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Overview of UAV Trajectory Planning for High-Speed Flight

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***Abstract*— The use of autonomous unmanned aerial vehicles has increased for High-Speed flights, leading to the need for improved performance. Trajectory planning is the primary approach to achieving high speeds, as it is safer and more flexible than other planning types. Some approaches include polynomial trajectories, optimization-based, search-based, sampling-based, and artificial intelligence, mainly reinforcement learning. This paper provides an overview of the main techniques for high-speed trajectory planning in UAVs and the challenges associated with them. It also describes essential UAV dynamics, control, and perception to reach high speeds. These techniques are demonstrated in several missions and environments, describing their methodologies. Finally, we discuss the open problems and potential future research directions in this field.**

I. Introduction

Currently, trajectory planning for high speed has been extensively studied due to its utilization of the advantages of both path and motion planning [1], [2], [3], as well as path parameterization methodologies, to make the path safer [4]. Furthermore, the traditional techniques from trajectory planning are highly consolidated, providing greater confidence in their use at high speed [5].

For autonomous flights, trajectory planning techniques choose the best path to reach the goal without collisions [6]. Several applications use these techniques to optimize time [7], [8]. However, some missions require the Unmanned Aerial Vehicle (UAV) to move faster [9], [10]. In this case, the trajectory planning techniques must be able to generate safe and high-speed trajectories.

These missions can be critical, such as identifying humans in a landslide [11] or decreasing the mission costs, such as completing an extended mission in a shorter time [12]. To ensure the UAV can perform as well at high speed as it would at its default speed, it must be able to dodge obstacles [13], do complete reconnaissance of the environment [14], or fulfill other mission specifications [15], [16].

In this work, we explore the challenges and considerations involved in trajectory planning for high-speed UAVs, as well as the techniques for solving it, including perception algorithms to understand and navigate the environment, integrating control systems to ensure stability and safety, and trajectory planning algorithms. With this, we provide an overview of the state-of-the-art trajectory planning for high-speed UAVs and identify future research and development opportunities.

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This paper is organized as follows. Section II presents the different types of planning. Section III shows the most commonly used environments. Section IV outlines the main applications and missions. Section V overviews the UAVs, control, and perception techniques for high-speed. The main trajectory planning techniques are explained in Section VI. Section VII showns the most used tools for high-speed planning. Next, Section VIII discuss the area challenges, followed by Section IX, which concludes.

II. Planning

Many researchers have been trying to find the best path between two points in literature [17], [18], aiming to improve time and distance [19]. This type of planning has been defined as motion planning, path planning, or trajectory planning. This section explains the differences between these approaches and how they are used at high speed to clarify any misunderstandings. Figure 1 summarizes the differences among the approaches.

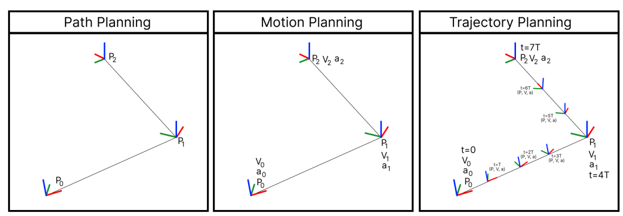

Fig. 1. Difference among Path, Motion, and Trajectory planning.

Path planning attempts to discover the shortest and obstacle-free path between two points, which can be followed by UAVs stopping at the waypoints. The paths returned must be continuous, and path planning algorithms do not need to specify acceleration or velocity, just the coordinates X, Y, Z, and Yaw from each waypoint [20].

It is common to need clarification on path and motion planning. Path planning refers to finding a safe and efficient path for a robot to follow from its starting point to its goal location, typically by searching through a map or model of the environment to avoid obstacles. In contrast, motion planning involves determining specific actions the robot must take to follow the path, taking into account the robot's dynamics, kinematics, and other constraints along with the uncertain nature of the environment [21]. In other words, path planning builds the path, and motion planning defines how to follow it.

Trajectory planning is more similar to motion planning because both use the path from path planning and need to control the velocity and acceleration of the robot, taking into account the dynamics. However, trajectory planning considers the time of each waypoint along the path and needs to return to a smooth and feasible path. Some missions use trajectory and motion planning for the same goal. However, for complex tasks, including high-speed missions, a better guarantee is needed that the UAV will follow and reach all the waypoints as planned. Furthermore, if the UAV cannot follow the trajectory for some reason, the trajectory planning needs to handle the uncertainty to ensure the UAV follows the next waypoints as planned [6].

