Trajectory Planning for Mission Survivability of Autonomous Vehicles

in Moderately to Extremely Uncertain Environments

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Outline

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Autonomous Vehicle

A vehicle that is capable of **sensing its environment** and **moving safely** with little or no human input.

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The Range of Uncertainty

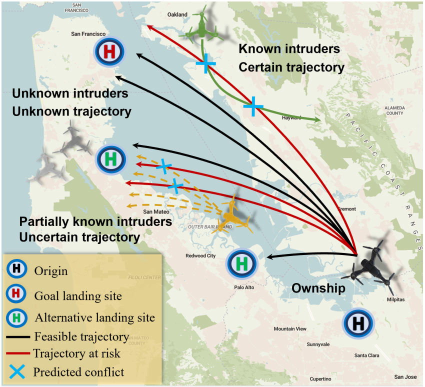

Figure 1: Illustration of the three types of intruders present in the operating environment.

- Known
- Partially known
- Unknown

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Traditional Trajectory Planning Algorithms - Principles

To plan a safe trajectory for autonomous vehicle in dynamic and uncertain environment...

1. Predict and estimate the impacts of the uncertainty on the feasibility of a trajectory
2. Determine the trajectory that minimizes the predicted risk or maximize the chance to survive

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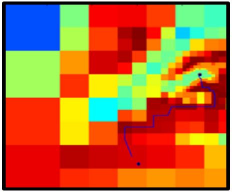
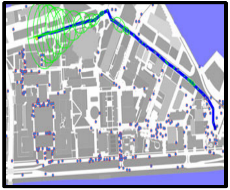
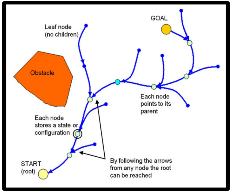
Traditional Trajectory Planning Algorithms - Examples



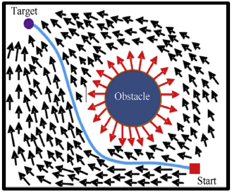
Cell Decomposition [1]



Probabilities Roadmap [2]



Rapidly-exploring random tree [3]



Artificial Potential Field [4]

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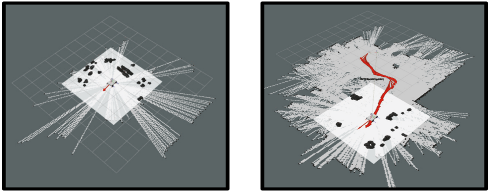
Noval Trajectory Planning Algorithms - Examples



(a) (b)

Deep Reinforcement Learning [5]

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Challegence Due to the Unknown/Unmodeled Risks

It's difficult to **characterize** or **bound** the behavior of highly unpredictable events, or model unobserved and complex dynamics.

Ex: non-cooperative intruder traffic, a flock of birds crossing the path of a vehicle

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Research Question

How to plan a safe trajectory for an autonomous vehicle when there are **external uncertainties**, i.e., when the locations and future trajectories of weather systems and other vehicles are **partially** to **completely** unknown?

To answer the question...

- **Two** fundamental metrics
- **Four** trajectory planning policies
- **Thirty-six** different traffic scenarios that simulate operating environments with varying degrees of uncertainty ranging from moderate to extreme.

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Metric I - Trajectory Flexibility

Flexibility [6]

Flexibility is determined by the amount and kind of change that can be made to the system in response to new knowledge.

Trajectory Flexibility Metric [7], [8], [9]

Let $\mathcal{L}$ be a set of independent, feasible trajectories that are available to the vehicle for accomplishing the flight mission.

$$N_f = |\mathcal{L}|$$

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Metric II - The Quality of a Trajectory

Definition 1 (Robustness of a trajectory plan)

The robustness of a trajectory $\mathcal{P}_l$ is defined as the likelihood that the trajectory l will remain feasible in the presence of disturbances. The robustness of a trajectory is expressed as:

$$\mathcal{P}_l = \Big(\prod_{i=0}^{T-1} p_i \Big) \alpha_T,$$

where p_i is the probability that the trajectory segment l_i remains feasible, and α_T is the probability that the corresponding landing site is available at time T.

