Adaptive Optimization for System Performance

Irene M. Gregory, Ph.D.

NASA Senior Researcher (ST) for Advanced Control

Michael J. Acheson, Matthew D. Houghton, Alexander Oshin, Andrew P. Patterson

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Why Autonomy in Aviation?

- **Autonomy enables** new **ECONOMIC** activity, **DIVERSITY** of missions
- **Autonomy changes** the nature of
  - Transportation system (local/regional), supply chain logistics
    - Regional cargo delivery competing in cost with trucking
  - Maintenance logistics and safety well beyond traditional aerospace
    - Oil platforms, pipelines, power lines, wind turbines, infrastructure inspection and maintenance
  - Agriculture, land management, first responders (e.g., rapid response to inaccessible disaster areas)
- **Long Term** Aviation Autonomy **Impacts**:
  - Enables rapid flexibility and facilitates resilience in local/regional economic activity
  - Reduces costs and environmental impact of automotive/rail infrastructure (e.g., roads, bridges etc.)
  - Alleviate ground transportation congestion and capacity limitations
- **Benefits of Autonomy**:
  - System wide **performance** improvements, maximizes capability for fleet/vehicle operations over human operator
  - Enhances aviation **sustainability**
  - Maintains and enhances **safety** as density of heterogeneous fleet of vehicles and operations increases

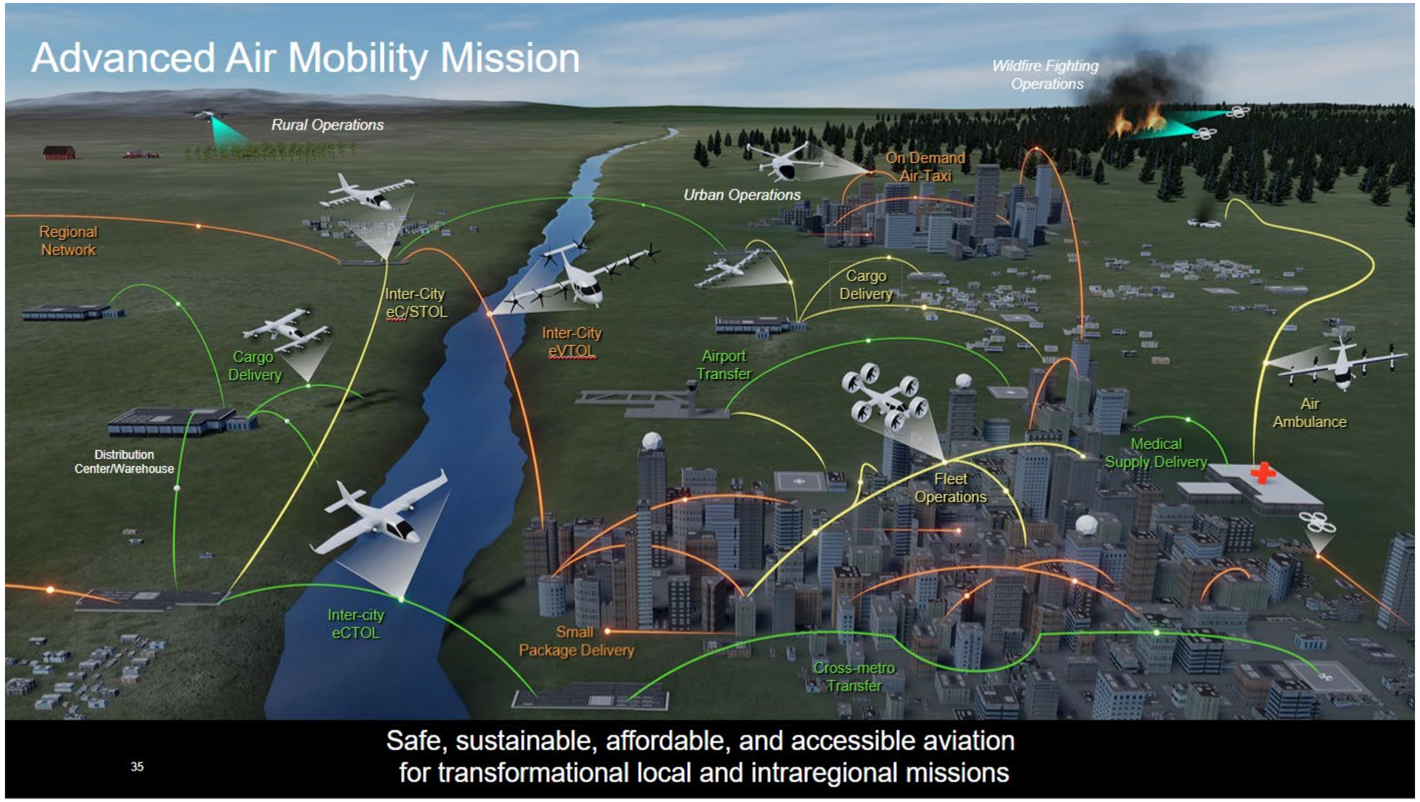
Autonomy is a REQUIRED GAME CHANGER to enable revolution in the aerospace industry