Depending on the mission difficulty, it may not be necessary to use path, motion, and trajectory planning together. Sometimes, a more straightforward approach focusing on path or motion planning alone may be sufficient to achieve the desired outcome. However, a more complex mission combining three approaches may be necessary in other cases. The choice of which approach to use will depend on the specific requirements and constraints of the task, as well as the capabilities of the UAV. For example, in simple missions, it is possible only to follow the waypoints returned from path planning at a safer velocity without changing the acceleration. However, for complex tasks such as high-speed ones, additional assurances of the completion and timely execution of the trajectory are necessary. It is also imperative to handle acceleration and acceleration adjustments along the trajectory and address uncertainties, such as dynamic obstacles that may alter the initial plan.

III. Environments

The main scenarios used for test trajectory planning at high speed are drone racing circuits, empty spaces, or an environment with a single obstacle. However, there are also tests in wild environments, which present different difficulties such as unknown and uncertainties or dynamic obstacles.

Drone racing environments, with ample space and several gates to UAV pass through, are very popular due to the competitions [10]. A good strategy for these scenarios is to use all the visible gates to detect simultaneous gates, aiming to compensate for drift in the state estimate and build a global map of the gates. In this way, navigating through the race course even when the gates are not immediately visible is possible, enabling one to plan a real-time and time-optimal path for the race course based on the UAV dynamics.

The drone racing environments can also have several uncertainties to make the challenge more complex [22]. In these scenarios, one of the solutions is to use a neural network policy to train the deep learning algorithm so it generates near-time optimal trajectories in real-time.

The environments that use trajectory planning are not only for drone racing. Numerous tests are conducted in empty rooms with a single obstacle to validate specific configurations. In [23], the authors use sampling-based techniques to test obstacle avoidance in indoor environments. Minimum-time paths, states, and input-constrained motion primitives are generated until a collision-free path is found. The tests are conducted at a speed of 3 m/s at a distance of 9 meters.

Only few works have attempted to avoid dynamic obstacles at high speed. For example, the authors in [24], employed a dimensionality reduction and rolling optimization to dodge obstacles in real-time with a velocity of 1 m/s.

Also, tests have been conducted in unknown and outdoor environments reaching up to 9.4 m/s [25]. This paper proposes enabling aggressive flights in unknown environments using a receding horizon trajectory planner. The approach can reason the environment's geometry in real-time while maintaining safety margins during fast, smooth, and robust flights.

Different scenarios are shown in [26], demonstrating high-speed flights in wild environments. The strategy uses global planning to initialize the environment sampling, an essential step for high-speed flights using depth cameras as an intermediate representation of action and a multi-modal network to predict the UAV action. This approach reaches a speed of 14 m/s.

Empty spaces are also used for trajectory planning at high speeds to perform acrobatics in the sky. The paper [27], written in partnership with Intel, proposes a deep learning algorithm to learn a sensorimotor policy to allow the UAV to perform extreme acrobatic maneuvers in free space in the sky, using only IMU data and images. This technique can reach a speed of up to 4.5 m/s.

IV. Applications

High-speed UAVs bring significant advances to mission performance, for example providing faster delivery times and improved navigation in delivery missions. As a result, they can travel quickly and efficiently to remote locations, bypassing traditional transportation barriers such as traffic congestion and limited infrastructure. Additionally, high-speed UAVs can safely deliver packages to hard-to-reach areas, such as islands or mountainous regions, which would otherwise be difficult or impossible to access [28].

UAVs operating at high speeds have advantages in exploration missions because they can efficiently and rapidly collect data over large areas. This ability can be instrumental in monitoring and mapping natural resources, tracking wildlife, and observing the effects of climate change. In addition, high-speed UAVs can be outfitted with various payloads, such as multiple sensors, to increase the data acquisiton in the mission [14].

Using high-speed UAVs in search and rescue operations allows for faster identification and rescue of distressed individuals and improved navigation capabilities. They can be deployed quickly and efficiently to remote or inaccessible areas where traditional search and rescue methods may be hindered. These UAVs can also be equipped with various payloads such as medicines, cameras, thermal imaging sensors, and loudspeakers, which can aid in search and rescue operations [29].