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Mission Performance

Definition 2 (Robustness of a mission)

Consider the set of trajectories $\mathcal{L}_g = \{l_1, l_2, \ldots, l_n\}$ that terminate at the **goal landing site**. With a slight abuse of notation, we denote the robustness of a trajectory l_i as $\mathcal{P}_{l_i} \in [0, 1]$, and the probability that the mission is successful as:

$$\mathcal{P}^{succeed}(\mathcal{L}) = 1 - \prod_{i=1, l_i \in \mathcal{L}_g}^{n} \left(1 - \mathcal{P}_{l_i}\right)$$

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Mission Performance Cond't

Definition 3 (Survivability of a mission)

Given the set of feasible trajectories $\mathcal{L} = \{l_1, \ldots, l_m\}$ that terminate at a **valid landing site** (i.e., at either the goal landing site or an alternative landing site), we denote the robustness of an individual trajectory l_i as $\mathcal{P}_{l_i} \in [0, 1]$, and the probability that the mission is survivable as:

$$\mathcal{P}^{survive}(\mathcal{L}) = 1 - \prod_{i=1, l_i \in \mathcal{L}}^{m} \left(1 - \mathcal{P}_{l_i}\right)$$

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Mission Performance Cond't

Remark: The robustness and survivability of a mission from a given point in space and time are dependent on two trajectory metrics:

- Metric I: The number of feasible trajectories available at that point
  - Estimate using Backtracking Algorithm
- Metric II: The robustness of each of the trajectories
  - Estimate using Monte-Carlo simulation

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Receding Horizon Planning

The autonomous vehicle generates the optimal control inputs over M time steps and executes the first control action. At the next time step, a new control problem with the most recent environmental information will be solved for the remaining M-1 time steps [10].

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Formulation

We optimize over control commands $z = \{a_t, \ldots, a_{t+T-1}\}$ for the remainder of the mission given the current knowledge of the environment stored in $\mathcal{B}(t)$ and terminal states in $\Omega(t)$ at time t.

$$\max_z \quad F(s_t, a_t) + \beta \sum_{k=0}^{T} V(c_{t+k})$$

$$\begin{aligned}
\text{s.t.} \quad s_{t+k+1} &= f(s_{t+k}, a_{t+k}) && \text{(Vehicle dynamics)} \\
s_{t_0} &= (x_{t_0}, y_{t_0}, h_{t_0}, v_{t_0}, t_0) && \text{(Initial state)} \\
c_{t+k} &= c(x_{t+k}, y_{t+k}, t+k) && \text{(Maps states to cells)} \\
c_{t+k} &\notin \mathcal{B}(t) && \text{(Avoid blocked cells)} \\
s_{t+T} &\in \Omega(t) && \text{(Valid end states)} \\
a_{t+k} &= (dh_{t+k}, dv_{t+k}) \in \mathcal{A} && \text{(Motion primitives)} \\
s_{t+k} &\in \mathcal{R}^3 \times [v_l, v_u] \times [t, t_{f_u}] && \text{(State space)}
\end{aligned}$$

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Four Trajectory Planning Policies

$F(\cdot) + \beta V(\cdot)$

π_R	$p_{c_t c_{t+1}} + \beta \sum_{k=1}^{T} \mathcal{P}^{succeed}(c_{t+k}.\mathcal{L})$	Mission robustness g.
π_S	$p_{c_t c_{t+1}} + \beta \sum_{k=1}^{T} \mathcal{P}^{survive}(c_{t+k}.\mathcal{L})$	Mission survivability g.&a.
π_{N_f}	$c_{t+1}.N_f + \beta \sum_{k=2}^{T} c_{t+k}.N_f$	Trajectory flexibility g.&a.
$\pi_{Avg(R)}$	$p_{c_t c_{t+1}} + \beta \sum_{k=1}^{T} \left(\frac{1}{c_{t+k}.N_f} \sum_{l_i \in c_{t+k}.\mathcal{L}} \mathcal{P}_{l_i} \right)$	Baseline g.&a.

