complex decomposition extends the critical-curve decomposition to three-dimensional problems. It bisects parts of the free space using critical surfaces. It is complete but not optimal, and runs in double exponential time.

g. Connected Balls in Free Space

This approach is designed to deal with un-structured obstacle fields, and operates by filling free space with overlapping balls (for instance, spheres are balls in three-dimensional Euclidian space) that are totally in free space. Vandapel et al. introduces unions of free-space balls as a roadmap in multi-dimensional space.

h. Rectanguloid Cell Decomposition

This divides the entire configuration space into rectanguloid regions, and labels each rectanguloid as being completely filled (black), partially filled (grey), or completely empty (white). It is proven to be resolution-complete. The most common example is that of the A* or D* search over a square or cubic grid of occupied or unoccupied cells. Ferguson et al. reviews this type of approach, with a focus on dynamic problems.

i. 2^m Tree Decomposition (Quadtree or Octree Decomposition)

This decomposition is designed to reduce the number of points needed to represent obstacles as compared to a full grid representation. This type of representation is becoming increasingly more common, and several new papers using tree decompositions have been published. Sinopoli et al. uses wavelet transform processing for path planning purposes. Behnke proposes a quadtree algorithm with weights put in to avoid obstacles by a longer distance. Soucy and Payeur compares a fixed resolution vs. quadtree characterization for similar problems. Tsenkov et al. describes a real-time implementation of planning over a quadtree representation of obstacles, demonstrated on an unmanned helicopter.

j. Approximate and Decompose cell decomposition

This decomposition is similar to the trapezoidal decomposition, but replaces the triangular end regions with rectangular mixed regions. This approach reduces the proportion of mixed area in comparison with a grid decomposition with mixed cells.

2. Discussion on Different Cell Decomposition Methods

The benefits of CD are that it provides assurance to find a collision-free path, if exists and is controllable. Therefore, it is a comprehensive algorithm for an unmanned or autonomous vehicle that can travel the path deprived of the risk of local minima incidence. Yet, the shortcoming of CD is that if the formed cell is too rough, at that time it will not be feasible to achieve the smallest path distance or length. Instead, if the cell is too trivial, then computation is more time-consuming. The CD approach also does not provide acceptable performance in a dynamic state and in real-time circumstance. It is required for CD to fine-tune with the situation as necessary; e.g. in exact CD, the cells are not predefined, but they are selected based on the site and shape of the obstacles inside the C-space.

Although RG is easy to apply, but the planner may not be complete if cell is too big, i.e. finding a path where one exists is not guaranteed. If the obstacle's size is significantly lesser than the cell size, then also the outcome for the entire grid square is not obstacle free or occupied. One more drawback of RG is that it inefficiently represents the C-space as in sparse area many same sized cells are required to fill the empty space. As a result, planning is costly because additional cells are handled than they are actually required. The outcome of ACD is a map that holds different size grid cells and concentrates with the cell boundaries to match the obstacle's boundaries closely. It produces lesser number of cells so that the C-space can be used more efficiently and hence, less memory and processing time are required. ACD maintains maximum details while regular shape of the cells is maintained.

ECD is complete. Still, the paths generated via ECD are not optimal in path length. There is no simple rule to decompose a space into cells. This method is not suitable to apply in outdoor environments where obstacles are often poorly defined and of irregular shape.

3. Sampling based algorithm

a. Probabilistic Roadmaps (PRM)

The PRM algorithm is primarily aimed at multi-query applications. In its basic version, it consists of a pre-processing phase, in which a roadmap is constructed by attempting connections among n randomly sampled points in Xfree, and a query phase, in which paths connecting initial and final conditions through the roadmap are sought. 'Expansion' heuristics for enhancing the roadmap's connectivity are available in the literature (Kavraki et al. 1996) but have no impact on the analysis in this paper, and will not be discussed. The pre-processing phase, outlined in Algorithm 1,begins with an empty graph. At each iteration, a point xrand ∈ Xfree is sampled, and added to the vertex set V. Then, connections are attempted between xrand and other vertices in V within a ball of radius r centered at xrand, in order of increasing distance from xrand, using a simple local planner (e.g. straight-line connection).

