Reports on Geodesy and Geoinformatics, 2025, Vol. 119, pp. 62–70

DOI: 10.2478/rgg-2025-0007
Received: 30 October 2024 / Accepted: 17 February 2025
Published online: 14 March 2025

ORIGINAL ARTICLE

Recommendations for planning UAV flight missions for geodata collection

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Abstract

A number of different types of information are generally associated with places. It is estimated that about 75–90% of information may contain an official link to a specific area, expressed as, for example, coordinates, or addresses, and therefore has a spatial character, making data collection a responsible and important stage, which reasonably affects the quality of its results. Information and its sources are treated with particular care and rigor in the scientific field: in most cases, the data must be relevant, reliable, technically simple, and collected quickly at reasonable costs. The analysis of geographic information makes it possible to obtain qualitatively new information and reveal previously unknown patterns. Modern data collection methods are divided into three distinct groups: terrestrial, cartographic, and remote. Remote or aerospace methods are considered to be those that allow information to be collected. It refers to objects on the Earth's surface, phenomena, or processes from space or the atmosphere, recorded by detecting electromagnetic radiation on the ground across various spectral ranges. The involvement of various platforms (providers) of surveillance equipment makes it possible to divide them into: space, aerial photography, and images from Unmanned Aerial Vehicles (UAVs). As a technology justified on security grounds, UAVs show great promise in many areas of application. Effective planning of drone missions allows for the collection of larger sets of data with a higher level of detail and in a shorter period of time. The continuity of information collection for a given territory allows for the most accurate and reliable three-dimensional modelling, spatial analysis and geostatistics of the local situation.

Key words: UAV, geodata, GIS, remote sensing

1 Introduction

1.1 The role and importance of geodata

More than 80% of all information is tied to a specific location on Earth, yet only 10% of the collected and stored data is effectively utilized (Burrough et al., 2015), meaning that this information, used by specialists for different purposes, contains geographical data (metric, spatial) and various information about the spatial or territorial distribution of objects, phenomena, processes, events (Zatserkovnyi et al., 2016).

"According to estimates by experts in geographic information

Publisher: De Gruyter

technology, the cost of collecting and entering data when implementing geographic information projects is 5–10 times higher than the cost of hardware and software of geographic information systems (GIS). This is explained by the fact that existing technologies for collecting graphic and text data automatically provide less than 20% of the total data volume. Therefore, further development of automatic methods for collecting all types of data is of particular importance for GIS" (Zatserkovnyi et al., 2016).

The terms "geodata", "spatial information", "geographic information", "geospatial data", or "location-based information" are used interchangeably (GGIM, 2015). Geodata, combining attribute information with location information (usually, the coordinates), is becoming easier to access every year and its number of users is increasing. The demand for accuracy and detail in the geographic data collected is increasing (Apollo et al., 2023). Geodata is covering increased areas and beyond solely collecting basic data, it also presents the results of its multi-purpose analyses. Understanding the characteristics of and possibilities of using geodata is premised on proper comprehension of the underlying concepts of space, time, and scale, contextualized within the Earth's framework.

Geodata is the core component of GIS, enabling the storage, querying, analysis, and visualization of data. In its modern sense, geodata encompasses a broad spectrum of information, extending far beyond the realm of Earth sciences. It offers detailed insights into phenomena both on and beneath the Earth's surface. Geographic data can represent human-made structures – such as buildings, roads, railways, trails, and hydraulic systems – or natural features, including reservoirs, streams, vegetation, and soils. Additionally, geographic information can integrate data from various disciplines, such as: economics, sociology, management, education, and even transient phenomena (e.g., weather systems) (Goodchild, 2005). The scope of GIS implementation reaches beyond the scope of the term that many people and organizations using GIS technology may not even be aware of (Dangermond and Goodchild, 2019).

The technological characteristics of geodata are that it is not obtained from direct measurements but is the result of post-processing of measured information. For decades, the creation, maintenance and distribution of geographic data has been the exclusive domain of government surveying agencies and commercial companies, due to the need for centralized and cost-effective distribution of geodata (Elwood et al., 2012). Geodata combines location information with characteristics or attributes of other datasets over a period of time, and it can be collected from maps, aerial photographs, satellite imagery, telematics devices, smartphones, Global Positioning System (GPS), Light Detection and Ranging (LiDAR), Internet of Things (IoT), Geotagging, and from other sources (Garg, 2020).