Where are we heading in Aeronautics? – Advanced Air Mobility

Safe, sustainable, affordable, and accessible aviation for transformational local and intraregional missions

Paradigm shift in Aviation

- Anyone, Anywhere, Anytime concept
- On demand air transportation
  - Urban suburban, rural, inter-city
  - Moves people and cargo
- Largely enabled by electrification and automation



Autonomy is REQUIRED to enable paradigm shift

Autonomy must be implemented in a safe, efficient, scalable, certifiable way

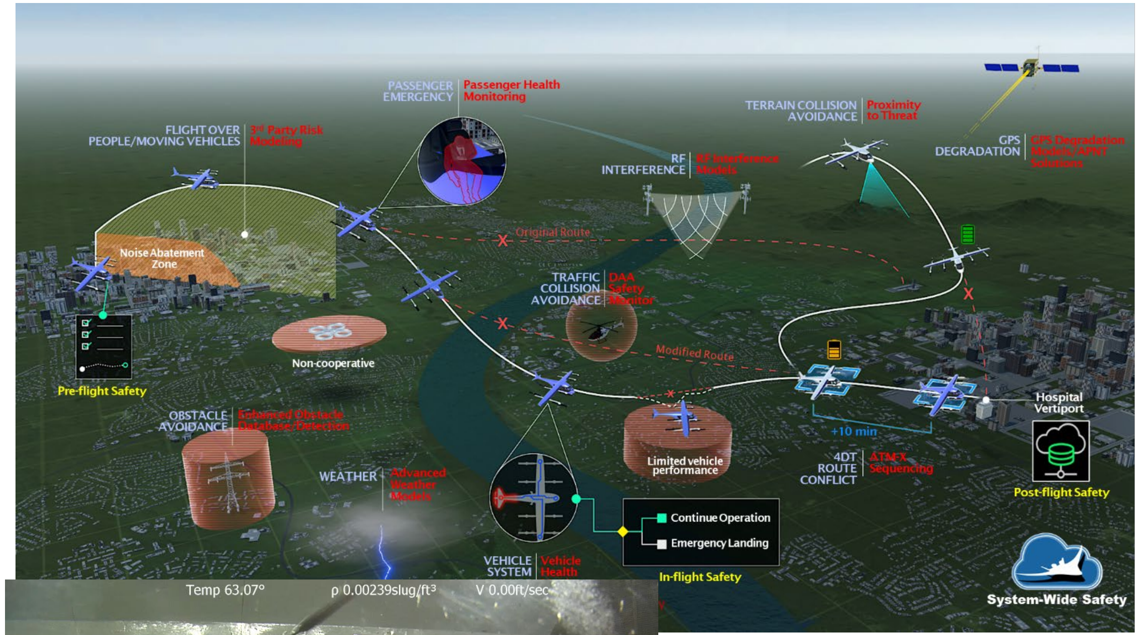
Autonomous Flight - Motivation for Intelligent Contingency Management

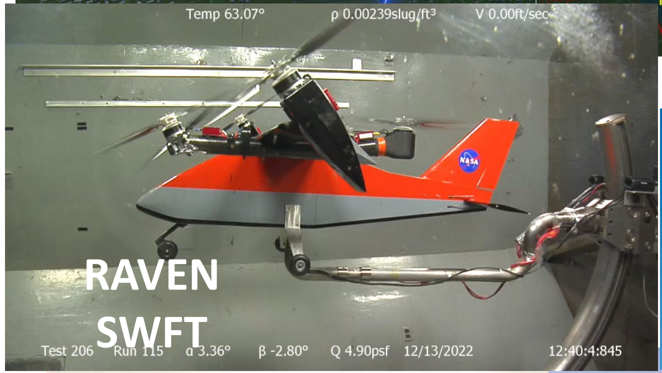
Emerging aviation characteristics:

