drones

Review

Survey of Path Planning for Aerial Drone Inspection of Multiple Moving Objects

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Abstract: Recent advancements in autonomous mobile robots (AMRs), such as aerial drones, ground vehicles, and quadrupedal robots, have significantly impacted the fields of infrastructure inspection, emergency response, and surveillance. Many of these settings contain multiple moving elements usually neglected in the planning process. While a large body of work covers topics addressing scenarios with stationary objects, promising work with dynamic points of interest has only recently gained traction due to computational complexity. The nature of the problem brings with it the challenges of motion prediction, real time adaptability, efficient decision-making, and uncertainty. Concerning aerial drones, while significantly constrained computationally, good understanding and the relative simplicity of their platform gives way to more complex prediction and planning algorithms needed to work with multiple moving objects. This paper presents a survey of the current state-of-the-art solutions to the path planning problem for multiple moving object inspection using aerial drones. The presented algorithms and approaches cover the challenges of motion and intention prediction, obstacle avoidance, planning in dynamic environments, as well as scenarios with multiple agents. Potential solutions and future trends were identified primarily in the form of heuristic and learning methods, state-of-the-art probabilistic prediction algorithms, and further specialization in regard to every scenario.

Keywords: path planning algorithms; trajectory planning; multiple objects; moving objects; UAV; aerial drone inspection

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1. Introduction

Recent advancements in autonomous robotic systems have extended the reach of humans in a number of key areas [1–7]. Today, there are autonomous systems performing critical infrastructure inspection and monitoring [1,3], assisting in search and rescue operations, and exploring new frontiers, such as neighboring celestial bodies [2] and the deep sea [7].

Understandably, most of these missions require that the robotic platform operate in dynamic environments where the objects of interest move, and the behavior of the autonomous robotic system should be planned accordingly [5–18]. In these scenarios, path or trajectory planning is of paramount importance to the success rate of the mission, reducing the cost of the mission and wear and tear, increasing the safety of the platform and other agents in the environment, optimizing energy consumption, etc. [1,6,14,19–22]

Moreover, due to the high stakes of these missions, such as the cost of the platforms themselves, it is imperative to guarantee their safety throughout the mission [12,14,22–27]. And, as they frequently operate in dynamic environments including static and dynamic obstacles, and possibly other agents, the planning process should include their prediction of the evolution of the environment. Examples of real-world scenarios where such algorithms are used are disaster response and search and rescue, livestock or wildlife monitoring, marine surveillance, crowd monitoring, and aerial sporting event coverage [1,3,7–10,23,28–34].

This paper presents a survey of the available literature closely connected to the topic of path planning algorithms for aerial drone inspection of multiple moving objects. Clear definitions of the subproblems of the topic are given as well as descriptions of the state-of-the-art algorithms and approaches developed though the years. Finally, the deficiencies of the current approaches are discussed, and the future direction of the field is outlined.

The paper is structured as follows. This chapter provides an introduction into the matter and an outline of the paper. The second chapter presents the theoretical background of key concepts and literature analysis of prior research in the field. The third chapter explores path planning with multiple static objects of interest. The fourth chapter delves into the topic of obstacle avoidance, whereas the fifth chapter focuses on path planning algorithms with moving objects of interest. Finally, the last two chapters present a discussion of the findings of the survey as well as the conclusion, summarizing the key insights, importance, and state-of-the-art approaches to path planning for autonomous aerial inspection of multiple moving objects.

2. Background

Before analyzing specific approaches connected to path planning for aerial drone inspection of multiple moving objects, the theoretical background and key concepts of the field will be outlined. Moreover, the research methodology used to obtain the most relevant literature will be described, including the databases, queries, and resulting metrics.

2.1. Theoretical Background

Several surveys on similar topics are available in the literature [28,35–44]. In the surveys, the covered topics range from multi-agent path planning [28,35,40–42], coverage path planning [38,39], moving target search [28,35], and general path planning [36,37,40,41,43]. However, none of them focus primarily on multiple moving objects of interest. An overview of the taxonomy of problems directly related to path planning for AMRs is given in Figure 1.

Path planning for the aerial drone inspection of multiple moving objects falls into the general topic of path planning for autonomous mobile robot inspection. The following crucial subproblems were identified through the study of the field: path finding, traveling salesman problem and variants, localization, filtering, mapping, obstacle avoidance, interception, chase, motion and intent prediction, etc. For clarity, the definitions of the principal subproblems connected to the topic is provided in Table 1.

Given the wide range of applications, it can be difficult to directly compare algorithms and approaches. Furthermore, since the algorithms and approaches draw inspiration from the wider topic of path planning for autonomous drones, it can be helpful to systematically divide the problems based on the aspects presented in Table 2.

Table 1. Definitions of principal subproblems connected to the topic.

Subproblem	Definition
Path Finding	Refers to the process of determining a route from a predefined starting point to a predefined goal point in the drone's domain, typically involving travel cost, obstacles, and terrain constraints as the optimization parameters [45–57].
Traveling Salesman Problem	Refers to a well-studied combinatorial optimization problem of finding the visitation sequence with the shortest possible route that visits a set of nodes in a graph exactly once. Famous for its exponential growth in complexity with the number of nodes, a number of extensions of the problem have been proposed to enable dealing with larger numbers of points. The most popular are Generalized Traveling Salesman Problem (GTSP) or the Traveling Salesman Problem with Neighborhoods (TSPN) [22,23,27,58,58–67].

Table 1. *Cont.*

Subproblem	Definition
Interception and Chase	In the context of path planning in robotics, interception refers to the maneuver by which a drone predicts the motion of and meets a moving object at a point in their future trajectories. Chase or pursuit, on the other hand, refers to the continuous tracking of a moving object by maintaining proximity with the object [8,10,19,68–72].
Obstacle Avoidance	Refers to the process of defining or changing the future trajectory of the drone in order to ensure the drone's safety and integrity based on the knowledge about static and dynamic obstacles in the environment [11–15,23–25,73–92].
Motion Prediction	Refers to the process of estimating the future trajectory of a moving object based on its current state and the available past trajectory. Motion prediction is usually focused on spatial movement in the object's domain [93–96].
Intent Prediction	Refers to the process of predicting future high-level goals and actions of a moving object based on its past behavior. Intent prediction aims to infer motivations to predict maneuvers such as direction changes, stopping, and interaction [30–34,73,97–101].