1.2 Using UAVs is the key to collecting high-quality spatial data

Unmanned aerial vehicles (UAV) represent a groundbreaking technology in the realm of intellectual advancements. Innovation permeates every aspect, from advanced composite materials to cutting-edge software and navigation systems. The broad range of applications, the complexity of tasks, and the variety of requirements are reflected in the multitude of UAV models. Currently, there are more than 1,500 models of drones of various types in mass production. Their total number has tripled in recent years. The use of drones allows its users to avoid dangers, perform activities that exceed the physical and psychophysiological capabilities of humans, among many other uses that previously seemed unrealistic (Hutsul et al., 2022). The data collection and logistics functions of drones must be implemented before optimal flight mission planning. The collection of geodata throughby drones has witnessed the highest growth (Berra and Peppa, 2020) in the second decade of the 21st century.

Drones are seen as a key technology that will enhance and improve a number of important services and processes, supported by the characteristics gained during their application: 1) energy efficiency; 2) speed; 3) security; 4) low cost (Alyassi et al., 2023). Small drones typically use less energy per kilometer of cargo transported than delivery trucks. Optimal energy efficiency is achieved when transporting light loads over short distances (within 4 km) (Stolaroff et al., 2018). The speed of drones is achieved when there is no traffic congestion and there is a minimum number of obstacles on the way. The safety of drones is related to their ability to be used for tasks and missions that could potentially harm humans. Expanding and improving the capabilities of drones helps reduce the cost of operating them.

Operating a drone always requires complex training of the operator. Rodríguez-Fernández et al. (2017) conducted a study on human factors in the field of control systems to improve operator productivity. Advances in drone autonomy have shifted the role of the operator to supervision, with the operator primarily involved in high-level mission control rather than manual low-altitude flight control. Increasing levels of autonomy and automation have created a need for faster and safer systems to perform complex drone operations (Thibbotuwawa et al., 2020).

Control and navigation are essential aspects of drone technology. The initial development of drone guidance and navigation relied on GPS with limited accuracy, which was later replaced through the integration of GPS and Inertial Navigation System (INS) with visual photogrammetry. Future trends focus on the use of advanced artificial intelligence and computer vision algorithms for navigation (Budiyono and Higashino, 2023). Given the substantial cost of such sensors, a more economical solution is the use of Real-Time Kinematic (RTK) positioning, whereby the accuracy of the on-board Global Navigation Satellite Systems (GNSS) receiver is improved via a correction signal sent by a fixed base station. Such RTK systems in theory allow for the absolute position of the UAV to be determined to less than ten centimeters (Ekaso et al., 2020).

Much research on drones has focused on increasing the autonomy of drones and the ability to perform pre-planned missions. Autonomy increases the economic efficiency of their operations. In terms of autonomy not operated by a pilot, current military drones are capable of performing entire pre-planned missions autonomously, often only requiring supervision to address real-time changes that result in changes in flight plans depending on dynamic changes in the environment (Miller et al., 2007). One of the current obstacles, overcoming which will mark a new development in the fields of logistics, e-commerce, video surveillance, etc., is beyond visual line of sight (BVLOS) flights (Ebeid et al., 2018).

Ramírez-Atencia et al. (2014) define the mission planning problem as the time constraint satisfaction problem (TCSP). Nikolos et al. (2003) define a scalable algorithm for drone navigation environments that is capable of generating offline and online optimal paths. The further development of drone control strategies is forecast to take two separate paths, one of which putting the operator in control of several vehicles (agents) at the same time. Therefore, multi-agent methods (MAPF – Multi-Agent Path Finding) must be considered when planning missions to avoid possible collisions in a swarm of drones (Ho et al., 2022).

Remote methods make it possible to obtain objective, operational and simultaneous data over large areas. They allow for the establishment of real boundaries and the identification of integral objects; the identification of patterns of territorial distribution, formation factors, operational features, man-made modifications, etc.

Drones are becoming popular among providers of geospatial data due to the relatively low cost of sensors/cameras equipment as well as the high speed of data collection and processing in the field of interest to create: orthomosaic sounds, digital terrain models, large-scale terrain plans, etc. (Karpinskyi and Lazorenko-Hevel, 2018).

Overall, planning a photogrammetric mission entails identify-

Table 1. Criteria for the optimality of the flight mission of civilian UAVs

Data source	Logistics tasks	Spatial data collection
Load capacity	+	–
Positioning accuracy	–	+
Requirements for speed of movement	+	+
Minimization of time costs	+	–
Distance minimization	+	+
Minimization of battery energy consumption	+	+
Mapping	–	+

ing the flyover locations and specifying the actions the vehicle will undertake (such as capturing photos) within a designated timeframe. The predetermined geometric elements (azimuth, distance, altitude) have a direct impact on the ultimate quality of the spatial data. Additionally, such factors as: the drone's flight area, including maximum flight time, speed, altitude, and distance, along with the information gathered by the sensor, as well as the orientation and position of the captured image, are also established (Gómez-López et al., 2020).