- **Complexity** of the environment
- Unconventional vehicle configurations with **multi-modal dynamics**
- **Highly nonlinear flight dynamics**

Challenges:

- **Off-nominal events – both common and unforeseen**
- **New technology** – more likely to experience performance degradation/failures
- **Narrow performance margins** – cannot afford conservatism
- **Accurate trajectory following** under system uncertainty and atmospheric disturbances
- **Safe control** while learning elements are engaged

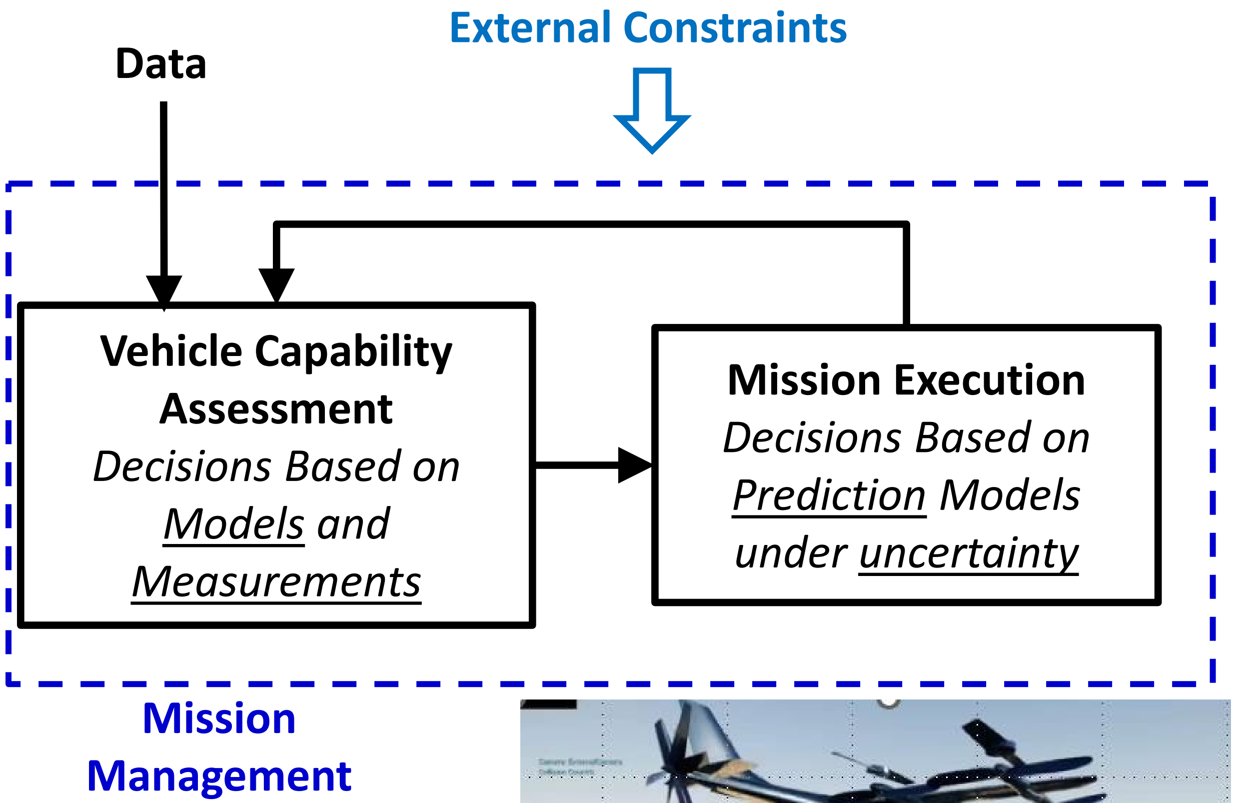




Autonomous Flight – Intelligent Contingency Management

Mission management system architecture requirements:

- **Robust contingency management** for off-nominal conditions and **graceful degradation** to unforeseen events
- **Resilient** and highly autonomous even at early maturity levels
- Hierarchical fault tolerance & **graceful degradation**
  – mission level
  – vehicle
  – subsystem
- **Fail-operational** stability
  – If physically capable, must maintain flight, gracefully end mission
- **Real-time** mission planning & trajectory generation
- **High** level of **assurance** and **safety**



* I. M. Gregory *et al.*, "Intelligent contingency management for urban air mobility," in *AIAA SciTech Forum*, 2021.