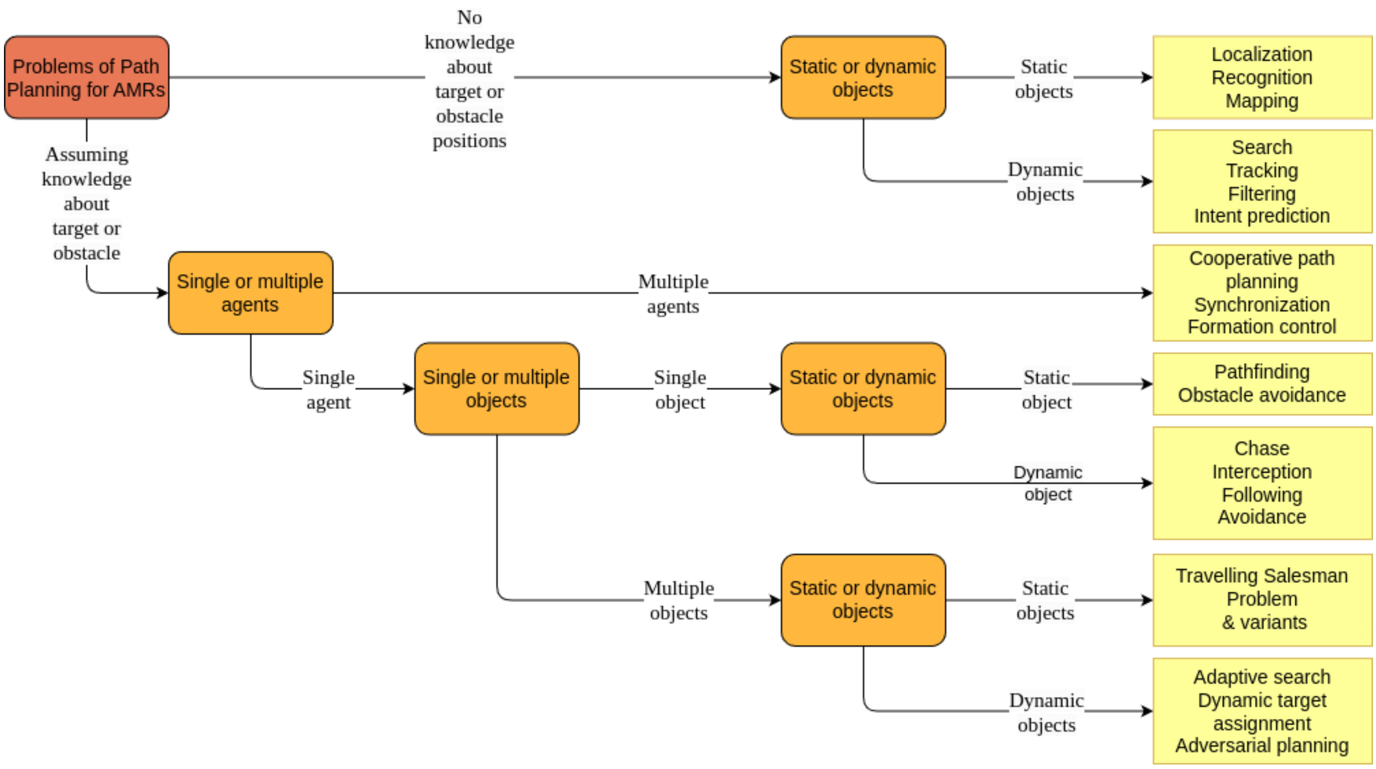


Figure 1. Taxonomy of the field of path planning for autonomous mobile robots.

Table 2. Descriptions of aspects of problems of path planning for autonomous drones.

Topic	Description
Single vs. Multiple Objects of Interest	With a single object of interest, the entire optimization effort can be directed to finding the optimal path for the drone. When planning inspection of multiple objects of interest, determining the **optimal sequence** of visiting becomes crucial to finding the optimal path, reducing resource consumption, such as travel time and energy.

Table 3. Cont.

Topic	Description
Static vs. Moving Objects of Interest	Path planning for static objects takes into account the positions of the objects and the layout of the environment as an optimization constraint. On the other hand, assuming the objects move at a non-negligible velocity relative to the drone, the optimization constraints must also include motion prediction (predicting the future trajectory of the object). Moreover, based on the level of autonomy of the moving objects, intent prediction must also be taken into account. The higher the level of autonomy, the greater the influence of intent prediction on the quality of the solution.
Single vs. Multiple Agent Algorithm	While the single-agent inspection setting allows the algorithm to focus on optimizing the individual path of the drone, working with multi-agent systems involves several additional challenges. Firstly, distributing objects of interest among drones through **task allocation** ensures full coverage and redundancy reduction. Secondly, through **synchronization** of the drone trajectories, the system avoids conflicts and collisions. This can also be performed **asynchronously** through a predefined set of rules as planning constraints (suitable for distributed planning systems).

2.2. Methodology

To perform an extensive survey of the available literature concerning path planning approaches for aerial drone inspection of multiple moving objects, a conventional two-step procedure was employed: searching for publications from digital libraries based on carefully defined queries and extending the search based on papers' references. With the goal of complete coverage, novel sources such as Elicit and Scispace were included in the search. The digital libraries used were the following:

- Web of Science (WoS)
- Scopus
- Google Scholar
- Elicit
- Scispace

These libraries were queried based on topics defining our survey subject. Based on the 50 most relevant results of the five databases, the survey was further extended based on referenced articles in the results themselves. In Figure 2, the growth in popularity of the topic can be observed, both in terms of publication and citation numbers. From each of the sources, the top 50 most relevant articles, according to the database, were compiled and evaluated. The results are presented in Table 4. The comparison metrics in the table are the following:

- Average number of citations per article.
- Number of articles from the top 50 that mention in **title** or **abstract** each of the principal queried topics. The topics are the following: moving objects, multiple objects, obstacles, interception, and multiple agents.

Table 4. Analysis of the top 50 most relevant articles obtained through the database searches (2024 publication data is incomplete, publications until 4 October 2024). Best results in category highlighted in bold text.

Source	Avg. Citation No.	Moving Objects	Multiple Objects	Obstacles	Interception	Multiple Agents
WoS	8.79	24/50	25/50	**20** /50	14/50	11/50
Scopus	14.78	16/50	21/50	12/50	7/50	14/50
Google Scholar	**176.9**	18/50	34/50	12/50	13/50	13/50
Elicit	65.1	**38**/50	**36**/50	14/50	**24**/50	**20**/50
SciSpace	2.78	17/50	16/50	15/50	13/50	10/50

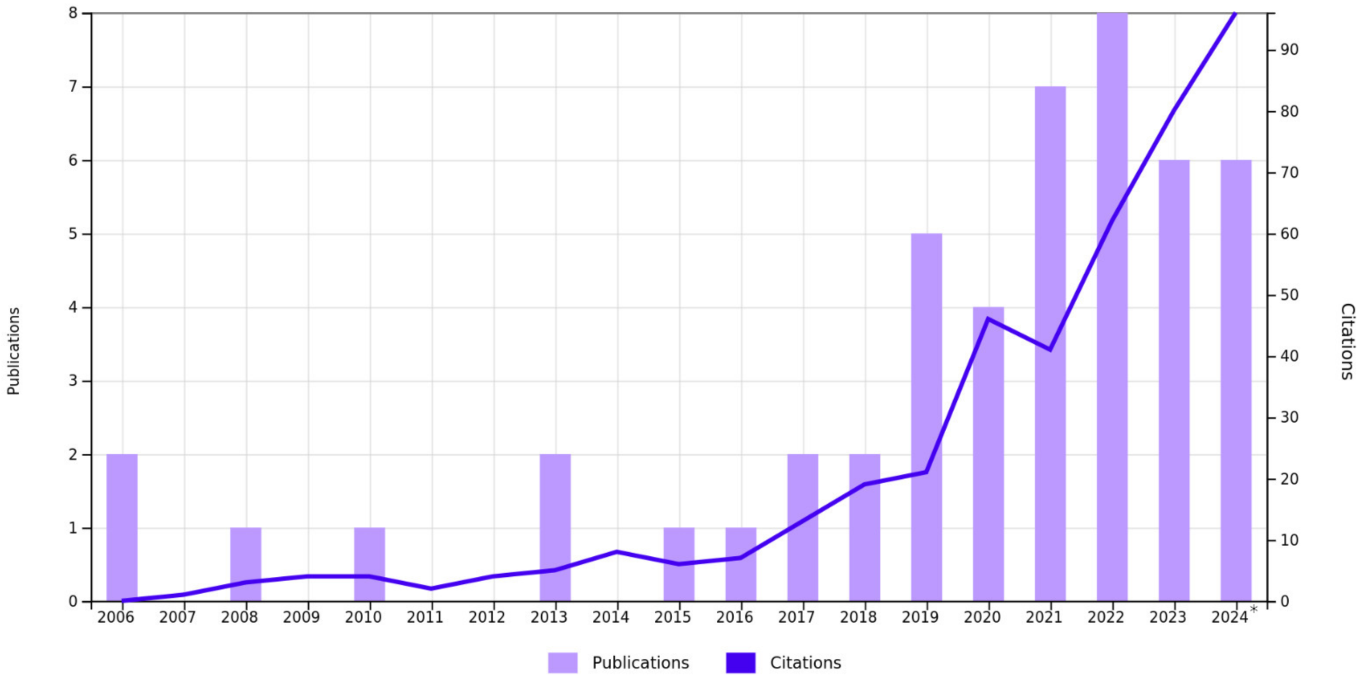


Figure 2. Number of publications and citations of papers found through the Web of Science search through the years (* 2024 publication data is incomplete, publications until 4 October 2024).