Successful (i.e. collision-free) connections result in the addition of a new edge to the edge set E. To avoid unnecessary computations (since the focus of the algorithm is establishing connectivity), connections between xrand and vertices in the same connected component are avoided. Hence, the roadmap constructed by PRM is a forest, i.e. a collection of trees. Analysis results in the literature are only available for a 'simplified' version of the PRM algorithm (Kavraki et al.1998), referred to as sPRM. The simplified algorithm initializes the vertex set with the initial condition, samples n points from Xfree, and then attempts to connect points within a distance r, i.e. using a similar logic as PRM, with the difference that connections between vertices in the same connected component are allowed. Note that in the absence of obstacles, i.e. if Xfree=X, the roadmap constructed in this way is a random r-disc graph. Practical implementation of the (s)PRM algorithm have often considered different choices for the set U of vertices to which connections are attempted

PRM Algorithm

Require: define params
Require: $G_i(V) \leftarrow p_{Init}$;
Require: $G_{i+1}(V) \leftarrow p_{Goal}$;

```
while i : N do
    p_rand = rand(x, y, z);
    if !(p_rand.collision) then
        G(V).add = p_rand;
        planer.metric(G(V), p_rand);
        G(E).add ← planner.connect(G(V), p_rand);
    else
        p_rand.discarded;
    end if
end while
return G;
```

4. Vision based path planning algorithms

According to the type of environment information utilized to compute an optimal path, this problem can be divided into two types: global path planning and local path planning. Global path planning aims to find an optimal path based on a priori global geographical map. However, global path planning is not enough to control a UAV in real time, especially when there are some other

tasks to be done immediately or unexpected obstacles appearing during the flight. Therefore, the local path planning is in need so that it constantly acquires sensors' information from surrounding environment, and computes the collision-free path in real time.

SL No.	UAV Brand/model	Type	Navigation System	Reference
1.	DJI Mavic 2 Pro	Commercial (Da-Jiang Innovations)	Sonar, Visible Sensors, Dedicated CPU, GPS	Perry and Guo (2021)
2.	DJI Phantom 4 RTK	Commercial	Internal inertial measurement system with triaxial accelerometer, 3 triaxial gyroscopes, Magnetometer, Altimeter, Barometer, Real Time Kinematic Position Correlation system with GPS	Ribeiro et al. (2021)
3.	Spectra-G Radio Controlled Helicopter	Commercial (Miniature Aircraft US)	Radio frequency communication with local processing/ memory - Pilot Controlled by Camera & GPS - AutoPilot using Altimeter & GPS locator	Todd et al. (2007)
4.	DJI Phantom 3 Pro	Commercial	N/A	Weng et al. (2021)
5.	DJI Phantom 4 Pro	Commercial	N/A	Ge et al. (2021)
6.	Aibot X6 V.1	Commercial	Automated by Waypoint Capability	Galarreta et al. (2015)
7.	DJI Mavic 2 Pro DJI Phantom 4 Pro	Commercial	Enhanced movement using Perspective-n-Point (PnP) techniques	Wang et al. (2021)
8.	DJI Jingwei M200	Commercial	Inertial Measurement Unit Pilot Controlled	Zhang et al. (2021)
9.	DJI S800 airframe	Commercial	Semi-automated using 3DRobotics Pixhawk	Meyer et al. (2015)
10.	DJI F550 frame Parrot Bebop Power	Modified programmatically	Pixhawk 2.1 with Telemetry, Electronic speed controller, Flight controller, Mobile	Kang & Cha (2018)

SL No.	UAV Brand/model	Type	Navigation System	Reference
		Commercial	bacon, vibration damper and camera Software development kit with bacon	

a. Global path planning

Global path planner requires the start and target locations within a constructed map to calculate an initial path, so the global map is also called a static map. The commonly used algorithms for global path planning include heuristic searching methods and a series of intelligent algorithms.

i. Heuristic search methods

A-star algorithm is a typical heuristic search method, which evolved from the classic Dijkstra algorithm. In recent years, the A-star algorithm has been greatly developed and derived lots of other improved heuristic search methods such as-

Modified A-star algorithm- Vachtsevanos et al. (1997) used an orographic database to build a digital map and used a modified A-star algorithm to search for the best track.