Intelligent Contingency Management – Fundamental Building Blocks

- *Planning/replanning for mission*
- Mission execution under off-nominal conditions
- *Collision avoidance*
- **Flight under failures**

External Constraints

Vehicle Current and Future State

Data

Vehicle Capability Assessment
Decisions Based on Models and Measurements

Decision making

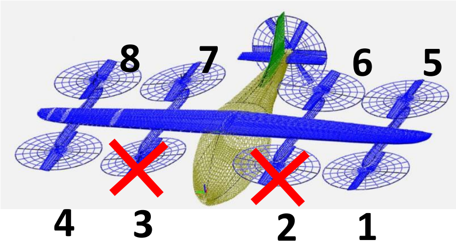
Mission Execution
Decisions *Based on Prediction under uncertainty*

- System Identification
- Machine Learning methods
- *Optimal Control (PDDP)*

Autonomous Flight Foundational Pillar – Fail-operational Stability

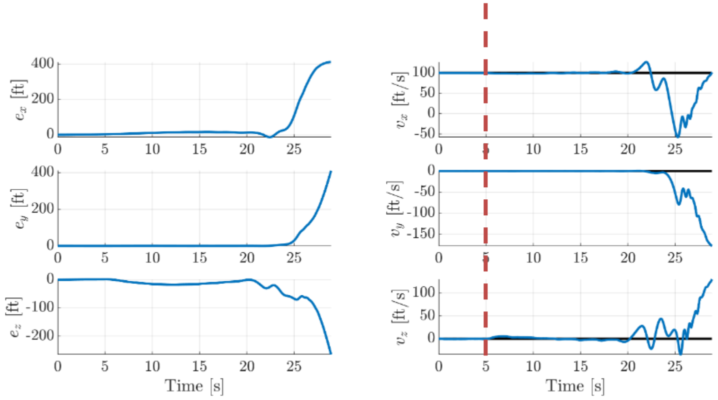
- **Fail-operational stability**
  - If physically capable, must maintain flight, graceful degradation to end mission
- During cruise – **rotors 2 & 3 fail -** vehicle loses half of the rotors that compensate for the longitudinal oscillatory modes, leading to **unstable** performance at this speed
- Without L1 adaptive control, the aircraft is **unstable**
- With **L1,** the aircraft is **stable - ** can run system identification algorithms to correctly identify failed propellers

- **Stable aircraft - ** apply learning methods to determine new dynamics, adjust control strategy, path-planning, mission objectives accordingly