Tasks for multi-UAVs also have the advantage of using them at high speed. High-speed UAVs provide enhanced speed and efficiency and superior navigation. Additionally, using swarms can accelerate flight time, resulting in decreased operational costs [30]. These capabilities make them ideal for simultaneous surveillance, data collection, and reconnaissance tasks [31].

In conclusion, high-speed UAVs offer advantages over traditional UAVs. Their ability to cover larger areas in shorter amounts of time, navigate through challenging environments and adverse weather conditions more efficiently and fly at higher altitudes to avoid obstacles make them a valuable tool for various mission types.

V. Unmanned Aerial Vehicles

The aerodynamics of UAVs significantly affect their ability to execute high-speed flights [32]. Therefore, the UAV must be optimized to minimize drag and maximize lift, which enables the UAV to achieve higher speeds while maintaining stability. Additionally, the design of the propulsion system, including the propellers or rotors, must also be carefully considered to ensure optimal performance at high speeds. The authors in [2] summarize the main UAVs used for research. The best UAVs in the study are first-person view (FPV) UAVs from DJI, which have more agility than others, and UAVs from multi-robot systems (MRS) [33], which have the best onboard computational capabilities.

A. Control

Alongside the significance of having a UAV that is capable of high-velocity operations, it is also critical that the control algorithm possesses the necessary robustness to manage high-speed flights. For high-speed flights, learning-based controls have been several used to the control. There are three main policies for reinforcement learning: individual rotor thrusts, collective thrust, body rates, and linear velocity commands. The authors in [3] have compared them and noted that policies that generate collective thrust and body rates demonstrate remarkable robustness against dynamics mismatch and are highly adaptable across domains while preserving a high degree of agility.

It is crucial to tune the UAV parameters and implement robust control for high speeds. Tuning the parameters of a control system involves adjusting various variables, such as gains, filters, and thresholds, to optimize its performance and stability. This procedure can be carried out via simulation, trial and error, or optimization algorithms. By tuning the parameters, the control system can achieve the desired level of performance and stability, even at high speeds. For example, recent work has tuned the controllers for high-speed flight due to noisy actuation and external disturbances [1]. The study examined the correlation between performance and various parameters in UAV control systems. It found that the controller becomes increasingly sensitive to parameter changes as the maneuver speed increases, leading to decreased stability. The authors presented a novel sampling-based tuning algorithm specifically designed for high-speed flight to address this issue. The algorithm does not require prior information about the UAV or its optimization function and has been shown to improve trajectory completion by up to 90% compared to conventional tuning methods.

Besides the learning-based controls, flights at high speed can use classical algorithms, such as the Model Predictive Control (MPC). MPC can consider both the current and future states in determining control decisions, enabling fast responses and effectively managing the high-speed dynamics of the UAV. Some optimizations from MPC, such as Model Predictive Contouring Control (MPCC) [34] concurrently addresses the time allocation problem and the control problem to generate time-optimal trajectories. The algorithm has been shown to return a path that approximates the true time-optimal trajectory and can be generated in real-time.

A comparison between another MPC optimization, the nonlinear-model-predictive controller (NMPC), and the differential-flatness-based controller (DFBC) is carried out in [35] for accurate trajectory-tracking control. The comparison is performed by tracking various agile trajectories at speeds up to 20 m/s, focusing on tracking accuracy, robustness, and computational efficiency. The results show that NMPC is superior in tracking dynamically infeasible trajectories, but it comes at the cost of higher computation time and the risk of numerical convergence issues.

B. Perception

Perception algorithms are essential to UAV trajectory planning in order to understand and interpret their surrounding environment. This includes the detection and localization of obstacles, as well as the identification of other vehicles and pedestrians. With this capability, trajectory planning algorithms would have precise information to make safe and efficient decisions at high speeds. Another advantage is that the perception algorithms provide accurate data critical systems, such as traction and stability control, enabling precise and safe decision-making [36].

Although perception algorithms are essential for high-speed flight, it is also possible to make flights with predefined paths in which it is unnecessary to identify obstacles along the trajectory as shown in the paper [12], where the UAV traveled a predefined trajectory at approximately 18 m/s.

LIDAR sensors can be used to identify obstacles around. However, using UAV cameras is much more common due to their low cost, small size, and weight. Furthermore, cameras can provide more detailed and distant information, which is essential for most UAV missions.