3. Planning with Multiple Objects of Interest

Traditional path planning algorithms for autonomous robots address the problem of navigating to a predefined goal position or state, taking into account both the robot's and the environment's constraints. In the context of autonomous inspection, this amounts to path planning with a single static object of interest, as presented in Figure 3. There exist numerous solutions available for this well-researched problem, such as optimal graph-based solutions [45–47], heuristic approaches [48,49], as well as sampling-based methods [50–57]. These methods are effective even when planning with multiple moving objects of interest, under the assumption that they move significantly more slowly than the robot performing the inspection. In that case, the problem can be approximated as static. However, as the number and relative speed of objects of interest increases, so does the planning complexity. Finding the optimal sequence in which objects are visited becomes critical, as does taking motion prediction and dynamic constraints into account. This chapter focuses on algorithms useful in static or mostly static environments.

Before exploring a setting with multiple objects of interest, it is worth mentioning that there exists a version of the path planning problem on the junction of single and multiple object of interest environments, when the task is to inspect a single static object from multiple points of view.

In [102], the authors address the automation of robotic inspection of real-world structures. To this end, they developed the multi-objective evolutionary optimization (MOEA) algorithm. The goal of the algorithm is to traverse the structure passing through a series of predefined positions in order to complete the inspection. For a given 3D structure model defined by triangles, the algorithm finds a 3D path that maximizes the coverage of the structure while minimizing the energy consumed by the robotic system. The approach is platform-agnostic, and it is applicable to systems such as UAVs or unmanned underwater vehicles (UUVs). However, in the paper, the approach was tested on a UUV.

A similar algorithm for structural inspection was developed in [103]. Based on a point-cloud representation of the structure to inspect, they created a simplified 3D model. From this model, a graph was created from its convex shell and used for the final planning step. To cover the entire surface of the object, the problem can be understood as an evolution of the TSP called Coverage Path Planning (CPP). It has traditionally been solved by iterations of two algorithms: the Art Gallery Problem (AGP), where the minimum number of positions to cover the volume is calculated, and the TSP. The authors of this paper presented an algorithm in which they replaced the AGP with sequential convex optimization and the TSP with a new path search algorithm. The authors used UAV drones that follow the planned trajectories to perform successful experiments.

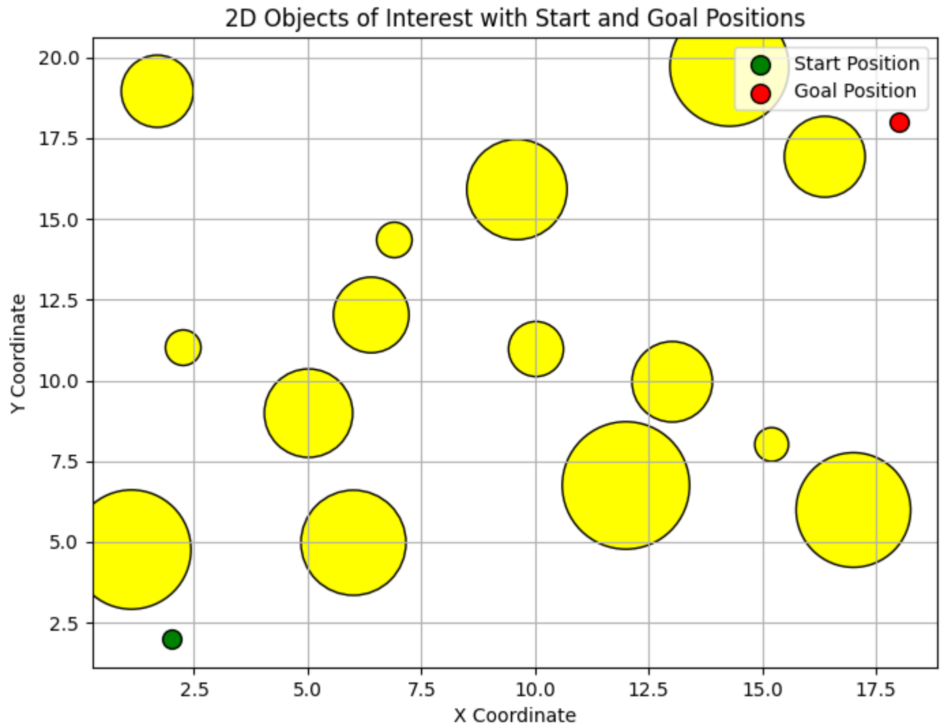


Figure 3. Illustration of a 2D path planning environment with a single static object (goal position; red) of interest and multiple static obstacles (yellow circles).

Most recently, CPP was performed with multiple agents by training policy networks in a reinforcement learning paradigm in [104,105]. In both works, authors leveraged the robust nature of such policies when trained in adequate simulators to respond to uncertainty, unknown obstacles, and complex situations. In [105], the authors developed a centralized two-level architecture, whereas in [104] a distributed online cooperation method was used. Both showed satisfactory performance in simulated scenarios.

Addressing the problem of navigating to multiple predefined goal positions or states, taking into account both the robot's and the environment's constraints, as presented in Figure 4, expands the original problem with the question of sequencing. In such cases, determining the optimal sequence of visiting different objects is paramount to the quality of the final solution. From TSP, two variants of the problem were constructed, the Generalized Traveling Salesman Problem (GTSP) [58] and the TSP with Neighborhoods (TSPN) [59]. The difference between the two is in the form of the representation of the nodes in the graph: GTSP combines discrete sets of points in a node, whereas TSPN presents continuous neighborhoods with nodes. In robot inspection scenarios, a problem could be modeled by representing objects in space with nodes and GTSP could be thought of as choosing among a predefined discrete set of approaches. TSPN, on the other hand, would make the choice by optimizing the approach in a continuous neighborhood around each object (i.e., node in the graph). In a real-world scenario, such relaxations do not hinder performance, as targets in inspection tasks generally only need to be approached. An exact solution to the GTSP problem can be obtained using Branch and Cut [60], Lagrangian relaxations [58], and conversion to an equivalent TSP problem [61]. Due to the complexity of the TSP, GTSP, and TSPN problems with larger number of nodes in the graph, numerous examples also use heuristics in solving GTSP and TSPN problems. For example, application of the ant algorithm [62] and genetic algorithms [63]. However, it is important to note that the result of solving these problems is the optimal sequence in which to visit the nodes, not a trajectory or a path.