2 Justification of the optimality criterion of the flight mission

Optimum (from Latin "optimus" – best; in English "optimal", in German "optimal") – the best possible choice for something, the most suitable for a given task, under given conditions. The variety of tasks applied determines the definition of the optimality criterion by combining one or more conditions (Table 1). A flight mission can be described as a target to attain. The planning of a drone mission involves identifying the locations to be visited (waypoints) and the tasks the vehicle can perform, such as: loading or unloading cargo and taking videos or photographs, usually within a certain time frame. In the context of our study, the purpose of the flight mission is precisely expressed in demonstrating the optimality of geodata collection.

A review of the literature on the topic of determining decision criteria when planning an unmanned aerial vehicle mission is convincing due to their large number and complexity (Thibbotuwawa, 2019; Thibbotuwawa et al., 2019). The decision space encompasses factors related to routing and planning, variations in weather conditions, technical specifications of the drone, and energy consumption influenced by weather conditions, as well as payloads carried by the drone, avoiding collisions with moving objects and stationary obstacles (Thibbotuwawa et al., 2020). All of these factors highlight the capability and the complexity of mission planning, as it is difficult to create models that consider all of these influential aspects at once (Thibbotuwawa, 2019). By far the most important constraint of any mission is minimizing the risk of losing the drone (Stecz and Gromada, 2020).

The main difference between drones for logistics and spatial data collection lies in the priorities placed on them. Logistics drones focus on minimizing payload and time, while spatial data collection drones focus on positioning accuracy and mapping quality. Minimizing distance and battery power consumption are high-priority criteria for logistics and spatial data collection missions because they affect the efficiency, and quality of the mission. For logistics, these criteria are important to ensure fast, dependable, and cost-effective delivery, while for spatial data collection, they help enhance the precision, range, and quality of the gathered data.

In recent times, methods of optimizing flight missions are primarily categorized into three types: minimum trajectory optimization, hard constraints, and soft constraint optimization (Yu et al., 2021). Hard constraint optimization establishes boundary values, whereas soft constraint optimization considers connection strength to help the drone navigate around obstacles. Contemporary methods frequently integrate pathfinding and trajectory optimization to develop a safe, smooth, and adaptable mission suitable for drone operations.

Careful mission preparation is a prerequisite for a successful outcome, subject to specific legal constraints. In numerous countries, civil aviation authorities are striving to establish suitable rules and regulations to enhance the safety of drone operations (EASA, 2023). For example, no-fly zones are designated areas of airspace that are restricted above a specific landmark, event, or geographic region in which manned or unmanned aircraft are prohibited from flying unless specifically authorized.

The rapid growth of UAVs in recent years and the diversity of their usage at the global level have led to significant regulatory differences and discussions on the effectiveness of their operation and the minimization of the associated risks. Although at the international level there exist general recommendations for UAVs developed by the International Civil Aviation Organization (ICAO), this area requires further research and improvement of regulatory acts. According to Henderson (2022), there has not yet been a systematic scientific study that analyzes the views of end-users regulating the system regarding UAV, which, in our visit, may lead to additional costs during their use.

In general, the task of planning a flight, especially planning a photogrammetry exercise for collecting spatial data, is essentially similar to the well-known task of terrain navigation, which is a generalization of the "traveling salesman" task. When addressing the traveling salesman problem, the optimality criteria for the path (shortest, least expensive, global criteria, etc.) and the corresponding distance, cost, and other variables' matrices are specified. It is often stipulated that the path must pass through each point on the path only once, in which case the solution lies in a Hamiltonian cycle.

Operating in complex environments, such as mountainous regions, requires more sophisticated planning strategies. This reaches beyond such standard approaches as 2D terrain mapping and waypoint selection based on ground sampling distance and overlap parameters. Although terrain models are publicly available, users can use their own high-resolution digital terrain models (DTMs, including surfaces) to improve image acquisition sounds in terms of coverage, overlap, and resolution. This significantly reduces the risk of travel in un-covered areas. Simple 2D path planning methods cannot manage complex 3D environments with a number of constraints and structural uncertainties (Yang et al., 2014).

Changing the distance to the photographed object primarily affects the ground sampling distance/spatial resolution of the image. When the distance to the object changes following, among others, the change in relief, the overlap of the image changes, the ground sampling distance/spatial resolution changes. Since the distance from the object of photography to the UAV is usually small compared to light aircraft (airplanes), the differences in terrain significantly affect the quality of the output data. A single flight without considering the terrain elevation will affect the pixel size, which will not be the same throughout the project due to variations in the terrain (Medvedskyi et al., 2024).

