

UAV Trajectory Planning with Path Processing

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Trajectory planning is a critical aspect of autonomous Unmanned Aerial Vehicle (UAV) operations, defining the vehicle's path, velocity, attitude, and in some cases control signals as functions of time (LaValle (2006)). Several distinct approaches exist, including graph-based algorithms for path planning and subsequent trajectory generation, potential field methods, and model-based optimal control problem (OCP) formulations (Betts (2010)).

When dealing with nonlinear dynamics, OCP becomes intractable. To address this challenge, we employed the Chebyshev single and multisegment pseudospectral method (PSM) (Trefethen (2000); Young (2019)), a collocation technique that approximates the nonlinear dynamics at collocation points using Chebyshev polynomials. The resulting discretized nonlinear program can be solved using solvers such as IPOPT (Wächter and Biegler (2006)).

However, obtaining an optimal trajectory can still be challenging. To streamline the search, we explored leveraging path-planning algorithms and an understanding of the UAV's dynamic model to generate an initial trajectory guess, facilitating the optimization process.

1 Initial Guess through Graph-Based Path Planning

The considered UAV model is based on quaternion rotational dynamics, incorporating effects like air drag and blade flapping, with parameters corresponding to the 32g Crazyflie microUAV (Förster (2015)).

While a common approach is to use a simple linear interpolation between boundary conditions as an initial guess, this can be ineffective in scenarios with non-linear constraints or non-convex obstacles. Therefore, we proposed a set of more complex initial guesses with varying degrees of influence on the trajectory, as shown in Table 1.

Table 1: Summary of initial guess construction for state and control (separated by the line)

Component	Method	Purpose
Simple	Straight line interpolation	Basic path planning
Position	Spline	Smooth path following
Velocity	Differentiation of position	Smooth velocity profile
Orientation	Quaternion curve	Align with forces
Angular rate	Quaternion derivative	Orientation changes
Thrust	Rotation of force	Translation and orientation
Torque	Dynamic equation	Desired angular motion

The initial guess leverages the Lazy Theta* (LT*) graph-based path planning algorithm (Nash et al. (2006)), an extension of A* that identifies direct paths between visible gridmap nodes. Time parametrization follows known velocity constraints, providing an optimistic time frame. Other state and control guesses are derived from the UAV dynamics (Table 1).

Figure 1a illustrates an LT* path example. Figure 1b shows an optimal trajectory with a speed profile, while Figure 1c depicts the position at the collocation points and obstacles constraints. We evaluated the impact of the initial guess on computational time, approximation error, and constraint violation across constructed environments.

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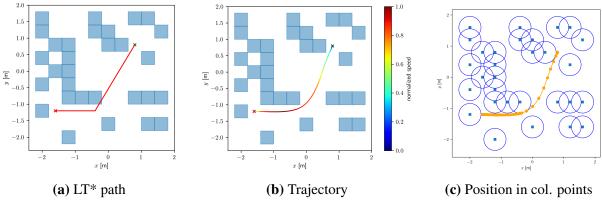


Figure 1: Path and trajectory in the environment

2 Conclusion

We evaluated different levels of initial guessing. While the values differed between levels, the use of a simple guess based on boundary conditions alone, without path information, failed to find trajectories for scenarios with one or two obstacles. Conversely, the multi-segment PSM with segments composed according to a multi-segment initial position guess gave stable and interesting results for all criteria but often resulted in collision trajectories.

Future efforts could focus on improving trajectory finding by assessing collision rates and potential constraint violations or providing more precise dynamics-based initial guesses.

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