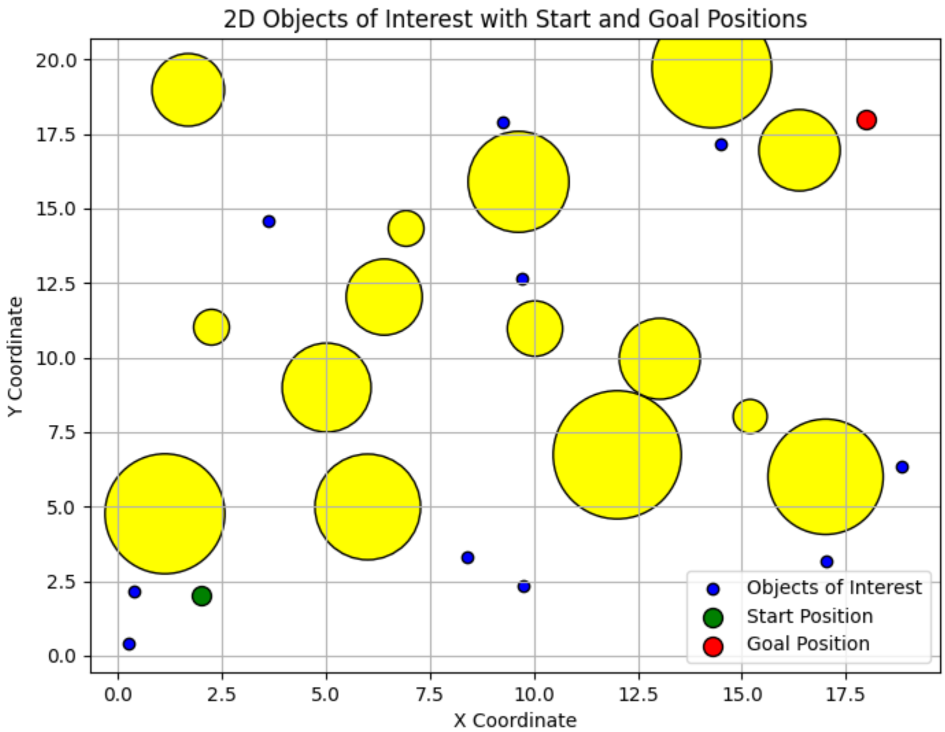


Figure 4. Illustration of a 2D path planning environment with multiple static objects (red and blue points) of interest and multiple static obstacles (yellow circles).

Recently, a more general class of problems called Graphs of Convex Sets (GCS) has gained popularity due to a novel strong and lightweight mixed-integer convex program [22,27,64]. It combines high-level discrete problems, such as the Shortest Path Problem (SPP) or the TSP with low-level continuous optimizations methods ubiquitous in robotics. As it relates to multiple goal coverage, formulating a TSPN in the GCS framework is a very natural approach to solving actuation and planning tasks for complex robotic architectures, such as humanoid and quadruped robots [27].

In robotics, a version of the TSP called Multi-Goal Path Planning is used, where the nodes are locations in the space in which the robot moves and the lengths of the links between them are distances. The result of such an algorithm is a trajectory without collisions with the environment and often includes the dynamic limitations of the robot itself in the calculation. Examples of solutions to this problem are given in [65] with the Minimum Spanning Tree (MST) algorithm and [66] Synergistic Combination of Layers of Planning (SyCLoP) algorithm.

Another level of complexity to the problem is planning the approach to each object of interest in addition to simply reaching it. This version of the problem is considered in [23], where they call the objects of interest Targets of Interest (TOI) and the relative pose for the approach is the Pose of Interest (POI). Researchers developed a safe multi-goal (SMUG) planner for exploration or monitoring missions such as the ANYmal quadruped robot [29]. The input into the planner is a set of predefined targets to be visited from multiple potential locations. SMUG uses a hierarchical state validity checking scheme, LazyPRM* to obtain collision-free paths, and iterative dynamic programming for planning optimal approaches to objects. The planner solves the GTSP problem with collision-free paths with more than ten objects in seconds. The researchers find a 30% reduction in planning time and increased safety by avoiding high-risk regions.

In [67], the authors used the RRT algorithm as an inspiration for planning the path with multiple static objects of interest. The developed Space-Filling Forest (SFF*) algorithm generates a tree from each of the objects of interest. Once the trees are built and connected, the algorithm uses TSP to find the optimal schedule to visit the objects of interest. The method was compared to other planning algorithms and was shown to be more efficient.

In [106], the authors used a geometric arc parametrization method to solve the problem of trajectory planning for aerial drones (UAVs) when visiting multiple static objects of interest positioned at the same altitude. The problem was described as an optimization in a nonlinear system with constraints. Furthermore, the geometric nature of the generated trajectories makes it inherently efficient with fixed-wing drones. The approach was validated in several numerical experiments in which, although suboptimal, the approach proved to be computationally efficient.

In [107], the authors once again dealt with trajectory planning for unmanned aerial vehicles (UAVs), this time as a radar evasion technique in a war zone. The problem is described as reaching a desired target while avoiding radar detection from radars with known positions. Based on their positions, the authors proposed the generation of a graph based on a Voronoi diagram of the positions. Often used as a tessellation method, in mathematics a Voronoi diagram partitions a plane into regions close to each of a given set of objects. The boundaries of the partitions are then used as a graph in which to seek a trajectory. Their approach plans a trajectory with the Dijkstra algorithm [46] on the created graph.

In summary, although they evolved over time, the old ideas presented in solutions to SPP, such as A* and Dijkstra, and TSP, GTSP, and TSPN, circulate in most algorithms to this day. , For example, the previously presented SMUG planner, a state-of-the-art solution for path planning for a quadruped robot with multiple static objects, interleaves LazyPRM*, a TSP solver, and dynamic programming. Most recently, more powerful tools for modeling problems have shown promise. GCS, a more general class of problems combining high-level discrete with low-level continuous problems, gained popularity in a number of areas, such as robotic manipulation or long-horizon trajectory generation for UAVs.

4. Obstacle Avoidance

To guarantee the safety of a robotic system, be it a UAV or a different autonomous vehicle, obstacle avoidance must be implemented as part of the system's operation. Depending on the use case, this can be performed on a number of levels, e.g., global [11,23,78] or local planning [73]. For what concerns planning in static worlds, the proposed solutions use a wide range of algorithms [12,13,74–77]. On the other hand, planning safe 3D trajectories in dynamic worlds brings with it new challenges that are taken on in projects such as [11,78].

When it comes to state-of-the-art solutions for UAV trajectory planning with obstacle avoidance, a series of papers [11,14,24,79,80], culminating in the thesis [25] provides the most advanced solutions available.

In both static and dynamic environments, most approaches to obstacle avoidance are based on the discretization of trajectories [15,81–84]. If the process is not dense enough, this renders guaranteeing safety between two discretization points difficult or impossible. Therefore, it is desirable to check for collisions in continuous space. To this end, in [79], authors introduced the MINVO basis as an alternative to the B-spline and Bernstein bases. MINVO is a polynomial basis that attempts to enclose a given n^{th} -degree polynomial curve with the smallest n-simplex generated in $\mathbb{R}^n$. The paper provided proof that the MINVO basis also solves a similar problem of obtaining the n^{th}-degree polynomial curve with the largest convex hull enclosed in a given n-simplex. The approach is proven to be globally optimal for $n \leq 3$ and locally optimal for $n = 4$. For $n = 3$, the simplex found by MINVO is 2.36 and 254.9 times smaller than those of the Bernstein and B-Spline bases.