The drone's trajectory over an area with different surface elevations results in increased pixel size, which reduces the detail and accuracy of the data in the lower elevation areas. The flight altitude variation due to the complex terrain of the area affects the quality of the overlapping flight sections. Images whose adjacent scenes do not overlap will create serious problems for photogrammetry and may render part of the data unusable for further use.

A study by Lopes Bento et al. (2022) assessed the accuracy of digital elevation models acquired by drones with different parameters, vertical and horizontal overlap ratios, and flight paths. The findings obtained by the drones were compared with data from GNSS

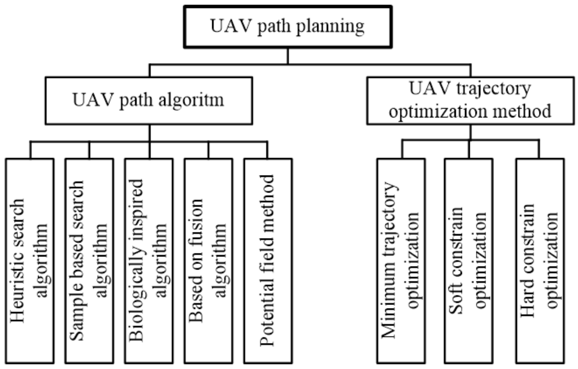

Figure 1. UAV path planning (Yu et al., 2021)

topographic surveying in RTK mode. Twelve aerial plans strategies were developed, each featuring a different overlapping area (90×90, 80×80, 80×60, 70×50, 70×30, and 60×40%) and directions (horizontal and vertical to the landing line). The altitude and speed were established at 90m and 3 m/s, respectively, along with the ground sampling distance of 0.1m for all flights. The 70×50% overlap yielded reliable results while requiring less flight time and data processing – being approximately 1.5 hours shorter than the 90×90% overlap. This configuration achieved a root mean square error (RMSE) of 0.589m and met the minimum overlap needed for aerial photogrammetry of 60×30%. Additionally, the results were statistically comparable to those obtained from higher overlap levels of 90×90% and 80×80%.

3 Comparison of optimal path search algorithms

The motion planning issue can be broadly described as the endeavor to determine trajectories that avoid collisions between the initial and final states. This process must also meet specific kinematic and dynamic requirements.

The classification of existing algorithms for finding and optimizing suitable flight paths for drones (Yu et al., 2021) is given in Figure 1. They are conditionally divided into two groups from the initial discrete trajectory search and the background optimization of a continuous trajectory.

Elmokadem and Savkin (2021) classify classical short path planning algorithms into:

- search-based algorithms (e.g., $A*$, $D*$, Dijkstra, and others);
- potential field algorithms (e.g., navigation functions, wavefront plans, and others);
- geometric algorithms (e.g., cell decomposition, generalized Voronoi diagrams, visualization graphs, and others);
- pattern-based algorithms (e.g., BIT, FMT, PRM, RRT, RRT*, and others);
- optimization-based algorithms (genetic algorithms, PSO, and others).

Many of these short path planning algorithms can determine the best route if they exist due to the need for complete knowledge of the environment, which is not suitable for dynamic and unfamiliar surroundings. For more details on these planning algorithms, Elmokadem and Savkin (2021), refer to LaValle (2006).

The main challenge with short path finding problems is the lack of a universal algorithm to solve them. These algorithms can be easily implemented with a small number of graph vertices. The path network is illustrated as a graph model, and the graph structure can change under the influence of many distinct factors. As their number increases, finding the optimal path becomes more difficult (Table 2).

Table 2. Computational complexity of algorithms for finding the shortest path

Algorithm	Complexity	Calculated complexity, calculation date	Author of the algorithm, date of appearance
Dijkstra	$O(n2 + m)$	Alekseev and Talanov (2005); Cormen et al. (2009)	Dijkstra (1959)
Bellman-Ford	$O(n \times m)$	Cormen et al. (2009); Levitin (2006)	Bellman (1958)
Search algorithm $A*$	$O(\log(h(x))$	Cormen et al. (2009)	Moore (1959)
Floyd-Warshall	$O(n3)$	(Levitin, 2006)	Hart et al. (1968)
Lee's algorithm (wave)	$O(n2)$	–	–

Marking: O – notation of the complexity assessment of algorithms (Bachmann–Landau notation); m – number of edges; n – number of vertices; $h(x)$ – heuristic estimation of the distance from the considered vertex to the final one.