There are two approaches to using cameras in UAVs. The first is to learn environmental behavior based on simulations. Moreover, the camera identifies and avoids obstacles based on already trained information in the real environment. One of the pioneering studies in this area was conducted by [37], in which they employed a training strategy utilizing all data generated in simulation and subsequently deployed it on a physical UAV without the need for fine-tuning. The extensive simulated data generated through domain randomization techniques resulted in a system that displayed robustness to variations in illumination and obstacle appearance.

Another approach is to decide in real-time, not necessarily using an artificial intelligence technique. For example, in [23], the authors identify the obstacle in real-time using a RealSense camera and turn the image into a point cloud. Then, the collision avoidance is made by a real-time sampling-based algorithm.

The perception can also be used to improve the stability and control of the UAV at high speed. In some cases, the perception can be used as the control, as presented in [38] where the proposed algorithm, Perception Constrained Visual Predictive Control (PCVPC), is used to enable aggressive flights without using any position information. The algorithm leverages NMPC to formulate a constrained image-based visual servo (IBVS) problem. As a result, the UAV speeds up to 9 m/s in trajectory tracking without losing the target using this technique.

Perception algorithms play a vital role in replanning high-speed flights. These algorithms enable the UAV to gather real-time information about its surroundings and make rapid decisions based on the acquired data. This information is then used to develop a new trajectory considering the current environment and the UAV's dynamic capabilities. It allows the UAV to replan in real-time and navigate through high-speed flights more safely and accurately. Using trajectory planning algorithms to replan is possible, as [39]. They proposed a sampling-based method for efficiently generating time-optimal paths. The algorithm can handle flights at velocities more significant than 17 m/s in a racing track with moving gates, and it can effectively manage strong disturbances caused by winds with speeds of up to 19 m/s.

Besides, frameworks can also be used to replan the trajectory more robustly, as proposed from [40]. They proposed a trajectory replanning framework designed explicitly for unknown environments. The primary focus of this framework is to ensure the feasibility and quality of solutions. Therefore, the method incorporates a path-guided optimization approach that considers multiple topological paths to identify feasible and high-quality trajectories within a limited time. Furthermore, a perception-aware planning strategy is also introduced to perceive and avoid unknown obstacles actively. Moreover, a risk-aware trajectory refinement approach is proposed to ensure that unknown obstacles threatening the UAV can be identified and avoided on time.

VI. Trajectory Planning Approaches

A UAV with dynamic capabilities that facilitate high velocity and an effective perception method for navigating unknown or intricate environments is imperative for executing high-speed flights. Also, trajectory planning is crucial for ensuring the UAV reaches its maximum speed accurately and safely. Therefore, the authors in [26] made a taxonomy of existing approaches for UAV navigation at high speed. These approaches are mainly divided into five categories: polynomial and spline trajectories, optimization-based, search-based, sampling-based, and reinforcement learning.

In the field of high-speed trajectory planning, the selection of the trajectory planning algorithm is one of many important considerations. Determining the algorithm's primary objective and design principles as horizon planning and planning spaces is vital. Trajectory planning algorithms typically have two primary goals: finding the shortest and fastest paths to complete a mission. While the ideal situation would be to achieve both objectives, more is needed. Thus, it is crucial to carefully evaluate the trade-offs between these two goals and determine the most appropriate approach for a given application. Furthermore, the trajectory's reliability and smoothness must also be considered to ensure safe and efficient operation.

A. Approaches

High-speed trajectory planning algorithms determine the optimal path for a vehicle to safely and efficiently reach its destination in high-speed environments. These algorithms take into account factors such as the UAV's dynamics, the environment, and any constraints or objectives that must be found. There are several approaches to high-speed trajectory planning, each with advantages and disadvantages.

1) Polynomial and Spline: One of the approaches is polynomial and spline trajectories, which use mathematical equations that can be easily parameterized to conform to specific constraints. This approach is particularly well-suited for scenarios where the vehicle dynamics are well-understood, and the environment is relatively unchanging. However, it may possess a different level of adaptability in dealing with more dynamic or uncertain environments. Additionally, polynomial trajectories cannot represent true time-optimal trajectories; they can not maintain the maximum acceleration during extended periods while also being able to make quick changes [41].

Besides it, polynomial trajectories can enhance trajectories for autonomous drone racing [42]. This method jointly optimizes control effort and regularized time, while penalizing dynamic feasibility and collisions.