In [11], the authors introduced a 3D trajectory planner for UAVs called MADER. The planner is decentralized and asynchronous and generates collision-free trajectories in environments with static and dynamic obstacles, and other planning agents. Collision-free trajectories are found by leveraging the aforementioned MINVO basis. The trajectories of both the UAV and other agents are represented as polyhedra which are then checked for collisions in continuous space in the optimization problem. As it relates to the cooperation of the agents, the authors developed a decentralized and asynchronous algorithm through which the agents use committed trajectories as optimization constraints. Compared to other approaches, simulations in cluttered worlds show up to a 33.9% reduction in the flight time, and an 88.8% reduction in the number of stops. An evolution of the algorithm robust to communication delays was presented in [85].

In [24], authors took another step towards autonomy by considering obstacle avoidance for UAVs with a forward-facing depth camera, a downward facing monocular camera, and an IMU. They presented a real-time perception-aware trajectory planner for UAVs in dynamic environments called PANTHER. The algorithm generates trajectories through the joint optimization of UAV rotation and translation with the goal of obstacle avoidance, keeping the obstacles in the sensor's field of view (FOV), and blur minimization. The algorithm exploits the differential flatness of multirotors and implicitly imposes the underactuated dynamics through the Hopf fibration. The results show a 7.9-fold improvement in keeping the obstacles inside the FOV compared to other perception-aware approaches while reducing blur by 18%.

The work was continued in [80] with a learning-based evolution of the algorithm called DeepPANTHER, which generates multiple candidate trajectories for obstacle avoidance. The authors leverage imitation learning to achieve real-time performance by imitating a multimodal optimization-based expert. This approach achieves a speedup of two orders of magnitude while retaining similar cost performance.

In line with the current trends of learning-based approaches [80,86,87], in ref. [87] researchers proposed NoMaD (Navigation with Goal Masked Diffusion). The novel architecture for robotic navigation uses a unified diffusion policy to handle both goal-directed navigation and goal-agnostic exploration in previously unseen environments. Researchers used a Transformer-based policy trained on data from different UGVs and a diffusion model decoder. Compared to traditional approaches with sub-goal modules, e.g., obstacle avoidance, exploration of environment, etc., NoMaD produces lower collision rates and better overall performance. However, while the approach provides an excellent proof of concept, the unified policy has a number of limitations, primarily the constrained task description.

Other approaches leverage probabilistic methods due to the resource heavy nature of obstacle avoidance [88–92]. Algorithms such as the Cross-Entropy Method (CEM) or the model predictive path integral (MPPI) use sampling from carefully selected probability distribution spaces to obtain families of solutions. From these families, the probability distributions are updated and the elite set of collision-free trajectories and paths in the operation or task space is selected.

In [88], the researchers presented novel improvements upon the original Cross-Entropy Method [108,109] when used as a trajectory optimizer for robotic systems instead of model-free reinforcement learning methods to develop iCEM. To improve the inefficient sampling procedure, their approach uses bootstrapping sequential sampling steps, population decay, etc. Furthermore, instead of the Gaussian inputs, the researchers introduced colored noise into the process, resembling exploration strategies in animals. In comparison with other model-based trajectory optimizers for model-based reinforcement learning, such as the original CEM, the novel additions yield a performance increase of 1.2–10 times whilst reducing the number of needed samples by 2.7–22 times. Further evolution of their approach is available in [110].

In [89], the researchers built on the path integral optimal control framework [90–92] and developed the model predictive path integral (MPPI) control algorithm and an optimized parallel version for usage on a graphics processing unit (GPU) are presented. The algorithm is based on the generalized importance sampling scheme and handles nonlinear systems without needing derivative information. Compared with Differential Dynamic Programming (DDP) in complex control tasks, such as racing car, quadrotor, and cartpole control, it demonstrates superior performance. The contributions of the paper are a generalized likelihood ratio derivation in order to tune exploration variance and the adjustment of the algorithm to leverage GPU parallelization. Moreover, the authors further developed MPPI approaches in a series of articles [26,111–113], covering robust, local, adaptive, and information-based versions of MPPI.

In summary, the primary goal and motivation with obstacle avoidance is ensuring the safety of the robotic platform. Hence, state-of-the-art solutions prefer exact algorithms as opposed to probabilistic or approximate ones. For example, in MADER and PANTHER, the authors leverage the novel basis called MINVO to generate small simplexes and check for collisions in continuous space. Furthermore, when it comes to dynamic obstacles, real-time function is always required. To this end, a trend towards sampling-based trajectory optimization and GPU utilization can be observed, as in iCEM and MPPI.

5. Planning with Moving Objects of Interest

As we have seen from the provided examples, the problem of planning for autonomous mobile robots in static or mostly static environments has been thoroughly covered in literature. Depending on the use case and the number of objects of interest, an appropriate balance between optimality, completeness, and efficiency has to be struck. These solutions prove useful even if the objects move significantly more slowly relative to the robot and are far enough from each other. However, when these conditions are not met, the static sequencing and path planning solutions lose value.

The dynamic nature of the environment has a multifaceted meaning. It can signify moving obstacles to be avoided, moving objects of interest to be intercepted, and changing attributes, such as wind or waves. This article focuses on the former two, as presented in Figure 5 for a single moving object and in Figure 6 for multiple moving objects. In Figure 6, Figure 6a presents slow objects with regards to the robot And Figure 6b the fully dynamic environment.

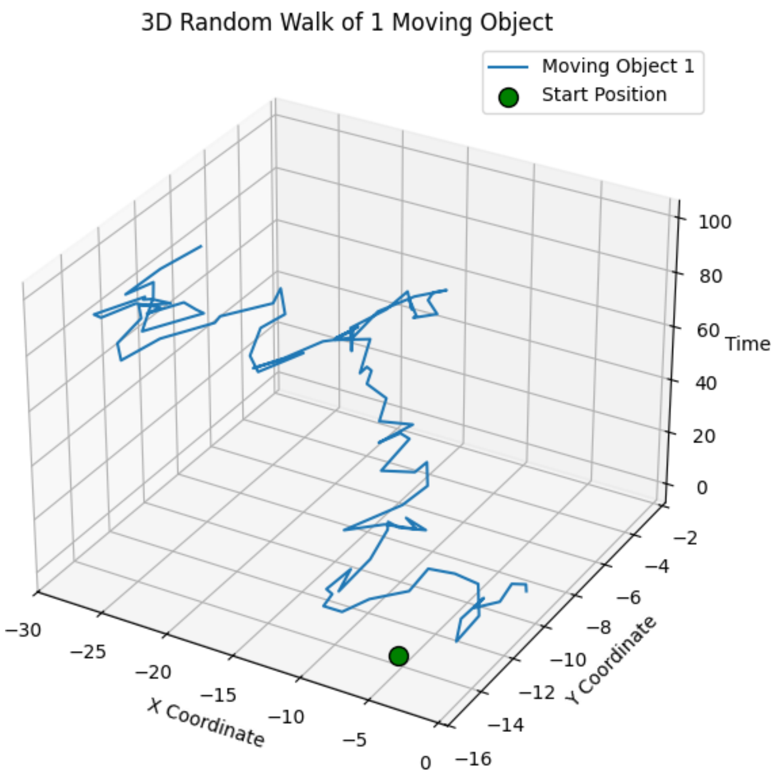
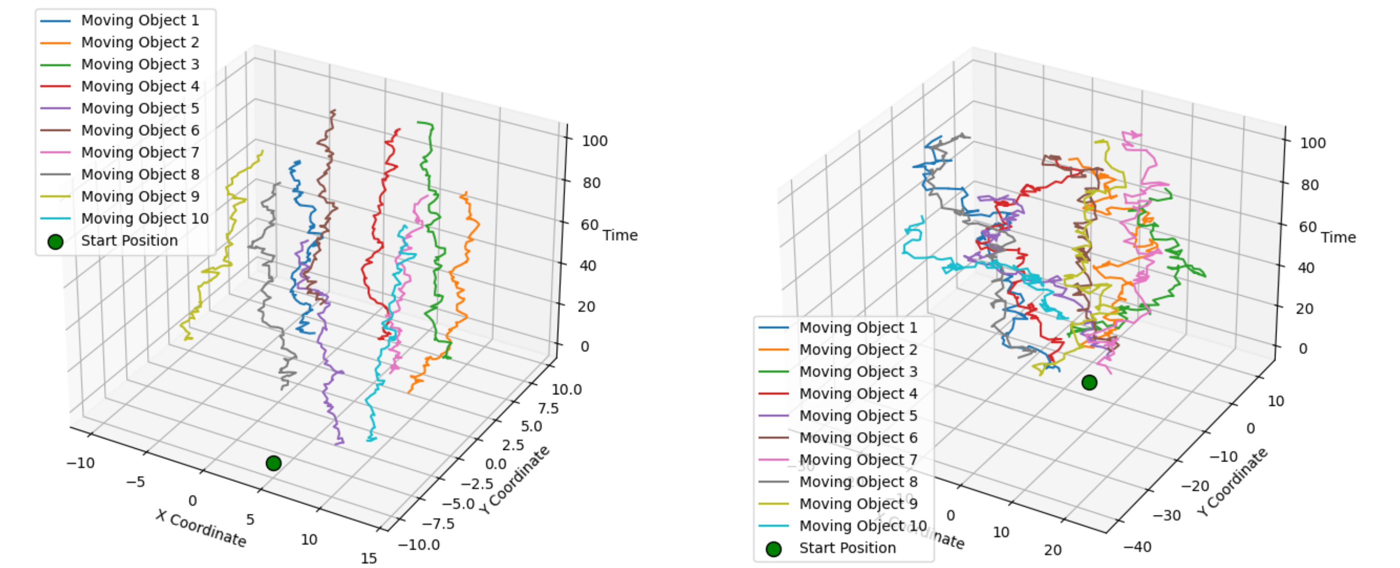