Drone navigation algorithms based on environmental information acquisition are classified as opportunistic or deliberate (global planning), perceptual (local planning), and hybrid (Elmokadem and Savkin, 2021).

In recent years computational intelligence techniques have been increasingly employed to tackle combinatorial optimization issues. These algorithms have a number of undeniable advantages, including being sufficiently simple to be widely implemented, their flexibility of parameters, high efficiency, and the ability to find global solutions or ones close to them in polynomial time (Hutsul, 2019).

In classical theory of artificial intelligence, an intelligent system is created to solve a problem that contains all the necessary resources. In multi-agent system theory, the opposite principle is used: It is assumed that a single agent has an incomplete view of the overall problem, so a set of agents and their interactions are created. The overall behavior of the entire system is considered to be the result of the interactions of individual agents.

Multi-agent optimization algorithms are based on the definition of the term agent. In a broad sense, an agent is a part of a system that is responsible for making decisions. In a more rigorous sense, agents model certain biological objects and their behavior (e.g., an ant or bee algorithm). Each individual agent is quite primitive and possesses knowledge only about a certain local situation, but a collection (aggregate) of such objects demonstrates an extraordinary ability to solve the most complex NP-complete problems of our time (e.g., the traveling salesman problem, task scheduling,). Currently, there exist three main multi-agent optimization algorithms: ant algorithm (ACO), bee colony algorithm, and swarm optimization.

Most ACO methods can be used on a plane, without the need for considering the impact of terrain slopes on route selection. Meanwhile, the parallel ant colony approach enables planning within three-dimensional (3D) terrains. Rasterizing the map using the application of the bilinear interpolation method facilitates the transition from spatial to planar based on a certain slope step. Modelling results show that it is suitable for path planning on 3D surfaces (Hutsul and Karpinskyi, 2021). Moreover, with the evolution of area and parallel computation, its performance increases threefold (Zhang et al., 2017). The modelling results (Zhang et al., 2010) also demonstrate that ACO can perform drone trajectory planning efficiently.

In a multi-entity system, tasks are distributed among agents, each of which is considered a member of a group or organization.

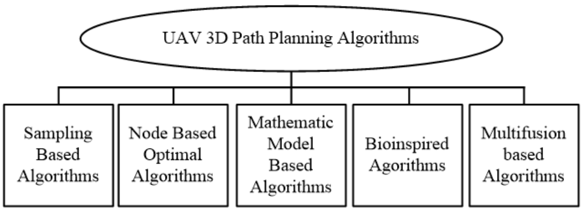

Figure 2. Taxonomy of UAV three-dimensional path planning algorithms (Yang et al., 2014)

Task assignment entails allocating roles to each member of the group while defining their level of responsibility and the necessary experience requirements. Each autonomous agent decides on the feasibility of utilizing a cell to transmit a segment of a linear object as a future trajectory. At the same time, the initial data can be geospatial information layers (e.g., DTM, a no-fly zone). Deliberate (opportunistic) approaches to comprehensive planning are based on an environmental approach presented in the form of a map. Therefore, with a high probability, it is possible to immediately "reject" parts of the territory of the layers, the conditional adoption of which would contradict current regulatory requirements or incur significant energy costs.

Sensor-based (local planning) approaches rely directly on present sensor data or a concise history of sensor observations (i.e., a local map) to devise safe trajectories in real-time. The planning horizon can frequently be quite short, set for a brief period in advance, or it may occur during each control update cycle at progressively shorter time intervals.

Path planning in 3D environments has an enormous potential, but unlike 2D path planning, the difficulty increases exponentially as the dynamic and kinematic constraints become more complex. Many algorithms for 3D drone trajectory planning have been developed. Figure 2 shows the systematics of modern approaches to 3D trajectory planning algorithms (Yang et al., 2014).

Sampling-based algorithmic methods require previously known information about the work site where the drone is operating. This is usually an environmental sample in the form of a collection of nodes or alternative structures through which the optimal path is randomly searched.

Optimal node-based algorithms create a path using a collection of nodes. Sampling-based algorithms can be classified into two types, with one being passive, like a probabilistic path map (PRM) and cannot find an output on its own, the other is in the form of complementary algorithms that search for an optimal path. These algorithms search through a collection of nodes on a graph or map where initial information gathering and processing tasks have been completed.

Mathematical model-based algorithms include approaches like linear programming and optimal control, among others. These techniques depict both the environment and the entity, considering kinematic and dynamic constraints. They then associate the cost function with various inequalities or equations to obtain the optimal solution.