In terms of computational complexity, these algorithms are generally less complex than other alternatives. The algorithm complexity is primarily determined by the degree of the polynomials or the intricacy of the splines. Despite this, they can be relatively simple to implement and computationally efficient. However, they may need to be more versatile in dealing with dynamic or uncertain environments.

2) Optimization-Based: Another approach is optimization-based trajectory planning, which involves formulating the trajectory planning problem as an optimization problem and using numerical methods to find the optimal solution. This approach is efficient and well-suited for problems with many constraints and objectives.

Optimization-based techniques allow for truly time-optimal trajectory planning for UAVs using optimization-based algorithms. The first approach was proposed by [43]. The method optimizes waypoints trajectory and time allocation by introducing a progress-bound constraint simultaneously. Unfortunately, although these algorithms can generate time-optimal trajectories that pass through specific points, they require significant computational resources, making them impractical for real-time applications.

hese algorithms are more complex than polynomial and spline-based algorithms. The complexity of the algorithm depends on the number of constraints and objectives, the complexity of the vehicle dynamics, and the size of the state space. Therefore, this approach can be computationally expensive and require a significant amount of data [41].

3) Search-Based: Search-based trajectory planning algorithms are another approach, similar to optimization-based methods but differing in their method of exploring the solution space. These algorithms can optimize flight time up to the point of discretization, but they can be hindered by the curse of dimensionality, which results in a significant increase in computational demands as the complexity of the UAV model increases. Furthermore, using per-axis dynamic limits, such as velocity, acceleration, and jerk, may not accurately reflect the true dynamics of the UAV model, leading to a decrease in the quality of the generated plans. Additionally, while these methods are designed to search for trajectories with minimal flight time, they are currently limited to planning between two states, making them unsuitable for high-speed trajectory planning.

One of the primary benefits of this approach is its simplicity and ease of implementation. However, the complexity of the algorithm depends on the size of the state space and the number of iterations of the search algorithm.

A common search-based algorithm is the Dijkstra algorithm, which finds the shortest path from a source node to all other nodes in a graph. The Dijkstra algorithm has a simple implementation and reliable solutions. For example, the authors in [10] used the Dijkstra algorithm in Alpha Pilot Challenge in 2019 and won traversing 74 meters in 11.36 seconds at a speed of up to 8 m/s.

4) Sampling-Based: Sampling-based trajectory planning algorithms are a popular approach for high-speed environments. These algorithms employ random sampling to survey the solution space and are particularly well-suited for problems characterized by high-dimensional state spaces and intricate dynamics. However, it should be noted that these methods can be computationally intensive. As the dimensionality of the state space and the number of samples required to find a solution increase, the complexity of the algorithm also increases correspondingly.

One example of using sampling-based algorithms is identifying paths in various topologies to guide subsequent trajectory searches for a kinodynamic point-mass model. This proposal was made by [44] employing an asymptotically-optimal, kinodynamic sampling-based method based on a full quadrotor model on top of the point-mass solution to discover a feasible trajectory with a time-optimal objective. This technique demonstrates superior performance compared to traditional methods due to its ability to replan and its emphasis on maximizing progress through a full UAV model [45].

5) Reinforcement Learning: Reinforcement learning is a newer approach gaining popularity in high-speed trajectory planning. This approach involves training an agent to learn a policy for selecting actions in a given state based on feedback from the environment. This approach is well-suited for problems with complex dynamics and uncertain environments.

Deep reinforcement learning techniques are highly used to solve trajectory planning and reinforcement learning techniques. The agent can learn simultaneously to solve the planning and control problem online to account for disturbances, thus achieving much greater robustness, as was proven by [46]. In addition, they use deep reinforcement learning to improve flights in cluttered environments. The tests were simulations in simulation and real worlds, with UAV speeds of up to 42 km/h and accelerations of $3.6g$.

The complexity of a reinforcement learning algorithm depends on various factors, such as the complexity of the environment, the size environment, and the number of iterations needed to learn a policy. Despite this, the increase in computational cost is comparatively lower than other methods, such as optimization-based algorithms. The research [22] has shown that using reinforcement learning techniques in complex environments leads to lower computational costs. The authors propose a deep reinforcement learning approach for predicting trajectories in autonomous drone racing and compare their results with those of [43]. While the complexity of the reinforcement learning technique may be greater in scenarios with a limited number of gates, the complexity of optimization-based algorithms increases exponentially as the number of gates grows, whereas the complexity of reinforcement learning techniques increases only slightly linearly.