Figure 5. Illustration of a single object moving in X–Y space representing a 2D environment evolving through time.



(**a**) Illustration of multiple objects moving slowly in X–Y space representing a 2D environment evolving through time.

(**b**) Illustration of multiple objects moving with high velocity in X–Y space representing a 2D environment evolving through time.

Figure 6. Illustrations of the time evolution of 2D environments with multiple objects of interest moving at different velocities.

5.1. Motion and Intent Prediction

The quality of the generated paths of the planning algorithm depends directly on the quality of the prediction of future paths of the objects in the scene. These problems are solved in the field of motion and intent prediction. The approach heavily depends on the setting, ranging from projectile trajectory prediction to pedestrian movement [30–32,73,93,97–101].

On one end of the spectrum are passive objects. An example of such objects are projectiles prevalent in military applications, whose trajectories are defined by the laws of physics [93]. Given knowledge about their properties, the prediction process is relatively straightforward [94–96].

On the other hand, non-passive moving objects add another dimension to the problem in the form of their autonomy. Their future trajectory depends to a certain extent on their intent, bringing significant uncertainty to the prediction process. A great example illustrating the difference is [114], in which the authors developed a cooperative active defense guidance law based on three-body engagement. Three actors influence each other's motion: one running away, one chasing, and one intercepting. In this scenario, a missile is no longer passively moving, but actively pursuing the fleeting asset, and the third agent attempting to intercept its motion. A review of scenarios with multiple targets is given in [115].

Lastly, in situations such as predicting future pedestrian or car trajectories in intersections, the lack of significant physical constraints allows for multimodal solutions. That is, multiple different future trajectory that are equally plausible.

For example, in [30] researchers focus on predicting individual movement of pedestrians in crowds. Motivated by the common expression that individual movement can be described as if it were subject to "social forces" presenting internal motivations, they develop a nonlinearly coupled set of equations named the social force model. The model takes into account the acceleration towards a desired velocity, the distance kept from other elements in the environment, and attractive effects. The set of rules resulted in a highly realistic simulation of crowds.

In [97], the authors presented an Intention-aware denoising Diffusion Model (IDM) algorithm, which predicts the future trajectories of pedestrians in the environment with the help of the diffusion deep learning algorithm. The two main problems encountered using such an approach are connectivity between the intentions of agents with the uncertainty in the environment and the slowness of the diffusion process. IDM solves both the problems by separating the uncertainty of the intention and the action in the diffusion process. The method was tested on the well-known Stanford Drone Dataset and ETH/UCY databases [33,34] and achieved top results.

A different generative deep learning approach, the Generative Adversarial Network (GAN), was used in [73]. In this paper, the authors combined GAN networks with rasterization methods of bird's-eye view of the scene in an algorithm they call Scene-Compliant GAN. The method was tested on the ATG4D database [116]. Unlike the iterative diffusion process in the IDM algorithm, once trained, GAN networks are significantly faster as they require one pass to generate a prediction. These networks have proven useful for predicting traffic movements in the following works [31,32].

In [98], instead of presenting the traffic situation as a bird's-eye view, the authors used a Graph Neural Network (GNN) architecture. The advantage over traditionally used convolutional networks is the vectorization of the high-resolution environment skipping the expensive image encoding process. The developed VectorNET architecture achieves equal or better trajectory prediction results compared to other methods while reducing the used resources by an order of magnitude.

The same team continued the research in [99], in which they proposed the target-driven trajectory prediction algorithm (TNT). TNT is based on the assumption that the behavior of the agents in the scene can be represented by future goal states. The first module predicts these goal states based on which the second module predicts sequences of states representing the future trajectory are then generated given these predicted target states. This approach solves the problem of the multimodal nature of behavior agents in the scene.

It is interesting to note that TNT creates a division between the prediction of intent and motion. The two-step process first predicts the desired goal position, or the agent's intent, and then predicts the motion the agent takes to reach the goal.

In [100], the authors solved the problem of predicting traffic movements by combining vehicle kinetic models, Dynamic Bayesian Network (DBN), and Markov decision process theory (MDP). DBN networks are used to model relationships between the states and unmeasurable intentions of agents in a scene. The Markov chain created from the kinematic model was used to predict the future trajectories of the vehicle based on the current state, intentions predicted by the DBN network, and uncertainty in the predictions themselves. These multimodal predictions are then sent to the vehicle itself for route planning. The method proved successful on real examples from publicly available databases.

Lastly, in [101], researchers explored a meta topic in the field of traffic prediction. In the process of training neural networks, they researched the impact of frequent uncritical scenarios (well represented in popular datasets) versus the rare critical ones (sparsely represented in popular datasets) on the prediction of traffic actors. They found that common uncritical scenarios dominate the predictions even in critical scenarios. To improve, they proposed upgrading the loss terms in the learning process to place the challenging cases closer together in the embedding space. This approach leads to improved performance on critical cases, while retaining stable overall performance.

5.2. Single-Agent Single-Object Scenario

One of the original algorithms developed to solve the problem of reaching a moving target is the 1995 Moving Target Search (MTS) algorithm [68]. Created as a generalization of the Learning Real Time A* (LRTA*) algorithm, MTS uses heuristic information about all possible target locations in its matrix. The authors proved that the algorithm is guaranteed to reach the object of interest when it moves slower than the agent that is chasing it. Moreover, two versions of the algorithm were developed for different applications, a complete and a computationally efficient version.