Biomimetic algorithms are heuristic methods coming from simulating biological behavior for solving a problem. This way of planning the path eliminates the process of building complex unstructured models of the environment and provides an efficient search method that allows you to gradually approach the goal. This type of algorithm can only work in the offline mode. Current 3D trajectory planning algorithms are often integrated with other algorithms or combined in turn to plan optimal trajectories (optimal in terms of length, time, energy, or threats).

Multi-combination-based algorithms solve problems when the proposed algorithm cannot achieve optimal results individually. Table 3 presents a visual idea of the time complexity when applying each type of 3D drone trajectory planning method.

4 Overview of popular flight mission planning software

Current technologies (cloud computing, big data) cannot solve the problems of pathfinding and object localization, as drones are not capable of finding solutions on their own (Aggarwal and Kumar, 2020).

Today, the market offers a wide variety of platforms that are compatible with different mission planners. These planners can be categorized into three main groups: The first category includes proprietary software designed for specific platforms (eMotion or MAVinci Desktop; Mikrokopter Tool; mdCockpit or DJI Ground Station, etc.); the second – open-source mission planning tools (ArduPilot; Mission Planner, RPAS, etc.); the third – universal software that is not specific to a specific platform (QGroundControl). When working with drone modelling and control, it is important to distinguish between two types of software: autopilot software and ground control station (GCS) software. A comparative analysis between popular autopilot programs and ground control stations is provided by Hentati et al. (2018).

eMotion is beginner-friendly but equipped with advanced features for the most demanding tasks. It lets you quickly launch your drone and focus more on analyzing geospatial data. eMotion allows for terrain tracking by default, also facilitating the import of own elevation data. Exported KML flight trajectories can be verified in Google Earth Pro. Moreover, eMotion connects wirelessly to the user's existing drones, industry cloud solutions, geodetic layer base stations, airspace data, and it even includes real-time weather updates. If the map data has been downloaded in advance, offline work is supported in case of loss of internet connection. Loss of radio contact for more than 5 minutes will return the drone to the home point and land it.

The Mikrokopter tool facilitates the uploading of imagery by connecting to a browser-based mapping tool to generate a required image (with geodata) of the desired area of interest. The waypoint generator allows the user to create flight paths to capture terrain and circles of points of interest. There is also a panoramic flight path generator and a raster and circle drawing tool to support manual placement of waypoints. Creating a polygon-based scan area is not provided.

DJI Ground Station is available as one of the DJI drone control options with PC or iPad. Ground Station for PC uses the Google Earth plugin. Thanks to the 3D platform, the viewing direction is not limited to the lowest point. The software stores satellite images from Google Earth, allowing offline operation. The PC ground station's mission planning module has different models for generating flight trajectories. The initial step involves establishing a bounding rectangle for the required flight trajectory. Following this, various shapes such as point, line, triangle, rectangle, circle, or sweep can be selected. The sweep option refers to a band sweep that includes waypoints solely at the turning points. In contrast to the Asctec matrix, there are no intermediate waypoints between these turning points. All waypoints are maintained at the same elevation, which needs to be defined at this stage. After leaving the route template toolbar, the elevation of each waypoint can be adjusted (Israel et al., 2015).

ArduPilot is a versatile, open-source autopilot system that facilitates the operation of fully autonomous drones, ranging from FPV racing models to aerial photography platforms, ground vehicles, and even underwater drones. ArduPilot is distinct due to its comprehensive features and ease of use, making it a well-supported open-source project. It enables users to control a wide variety of autonomous systems through compatible ground station applications (ArduPilot Copter, 2021a). Specifically, the ArduCopter platform, as part of the broader ArduPilot ecosystem, fully integrates with

Table 3. Computational complexity of algorithms for finding the shortest path

Method	Time Complexity	S/D Environment	Real-Time
Sampling Based Algorithms	$O(n \log n) \leq T \leq O(n2)$	S and D	On-line
Node Based Algorithms	$O(m \log n) \leq T \leq O(n2)$	S and D	On-line
Mathematic Model Based Algorithms	Depending on the polynomial equation	S and D	Off-line
Bioinspired Algorithms	$T \geq O(n2)$	S	Off-line
Multifusion Based Algorithms	$O(n \log n) \leq T$	Depending on the algorithm	On-line

multirotor systems (such as: quadcopters, hexacopters, and helicopters), in addition to supporting VTOL aircraft. In common usage, ArduPilot often refers to the firmware installed on controllers to enable autonomous control. However, it is frequently mentioned alongside its companion ground control software, Mission Planner.