6) Discussion: Overall, different high-speed trajectory planning algorithms have advantages and disadvantages, and the choice of algorithm will depend on the specific constraints and objectives of the problem, as well as the nature of the environment. Their complexity is affected by the number of constraints and goals, the complexity of the vehicle dynamics, the state space size, and the environment. Therefore, it is essential to carefully consider the trade-offs between complexity and performance when choosing a trajectory planning algorithm for a specific problem.

B. Uncertainties

Uncertainties are a critical issue to consider in high-speed trajectory planning. These uncertainties can come from various sources, such as sensor noise, model inaccuracies, and external disturbances, which can lead to deviations from the planned trajectory, resulting in collisions, safety hazards, and reduced performance [47].

An approach to dealing with uncertainties is to use a trained neural network policy to complete the trajectory, which achieves a success rate of 97.5% in the most challenging scenarios [22].

C. Horizon Planning

Horizon planning in high-speed environments involves determining the optimal path for a vehicle to reach its destination safely and efficiently. Two main approaches are used: finite horizon planning, where a trajectory is planned a certain number of steps ahead, then re-evaluated as the vehicle moves forward, and infinite horizon planning, which entails formulating a trajectory plan that extends to the final destination without the need for re-evaluation. The choice between them depends on the environment. In high-speed missions, finite horizon planning is more commonly used due to its ability to adapt to dynamic situations.

The study presented in [25] proposes an algorithm utilizing finite horizon planning. The authors introduce the Triple Integrator Planner (TIP) algorithm, which can generate collision-free and dynamically feasible paths within five milliseconds using a point cloud as input. Furthermore, the algorithm aims to minimize the computational load by relying solely on instantaneous sensor measurements, enabling high replanning rates. Using finite horizon planning allows for real-time adaptation to environmental and constraint changes, making it suitable dynamic environments.It can also guarantee safety by ensuring the UAV stays within certain constraints, while being computationally efficient and robust to measurement noise and uncertainties in the UAV's dynamics.

Algorithms also use infinite horizon for high speed, for example, the technique presented by [43]. The methodology involves optimizing the trajectory and allocating waypoint. A progress measure is formulated for each waypoint along the trajectory to allow completion near the designated waypoint. The main advantages of infinite horizon planning include generating an optimal trajectory that considers the journey from the start to the goal node, being more suitable for environments where the conditions are relatively stable, performing global optimization and handling large state spaces, and the possibility of being used for offline planning and exploiting the structure of the problem to optimize the entire trajectory.

D. Planning Spaces

The planning space in high-speed trajectory planning refers to the set of all potential trajectories that a vehicle can take to reach its destination. Two distinct types of planning spaces can be utilized: discrete and continuous. Discrete planning spaces involve a finite number of discrete points or states that vehicle can occupy, and a sequence of these states determines the trajectory. Conversely, continuous planning spaces involve an infinite number of points or state that the vehicle can occupy, and a continuous function determines the trajectory. In high-speed trajectory planning, continuous planning spaces are more frequently used as they allow for more precise and flexible modeling of the vehicle's motion.

An example of continuous space is the deep neural network technique known as Proximal Policy Optimization (PPO), which is designed to handle high-dimensional environments. This technique can be used to enhance UAV flight in cluttered environments, improving the trajectory quality by up to 19% [46]. Furthermore, continuous action spaces in high-speed trajectory planning allow for higher precision in vehicle control, as the actions can take on any value within a range instead of being limited to discrete values. This results in more accurately representing the UAV's motion and dynamics.

There are also papers using discrete spaces for high-speed missions, such as the paper [48], in which the authors propose a Probabilistic Roadmap (PRM) to use in high-speed applications having speeds up to 4.5 m/s. The algorithm creates random nodes in the planning spaces, connecting the best to represent the feasible trajectories between the start and goal nodes. Using a discrete approach in the PRM algorithm allows for an efficient search for a path through the roadmap by considering a limited number of discrete points reducing the algorithm's computational complexity and making it suitable for problems characterized by high-dimensional state spaces or uncertain dynamics. Furthermore, implementing a discrete roadmap not only enhances the detection of collisions but also allows for an efficient updating of the roadmap in response to environmental changes.