In [69], the authors built upon the work presented in [68] and used the new Trailblazer Search algorithm to search and reach a single object of interest. Through the operation, the algorithm constructs a database of information in the map about the region believed to contain the object of interest. Through that map, the algorithm searches for paths to reach a new position in space and achieves better performance than the previous MTS algorithm.

In [70], the authors developed an adaptive dynamic trajectory planning algorithm for the task of intercepting a mobile target. Their solution represents an evolution of the L+Dumo algorithm and was tested on a simulation in C++. The original L+Dumo algorithm [71] is used to intercept a mobile target in 3D space by an aerial drone, a UAV, with efficient calculation. The results were tested on the problem of intercepting one object in 3D space.

5.3. Single-Agent Multi-Object Scenario

In environments in which multiple objects move with enough unpredictability and at a higher velocity relative to the inspecting aerial drone its physical constraints render chasing a single target at a time a valid approach. However, if that is not the case, computational resources should be diverted to combined prediction and planning algorithms.

In [117], the authors dealt with the problem of finding a path that covers multiple objects in a dynamic graph represented by a Spatial Network Database (SND). The developed algorithm finds the shortest path to the mobile objects in the SND by taking into account the movements of the agents and the changes that this produces in the SND. The complexity of the algorithm is $O(k \log(2 \cdot i))$ while the complexity of the original Dijkstra algorithm in this problem is $O((i + k) \cdot 2)$.

In [78], the authors developed a Partitioned Learning Real-Time A* (PLRTA*) algorithm for real-time motion planning in dynamic environments. Compared to other heuristic algorithms, PLRTA* works efficiently in environments with a higher number of dimensions, common in applications such as robotic manipulators. The algorithm plans trajectories with regard to the predictions of the movements of other objects in the scene and has been tested in both simulation and the real world.

In the thesis [118], the author discussed the effects of parameter uncertainty in dynamic environments for unmanned aerial vehicles (UAVs). For scenarios with non-negligible parameter uncertainty, a control hierarchy called the Receding Horizon Mixed Integer Linear Programming (RH-MILP) was developed. Faced with rapidly changing situations and uncertainties, the algorithm allows the robotic system to react quickly and replan optimal trajectories for the UAV. The author considered several objects of interest as well as obstacles in the domain in which the UAV operates. The algorithm was tested in simulation as well as in real-world experiments.

5.4. Multi-Agent Multi Object Scenario

An overview and taxonomy of the field of multi-robot object detection and tracking was given in [35]. The article provides definitions of classes of missions and problems, the analysis of numerous approaches in the field, as well as the reasoning behind each one of them. Among the examples of missions presented in the paper are search, tracking, patrolling, surveillance, hunting, and evasion.

When working with multiple moving objects and multiple agents performing inspection, task allocation, sequencing, and synchronization all play important roles in the performance of the system. One of the examples of a task including multiple moving objects and multiple agents is wildlife tracking. This setting is the topic of a series of papers from H.V. Nguyen, [8,9,119], culminating in the thesis [9].

In [119], the authors developed a multi-objective planning method for a multi-agent team with limited FOV to discover and track multiple mobile objects. Due to the limited FOV constraint, the authors formulated a Partially Observable Markov Decision Process (POMDP) to model the planning problem. Due to its exponential complexity, an entropy-based multi-objective value function that is monotone and submodular was developed.

This enabled low-cost suboptimal solutions via greedy search with a tight optimality bound. The capability and efficiency of the algorithm was demonstrated on a real-world taxi dataset.

Continuing on their work, in [10] the authors proposed an online path planning algorithm for joint detection and tracking of multiple radio-tagged objects. The focus of the project is using UAVs with onboard sensors in monitoring applications. Once again, the problem was described as a POMDP with a random finite set track-before-detect multi-object filter and two reward functions which also maintains a safe distance between the UAVs and the monitored objects. The results of the experiments show high effectiveness of the approach in the reduction in the estimation error of multiple objects in the presence of low signal-to-noise ratios compared to other approaches.

Finally, in [8] the authors focus on the improvement of studies on endangered species habitats and behaviors through the use of UAVs for monitoring with regards to manual methods. In the paper, the TrackerBots system is developed to track and localize multiple radio-tagged animals. To this end, the signal generated by radio-collars is used to calculate the location using the received signal strength indicator (RSSI). To reduce uncertainty and help with the nonlinearity of the system, a particle filter was integrated in the tracking and planning procedure. The approach was once again validated in real-time and online scenarios through extensive simulation and field experiments.

In [120], the authors work on path planning for multiple agents and multiple objects of interest in a domain approximated through a Markov Decision Process (MDP). In this setting, the agents do not communicate with each other. The complexity of the optimal approach in such an environment increases exponentially with the number of objects of interest. To avoid this, the authors sacrificed the algorithm's optimality for better time efficiency. In the real world, such an algorithm proves to be faster than optimal procedures and more optimal than available heuristic approaches.

In [19], a multi-agent game called "reach-avoid" is considered. The game consists of a group of attacking players that must reach the goal while avoiding a group of defending players trying to catch them. In contrast to the pursuit problem, it is required of the agents to both reach a specific goal and avoid the defending players. Depending on the number of agents, finding a solution to this problem is extremely complex. As a solution, the authors proposed an open-loop algorithm, where players commit to their behavior before the start of the game. This approach significantly reduces the complexity of the problem itself, rendering it solvable. Furthermore, the developed method was tested both in simulation and in the real world on aerial drones in 2D space.

In [72], a scalable suboptimal algorithm for tracking multiple objects of interest with multiple agents is developed. The paper focuses on the key detail of the assignment of the objects to the agents. The developed algorithm thus includes a dynamic recalculation of the allocations. In its optimal version, this procedure has limited scalability, while the main approach used in the paper, although suboptimal, retains the property of completeness while being executed in reasonable time. The approach was tested in numerous simulated scenarios in which scalability is proven, outperforming previous methods.

In [16], the authors developed a Hybrid Differential Evolution (HDE) approach that combines the Differential Evolution (DE) algorithm and two new update schemes to find path planning solutions with multiple moving objects in a scene. Based on the Bayesian theory of probability, the probability of meeting the object of interest is used as the optimized value in the optimization problem. In the discretized approximation of the environment, the search for the best solution, in this case DE, was subsequently performed using evolution methods. The algorithm has been thoroughly tested and shown to be superior compared to other approaches for this problem.

In [17], the authors worked on an environment with multiple mobile agents and multiple moving obstacles. The developed algorithm, the MultiplePursuers TrailMax algorithm, plans a path with the goal of avoiding other agents for as long as possible. The basis of the algorithm is the TrailMax algorithm [18], which is then upgraded for a multi-agent scenario. For the simulation, the authors obtained a discretized representation of the environment. Compared to other algorithms mentioned in the paper, their approach improves performance by 13%.

In summary, for scenarios with moving objects, the quality of motion and intent prediction algorithms directly influences performance of path planning. Depending on the application, methods range from physics-based prediction for passive objects (such as projectiles), to generative approaches (such as diffusion models and GAN algorithms). Furthermore, since high performance gains can be achieved by specializing with regard to the environment, our study finds that there is no "one size fits all" state-of-the-art solution. For what concerns multi-agent systems, path planning is further compounded by the additional problems of task allocation, synchronization, and formation control. In such scenarios, popular state-of-the-art solutions use reinforcement learning to achieve desirable performance and robustness.

6. Discussion

Having presented the theoretical background, the literature overview methodology, and the most relevant algorithms and approaches in the field, a discussion of the findings will follow.