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Mission and Flight Performance

Parameters	
Take-off	Santa Clara Towers
Goal landing site	UCSF Helipad
Alternative landing site	San Francisco International Airport
	Stanford Hospital Helipad
Required Time of Arrival	[00:40, 00:55] minutes
Start time t_0	00:00 minutes
Vertical take-off and climbing	5 minutes duration
Vertical descent and landing	5 minutes duration
Maximum flight endurance	60 minutes
Decision-making window	Every 5 minutes

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Mission and Flight Performance

Parameters	
Cell size	$[1km, 1km, 1minute]$
h_f^G, h_f^A	$\{90^o, 135^o, 180^o\}, \{90^o, 180^o, 270^o\}$
d_h	$[-30^o, 30^o]$ in 5 equally spaced discrete increments
v_0, v_{t_f}	$0 \ m/s$
$v_t, t \in (0, t_{t_f})$	$[0, 40] \ m/s$
d_v	$[-10, 10] \ m/s$ in 5 equally spaced discrete increments

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Traffic Scenarios

- Type of intruders
  - **Partially known intruders** whose trajectories associate with an uncertainty radius $r = 5\ km$. They are known to the ownship at the start of the flight mission.
  - **Unknown intruders**. They are unknown to the ownship until they appear in the environment based on a stochastic process. After that, they become completely known.
- Number of intruders
  - Our experiment assesses 36 different traffic scenarios. Each scenario is characterized by the total number of partially known intruders $N_p \in \{50, 100, 150, 200, 250, 300\}$, and the total number of unknown intruders $N_u \in \{50, 100, 150, 200, 250, 300\}$

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Mitigating the Partially Unknowns

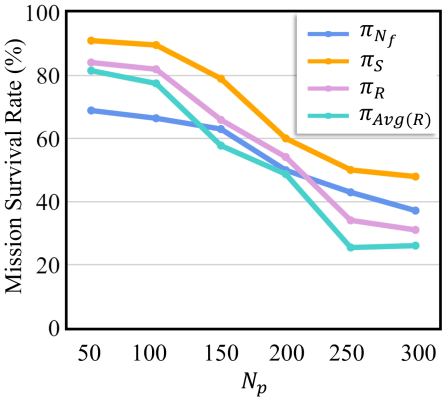

Figure 2: Performance of four trajectory planning policies as a function of the number of partially known intruders. ($N_u = 100$)

- Employing policy π_S results in the highest mission survival rate across all 5 traffic scenarios

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Mitigating the Unknown Unknowns

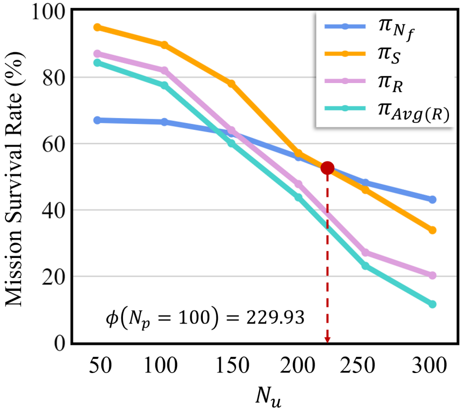

Figure 3: Performance of proposed trajectory planning policies as a function of the number of unknown intruders. ($N_p = 100$)

- Policy π_{N_f} outperforms all other policies when the number of unknown intruders exceeds the threshold value $\phi(N_p)$

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Increase the Ratio of Unknown Intruders in the Environment