Mission Planner, developed by Michael Oborn (ArduPilot Copter, 2021b), simplifies the creation of autonomous missions by using straightforward inputs through Google MapsTM (or other third-party maps) supported by Google Maps. Mission Planner can be defined as a ground control station for an aircraft, helicopter, or any other robot (Didulescu et al., 2018). Mission Planner also offers mission simulation capabilities, allowing users to predict the movement and behavior of a vehicle without endangering the real drone (Chintanadilok et al., 2022). This software provides two methods of geotagging images from mission logs. Geotagged images facilitate the integration of multiple images taken during mission/camera operations, which is essential for such applications as photogrammetry, orthophotogrammetry, and 3D terrain modelling. Mission Planner automatically checks for updates at startup and notifies the user if an update is available. The latest version of Mission Planner software should always be used.

Remotely Piloted Aircraft System (RPAS) is an open-source tool for flight planning. Designed for high-precision photometric mapping, the tool incorporates planning capabilities commonly found in professional mapping systems for manned aircraft, along with innovative features addressing GPS signal masking in challenging terrains, such as mountainous regions. By combining real 3D terrain for mission planning with selected advanced features, the tool will significantly facilitate the mission preparation process. Although the terrain model is available globally, users can use their own high-resolution digital terrain model (including surface) to improve the planning of imagery scene locations in terms of coverage, overlap, and resolution. The geodetic system employed in mission planning is the World Geodetic System 1984 (WGS84). Geometric elevations are linked to the Earth Gravity Model 1996 (EGM96). The system plans offline missions in high-resolution 3D space.

QGroundControl is an open-source application that provides comprehensive support for ground stations, flight control, and multi-drone configurations using MAVLink to operate ArduPilot and PX4 vehicles. A key advantage of QGroundControl is its intuitive interface, which is designed for beginners while also offering extensive features for experienced users. It includes an easy-to-navigate route planning interface that facilitates automated flights through waypoint insertion. Additionally, it allows users to view a flight map that displays vehicle locations, flight paths, waypoints, vehicle equipment, and live video streaming. However, QGroundControl, like other ground station software, only allows for the creation of plans manually by inserting waypoints for each drone, meaning it does not provide an automated planning algorithm. It does not allow you to create missions or drone zones to create missions to be scheduled automatically. However, QGroundControl only allows viewing of the waypoint map for one drone at a time, making it difficult for multi-UAV missions to control all vehicles at the same time (Ramirez-Atencia and Camacho, 2018).

5 Formation of recommendations for flight tasks for the collection of spatial data

Effective and flexible data collection methods are one of the crucial elements of military operations. Geospatial intelligence, known in English-speaking sources under the acronym GEOINT, GeoIntel or GSI, is an intelligence activity that involves the study and analysis of geospatial imagery and data, so that physical features and processes located geographically on the globe are described, evaluated, and visualized. The components of geospatial intelligence are: imagery, optical intelligence (species) and geospatial information.

Drones equipped with RTK can attain centimeter-level positioning accuracy, allowing for the absolute GNSS coordinates of ground targets to be derived from both the relative positions of these targets and the drones, as well as from GNSS coordinates. The primary source of error is largely dependent on the relative position error measured from the data image.

The hardware of the UAV remote sensing platform is divided into two components: the UAV flight platform and the installed sensors. One of the primary advantages of UAV remote sensing, in contrast to remote sensing satellites, is the flexibility to replace sensors. This capability enables researchers to utilize the same equipment by attaching different sensors to gather various types of spatial information. The choice of sensors to use is mainly dependent on the information requirements. The weight of the sensors and their installation reduces the flight range of the drone. Under such conditions, the parameters of changing the "cost" of covering the route and obtaining "profit" will be interdependent and decisive.

Drones typically utilize two primary types of sensors: visual sensors and 3D sensors. Among the most frequently employed sensors are thermal sensors, RGB cameras, multispectral cameras, hyperspectral cameras, and LIDAR. Less common sensors include: small radars, gas sensors, and air particle sensors (Zhang and Zhu, 2023). Additionally, ultrasonic, infrared, and time-of-flight vision sensors can be integrated into UAV communication systems to facilitate precise 3D positioning and monitor real-time collision detection and avoidance for UAVs (Paredes et al., 2017).

The flight altitude of a drone is crucial for determining the spatial resolution of the ground target information gathered by the sensors. Most drones operate at a fixed altitude while collecting data, a flight pattern that is suitable only for tracking targets on flat terrain. For targets that necessitate altitude information (e.g., those listed in Šipoš and Gleich (2020); Barnawi et al. (2023)), it is necessary to generate the digital surface model (DSM) in advance and take their surface altitude into account for planning subsequent flight missions.