Heuristic A-star algorithm- Rouse (1989) divided the whole region into several square grids, and used the heuristic A-star algorithm to achieve optimal path planning, which is based on the value function of different grid points along the calculated path.

Sparse A-star algorithm- Szczerba et al. (2000) presented the sparse A-star search (SAS) for path planning, and this algorithm effectively reduces the computation complexity by adding constraints to space searching during path planning.

Dynamic A-star algorithm- Stentz (1994) developed the dynamic A-star algorithm, which is also known as D-star algorithm for partially or completely unknown dynamic environment. It is capable of updating the map from unknown environments and replanning the path when detecting new obstacles on its path.

The sampling-based path planning algorithm, such as the rapidly exploring random trees (RRT) proposed by Yershova et al. (2005), are also another type of heuristic search algorithm. It can keep motion path planning from failure when there is no prior information of the environment provided.

ii. **Intelligent algorithms**

In recent years, researchers tried to use intelligent algorithms to solve global path planning problems, and propose lots of intelligent searching methods. Among those, the most popular intelligent algorithms are genetic algorithm and simulate anneal arithmetic (SAA) algorithm.

In (Zhang, Ma, and Liu 2012), the genetic algorithm and SAA methods are applied into the study of path planning. The adaptation function of the path is evaluated using crossover and mutation operation in genetic algorithm and Metropolis criterion, which improve the efficiency of path

planning. In (Andert and Adolf 2009), the improved simulated annealing algorithm and the conjugate direction method are used to optimize the global path planning.

b. **Local path planning**

Local path planning is based on the local environment information and UAVs' own state estimation, and aims to dynamically plan a local path without collision. Due to the uncertain factors, such as the movements of objects in the dynamic environment, the path planning in the dynamic environment becomes a high complexity problem. In this case, the path planning algorithms are required to be adaptive to the dynamic characteristics of the environment, by obtaining information (such as the size, shape, and location) about unknown parts of the environment through a variety of sensors. Traditional local path planning methods consist of

i. Spatial search method
ii. Artificial potential field – Bortoff (2000) gave an example of the use of the artificial potential field method for calculating the path through the radar threat area.
iii. Fuzzy logic methods
iv. Neural network methods – Neural network is a computational method established under the revelation of biological functions. Gilmore and Czuchry (1992) gave an example of a path planning using Hopfield networks.
v. Stochastic optimization method – The ant colony algorithm is a new kind of bionic algorithm that mimics the ant activity (Parunak, Purcell, and O'Connell 2002). As a stochastic optimization method, it imitates the behavioral characteristics of ants, so it could achieve results through a solution of a series of difficult combinatorial optimizations.

Global Path Planning	Local Path Planning
•Heuristic Search Method •A* Algorithm •Evolved from Dijkstra Algorithm •Modified A* (Vachtsevanos) •Heuristic A* (Rouse) •Sparse A* (Szczebra) •Dynamic A* - D* - Combination of both local and global •Sampling based path planning algorithms •Rapidly Exploring random trees - No prior information of environment- Yershova (2005) • Intelligent Algorithms • Genetic Algorithm • Simulated Annealing Algorithm	• Spatial Search Methods • Artificial Potential Field - virtual force method • Fuzzy logic method • Neural network methods - Hopfield networks (Sugihara and Suzuki) • Stochastic Optimization Method - Ant Colony Algorithm • Artificial Potential Field method • Genetic Algorithm

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