6.1. Literature Overview

Firstly, let us discuss the results from the literature overview process. Once again, five online databases were used to obtain relevant papers on the topic of path planning for aerial drone inspection with multiple moving objects of interest. Two of them official databases that provide citation and reference data, WoS and Scopus, the popular search engine Google Scholar, and two novel large-language model-based databases, Elicit and SciSpace.

From these results, interesting conclusions emerge about the current trends of state-of-the-art projects in the field, as well as the inner workings of the search engines themselves. Notably, with 176.9 average citations per result, Google Scholar yields by far the most popular results, with many of them being chapters in books. In the sorting of the results, this likely indicates prioritization of general popularity in the literature over strict intersection of topic and keywords. On the other hand, both WoS and Scopus seem to implement a more rigid search algorithm, producing results with a lower average citation count but more directly connected to the exact query used in the title and abstract. In the end, the two novel large-language model-powered literature overview tools, Elicit and SciSpace yielded very different results. SciSpace, unfortunately, failed to find a good balance between popularity and relevance. On the other hand, Elicit produced the highest quality results overall, covering all the queried topics while finding specialized papers with a comparatively high average number of citations. Furthermore, it seems that Elicit functions on a more abstract level, through synonyms, similar phrases, and high-level ideas.

Finally, it is important to mention that there is a significant recent rise in the popularity of the topic. Through all the databases, a trend can be observed in the last five years with the largest number of publications and citations connected to the topic (e.g., Figure 2 provides data on Web of Science).

6.2. Survey Findings

In the context of path planning for aerial drone inspection of multiple moving objects, the solutions to this task have a wide range of applications. Examples range from animal monitoring [8–10], disaster response, and search and rescue operations [1,3,7] to military applications [114,115].

Furthermore, in this interdisciplinary task, depending on the scenario, several important subproblems can be outlined: motion and intent prediction [24,97–99,114], sequencing [23,58–63,65–67], obstacle avoidance [14,24,25,75], and trajectory optimization [20,21,88,89]. Novel state-of-the-art solutions will, therefore, have to address these challenges in some form.

Generally, the following broad conclusions were observed through the extensive survey of the available literature. Firstly, while inspection of multiple static objects has been thoroughly covered [23,58–63,65–67,102,103], for moving objects, the same solutions can be used only after small variations or by including heuristic methods [68–71,106,107]. Secondly, the dynamic nature of the environment, be it obstacles or objects of interest raise the issue of motion and intent prediction. For this topic, although most research focuses on autonomous driving in road traffic [73,97–99] there are scenario-agnostic state-of-the-art solutions to prediction [14,24,25,75]. Thirdly, platform constraints fuel the need for algorithms that can function and react in real time. Particularly in highly dynamic multi-agent scenarios, this rules out an exhaustive search for optimal policies. Because of this, a shift can be seen from optimality and completeness of the algorithms towards efficiency through heuristic search and synchronization methods [11,68,69,88,89,106,107].

While this survey reflects significant advancements made recently in path planning for aerial drones with multiple moving objects, Table 5 outlines the open issues that we believe will be part of future trends.

Table 5. Principal topics of future trends in path planning for aerial drones.

Topic	Description
Multi-Agent Systems	With the decline in the cost of aerial platforms, the focuses of research groups slowly pivot towards multi-agent settings [8,9,11,24,72,104,105]. In the time of complexity that we live in, the problems of synchronization, communication, task allocation take precedence over incremental path planning algorithm improvements.
Prediction and Uncertainty	These traditional path planning algorithms do not usually work well with uncertainty and stochastic environment properties. Because of this, there is ample space for novel more sophisticated and efficient approaches that will take those dynamic aspects into account as well. Instead of optimal prediction algorithms, developing probabilistic and multimodal motion and intent prediction could improve the algorithm performance in unpredictable environments [73,86,97].
Combination of Learning and Traditional Approaches	Current trends in artificial intelligence are powered by methods such as large-language models, reinforcement learning, GAN networks, and diffusion models. State-of-the-art projects in robotics mostly use them for complex problems related to path planning, but not directly, such as for manipulator actuation in complex contact environments or actuation under disturbances and uncertainties. Enveloping both high-level decision-making and low-level optimization through these novel methods will be a rich field of research in the future [22,27,64]. Moreover, learning methods require a vast amount of diverse data covering the problem at hand to extract knowledge during training. Obtaining such data is often infeasible in robotics due to constraints in time, funding, gear, etc. Therefore, a shift is taking place towards transfer and imitation learning, self-learning, and combined approaches [20–22,24,27,80].
Specialization	With the great diversity of problems in the field of aerial drone inspection, there are fewer and fewer one-size-fits-all solutions. Instead, platform constraints call for more specialized architectures interlocking traditionally divided robot architecture modules, such as localization, mapping, navigation, planning, and control [22,27,86]. Finally, in dynamic environments the quality of future trajectory prediction greatly affects the quality of the planned motion of the aerial drone itself. Therefore, for every specific scenario, leveraging information about the nature of the objects' movement will be key, as it would narrow down the optimization space with more accurate predictions.

7. Conclusions

In conclusion, the field of aerial drone inspection for multiple moving objects is a prolific field of study, with a wide range of algorithms and approaches for specific applications, balancing optimality, completeness, and efficiency. Some key open issues still persist in terms of developing more accurate prediction algorithms, prediction multimodality, and algorithm versatility. However, algorithms such as conditioned diffusion processes for generating trajectories of arbitrary lengths already address them partially. A multitude of future research directions promising significant improvements is available, such as utilizing on-board GPU architecture or novel neural network architectures. Current innovations with large-language models, generative models, and powerful optimization methods such as GCS will soon find their way to the field of path planning in robotics. There is little doubt that future research in this area will greatly improve the performances and safety in complex inspection processes and further extend the reach of humans.

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Abbreviations

The following abbreviations are used in this manuscript:

AMR	Autonomous Mobile Robot
UAV	Unmanned Autonomous Vehicle
UUV	Unmanned Underwater Vehicle
UGV	Unmanned Ground Vehicle
CPP	Coverage Path Planning
AGP	Art Gallery Problem
TSP	Travelling Salesman Problem
GTSP	Generalized Travelling Salesman Problem
TSPN	Travelling Salesman Problem with Neighbourhoods
MOEA	Multi-Objective Evolutionary Optimization
SPP	Shortest Path Problem
MST	Minimum Spanning Tree
SyCLoP	Synergistic Combination of Layers of Planning
TOI	Target Of Interest
POI	Point Of Interest
SMUG	Safe Multi-Goal Planner
RRT	Rapidly exploring Random Tree
PRM	Probabilistic Road Map
SFF*	Space Filling Forest
IMU	Inertial Measurement Unit
FOV	Field Of View
MTS	Moving Target Search
LRTA*	Learning Real Time A*
PLRTA*	Partitioned Learning Real Time A*
SND	Spatial Network Database
RH-MILP	Receding Horizon Mixed Integer Linear Programming
HDE	Hybrid Differential Equation
DE	Differential Evolution
MDP	Markov Decision Process
POMDP	Partially Observable Markov Decision Process
RSSI	Received Signal Strength Indicator
CEM	Cross-Entropy Method
MPPI	Model Predictive Path Integral
NoMaD	Navigation with Goal Masked Diffusion
GPU	Graphics Processing Unit
IDM	Intention-aware Denoising Diffusion Model
GAN	Generative Adversarial Network
DDP	Differential Dynamic Programming
GNN	Graph Neural Network
GCS	Graphs of Convex Sets

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