Most mission planners rely on elevation data from Google Earth. The platform sometimes allows users to upload their own DEM files. Geostatistical analysis conducted in particular by Rusli et al. (2014) provides evidence that Google Earth DSM correlate well with ASTER and SRTM data. Hutsul and Smirnov (2017) determined the accuracy of the ASTER and SRTM global models relative to topographic map data at scales of 1:25,000, 1:50,000, and 1:100,000 for areas with different terrain conditions: flat, hilly, and mountainous. The results showed that the height scale of 1:25,000 was only suitable for flat areas; 1:50,000 – for mountainous areas; 1:100,000 – for highland area. Therefore, using DSM (by ASTER or SRTM data) to plan low-altitude drone missions from such altitude data sources can be dangerous.

Without a dependable battery consumption model, long-range drone routing can lead to downtime and excessive operating costs (Alyassi et al., 2023). Incorrectly assessed battery levels (e.g., due to ignoring adverse weather conditions) can reduce service quality or even cause mission failures (e.g., when a drone discharges before reaching a charging station or returning to a depot). Meanwhile, frequent skip charging can cause unnecessary delays and excessive power consumption.

LiPo-based batteries are used for targeted operations, while hydrogen fuel cells are used for long-duration drone missions. Using "green" energy sources (solar, wind) to charge drone batteries can help increase energy efficiency.

Some initial planning parameters may be uncertain as drones operate in dynamic, real-time environments. Weather conditions (changes in wind strength) increase the drone's power consumption. Ambient temperature has a significant impact on the energy capacity of the batteries utilized in drones. Cold temperatures can adversely affect battery performance until they reach a warmer state (Huawei, 2016).

Wind can be categorized into two types based on the characteristics of the airflow: turbulent and laminar (Jayaweera and Hanoun, 2022). In turbulent winds, air particles experience rapidly fluctuating speeds, influenced by various factors such as mountains, trees, sudden and irregular changes in temperature gradients, and friction, which cause velocity variations. Conversely, air particles in laminar winds move at consistently or slightly varying speeds, resulting in smooth airflow in any open environment. The impact of turbulent and laminar wind disturbances on drones varies according to wind speed, air particle mass, inertia, and drone speed. Therefore, the influence of wind will manifest itself in a completely different ways for rotary aircraft and drones. Modelling of the interaction between wind and aircraft-type drones has been performed (Choi et al., 2015) and it has been demonstrated that equipping an airborne data system (ADS) or a GPS sensor in combination with an INS allows for accurate measurements of air winds. In propeller-type drones, the propeller strongly influences the airflow around the drone (Meier et al., 2022), so measuring air flows with an anemometer or Pitot tube is not appropriate and only a combination of INS and GPS data must be considered.

The relative speed of the drone is the main factor that determines the power consumption. Direction and wind speed are related to the flight speed, because, depending on the wind direction, it can positively or negatively affect the flight behavior of the drone (Thibbotuwawa et al., 2018). The optimal speed is the speed with the least drag.

Drones frequently carry various types of payloads, such as photographic equipment or packages. The effect of differing payload weights can be substantial, necessitating consideration in the development of energy consumption models (Alyassi et al., 2023).

The diversity of modern drone missions and their increasing complexity require the development of reliable flight control systems for drones. Based on parametric and structural methods of system synthesis, algorithms and programs for autonomous drones control the laws in the modes of directional, speed and altitude stability, as well as control guidance, including the trajectory of movement.

6 Conclusions

The past few years have seen the popularity and use of drones in many applications. Geodata is one of the many popular means of analyzing spatial features and phenomena, a tool for learning about the world around us. They are used not only in geoinformatics but also in other scientific fields, especially artificial intelligence.

To obtain a uniform distribution of errors on the orthophotograph, it is recommended to calculate the aerial photography route in areas with significant height overshoots considering the DSM and select control points in flat and open areas.

Data collection continues to be the costliest and the most time-intensive component of the majority of GIS projects, often consuming as much as 60% to 80% of the total time and budget. The significant disparity between the high expenses associated with acquiring data and the relatively low levels of data utilization necessitates a new strategy to address and improve this situation.

Path planning is a critical issue in drone research, focusing on finding the most efficient route between the starting point and the destination. The challenge of determining an optimal path for a drone is markedly different from that of identifying a basic route for a ground vehicle.

Most modern mission planning software is not capable of optimizing flights based on, for example, the prevailing winds, the drone type and the mission. Therefore, research in this field and analysis of existing tools is a necessary scientific and technical task nowadays.

Off-line path planning methods cannot guarantee reliability in the face of model uncertainty, while online path planning methods may not provide optimal solutions to meet constraints such as time or distance constraints. Hybrid algorithms that combine the advantages of off-line and online approaches are the future research direction.

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