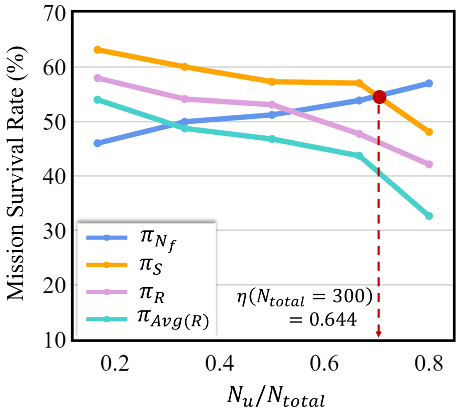

Figure 4: Performance of proposed trajectory planning policies as a function of the ratio of unknown intruders in the environment. ($N_{total} = 300$)

- As the ownship's environment becomes more uncertain, policies $\pi_S, \pi_R, \pi_{Avg(R)}$ policies become less effective
- The policy π_{N_f} performs better than the policy π_S when more than 64.4% intruders in the environment are unknown

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Conclusion

Policy π_S outperforms all other policies when the vehicle is exposed to partially known uncertainty and moderate levels of unknown uncertainty

- Maximize the probability of having at least one trajectory to any of the valid landing sites
  - A combination of number of feasible trajectories and robustness of feasible trajectories

Policy π_{N_f} yields the highest survival rates when the operating environment is dominated by completely unknown events

- Maximize the total number of feasible trajectories
  - Total number of feasible trajectories

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Future Work

- **Incorporate the proposed trajectory planning policies to NASA research in support of increasingly autonomous airspace operations**
- Examine the impact of the proposed metrics on collective autonomous behaviors among multiple agents
- Investigate the computational efficiency of the proposed methodology for practical applications
- Explore the impact of spatial and temporal quantization on metrics estimation

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Reference I

[1] R. V. Cowlagi and P. Tsiotras, "Beyond quadtrees: Cell decompositions for path planning using wavelet transforms," in *2007 46th IEEE Conference on Decision and Control*, pp. 1392–1397, IEEE, 2007.

[2] S. Prentice and N. Roy, "The belief roadmap: Efficient planning in linear pomdps by factoring the covariance," in *Robotics research*, pp. 293–305, Springer, 2010.

[3] J. Nieto, E. Slawinski, V. Mut, and B. Wagner, "Online path planning based on rapidly-exploring random trees," in *2010 IEEE International Conference on Industrial Technology*, pp. 1451–1456, IEEE, 2010.

This work was funded by the NASA Transformative Tools and Technologies Project.

Reference II

[4] B. Patle, A. Pandey, D. Parhi, A. Jagadeesh, *et al.*, "A review: On path planning strategies for navigation of mobile robot," *Defence Technology*, vol. 15, no. 4, pp. 582–606, 2019.

[5] X. Lei, Z. Zhang, and P. Dong, "Dynamic path planning of unknown environment based on deep reinforcement learning," *Journal of Robotics*, vol. 2018, 2018.

[6] M. Mandelbaum, "Flexibility in decision making-an exploration and unification.," 1980.

[7] H. Idris, D. Delahaye, and D. Wing, "Distributed trajectory flexibility preservation for traffic complexity mitigation," in *Proceedings of the 8th USA/Europe Air Traffic Seminar (ATM'09)*, Citeseer, 2009.

This work was funded by the NASA Transformative Tools and Technologies Project.

Reference III

[8] H. Idris, N. Shen, and D. Wing, "Complexity management using metrics for trajectory flexibility preservation and constraint minimization," in *11th AIAA Aviation Technology, Integration, and Operations (ATIO) Conference, including the AIAA Balloon Systems Conference and 19th AIAA Lighter-Than*, p. 6809, 2011.

[9] H. Idris and N. Shen, "Estimating airspace capacity based on risk mitigation metrics," in *Tenth USA/Europe Air Traffic Management Research and Development Seminar (ATM2013), Chicago*, 2013.

This work was funded by the NASA Transformative Tools and Technologies Project.

Reference IV

[10] J. Mattingley, Y. Wang, and S. Boyd, "Code generation for receding horizon control," in *2010 IEEE International Symposium on Computer-Aided Control System Design*, pp. 985–992, IEEE, 2010.

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Questions

Thank you!

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