VII. Simulation

There are some UAV simulators and frameworks to facilitate the algorithms for high speed safely. Additionally, simulators are beneficial due to the hardware-in-loop, which allows the same code used in the simulation to work in the real world.

The *RotorS* was the first widely-used high-speed simulation environment. This simulator extends the capabilities of Gazebo simulation to UAVs. The physics of both simulations are similar. RotorS features easy-to-use plugins for it, but there is a lack in both simulations, which is the few photorealistic details [49].

AirSim, developed by Microsoft, solved the lack of a photorealistic simulator for UAVs. The simulator was developed on the Unreal graphics engine with several control plugins. As the AirSim is a photorealistic simulator, it is possible to simulate the UAV perception in the real world. UAV international competitions use it to test their algorithms, and datasets for learning-based perception models can be created due to the high similarity, mainly because OpenAI Gym is integrated into AirSim [50].

FlightGoggles is also a photorealistic simulator. The main differences between FlightGoggles and AirSim are that the FlightGoggles was built in Unity Engine, and Flight goggles provides an interface with the real world using a motion capture system, allowing rendered images in the real world to be transferred to the simulation [51].

The simulation platform called *Flightmare* utilizes photorealistic graphics created with the Unity engine. Users can customize the physics engine to achieve the desired level of simulation accuracy. Additionally, it allows for the integration of hardware-in-the-loop functionality, which enables the use of a virtual camera image for UAV control and estimation, as described in [52].

Agilicious is a versatile framework that standardizes software and hardware for high-speed UAVs, allowing researchers to focus on the principal problems. Within Agilicious are the definitions of control, latency, hardware, and several high-speed algorithms, as trajectory track [2].

VIII. Future Directions and Challenges for High Speed

Trajectory planning for high speed is a recent area, so many gaps can be improved or developed to improve the algorithms and methodologies.

The main objective of trajectory planning for high speed is to achieve a shorter collision-free path in a minimum amount of time while using the smallest battery, thus allowing longer flights. In addition, achieving the criteria of robustness and completeness is necessary to avoid risks when implementing the algorithm. The major challenges include:

1) **Balance speed and accuracy:** The higher the speed, the more difficult it is to avoid obstacles or process new information. A high-speed algorithm is reliable when the whole system can handle it and the UAV does not crash along the trajectory.
2) **Lead to unstable communication:** For real applications, the communication with high-speed UAV can be unstable, leading to packet losses, which can hinder the collection of enough data or the safety of the UAV.
3) **Handle with delay in processing:** The trajectory planning algorithm's response needs to be as fast as possible. Otherwise, the UAV will not change the trajectory in time and can collide with an obstacle. Besides that, processing in real-time is also possible to improve stability control.
4) **Guarantee smooth trajectories:** It is essential to move at high speed to make the trajectories as smooth as possible. In this way, the UAV will not need to reduce the speed to make a curve, thus maintaining its high speed along the trajectory.
5) **Achieve max speed:** The main goal of high-speed trajectory planning is to reach the max speed according to the hardware from the UAV. Whenever the possible max speed is updated, pushing the UAV limits will always be a continuous challenge.
6) **Found the most reliable path:** Not always the shortest path will make the UAV complete the trajectory faster. This is because the shortest path can have many sharp turns or something else that decreases the UAV's speed. Finding the best path means finding a path that makes the UAV reach the goal faster, even if it is not the shortest path, because it can be completed faster when the UAV maintains its maximum speed.
7) **Robustness:** The algorithm must be able to tolerate and correct the trajectory when uncertainties arise at high speeds, such as device error, strong wind, unexpected obstacles, other UAVs, failure in communication, and others. As the UAVs will be traveling at their maximum speed, an error that is not handled properly or takes too long to be handled can result in a collision. Then, the algorithm must be prepared to make a new decision quickly.
8) **Completeness:** Ensure that the algorithm will always find a way to make the UAV move between the start node and the goal, if it exists.

IX. Conclusion

In this paper, we provided an overview of trajectory planning for high speed, including the importance and advantages of this technique and how several missions can be improved using it. The paper shows the main application and environments where trajectory planning is applied. It also explains the techniques and their various methodologies for use. Some techniques of control and perception for assisting high-speed flights were given, along with a list of all simulators that can facilitate high-speed flights. At the end of the paper, we enumerate the main challenges to high-speed trajectory planning for the following years. With these resources, researchers can understand the current state-of-art and look for gaps and areas to improve.

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