Propeller Failures

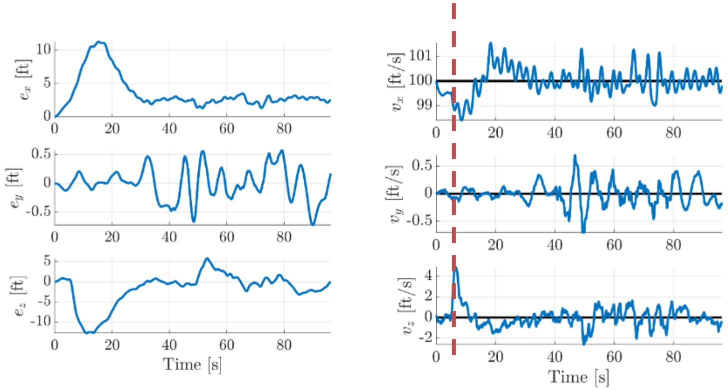
L1 AC Off
Unstable



Position error

Velocity Tracking

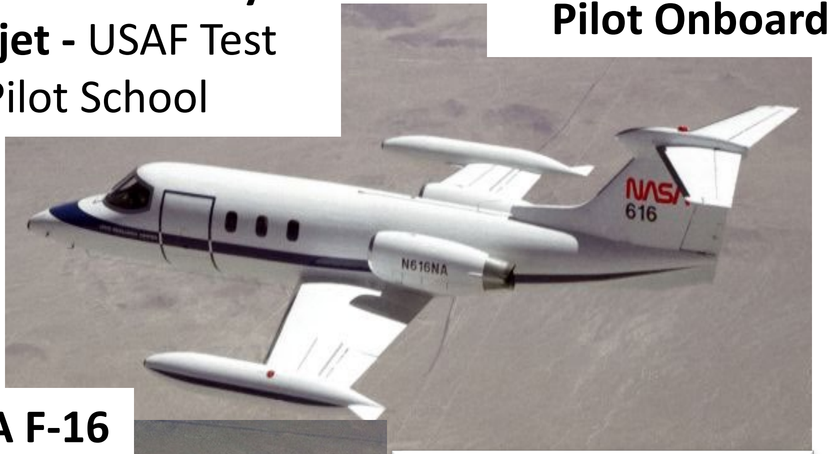
L1 AC On
Stable



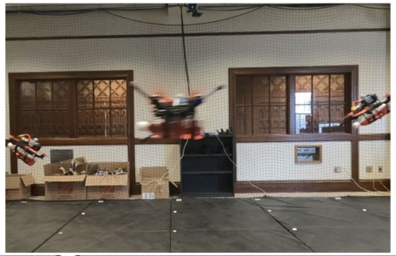
Foundational Pillar – Robust + L1 Adaptive Control (Safety)

Variable Stability Learjet - USAF Test Pilot School

Pilot Onboard



VISTA F-16



Autonomous

Robust flight control

Uncertainty compensation

Uniform performance bounds

Remotely Piloted

NASA Subscale Transport

Source: NASA.gov

Performance: Adaptation rate Γ

$$\|x_r(t) - x(t)\| \leq \rho_a(\Gamma^{-1})$$

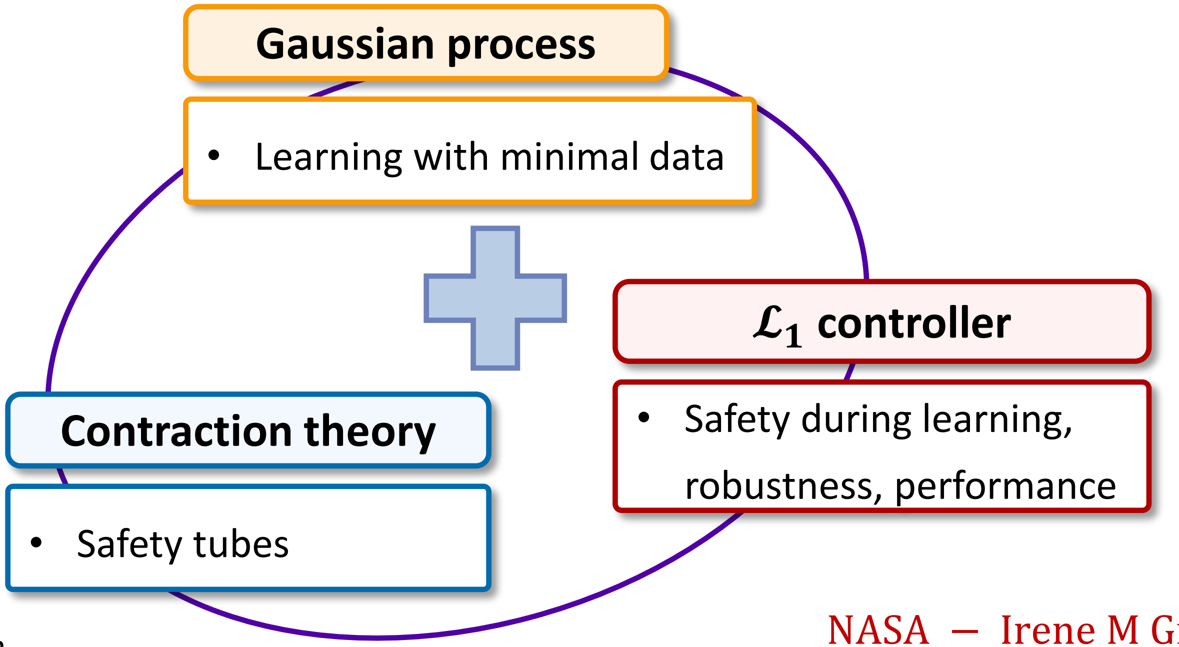
Decoupling

$$\|x^\star(t) - x_r(t)\| \leq \sqrt{ke^{-2\lambda t}\|x^\star(0) - x(0)\| + \rho_r(\omega^{-1})}$$

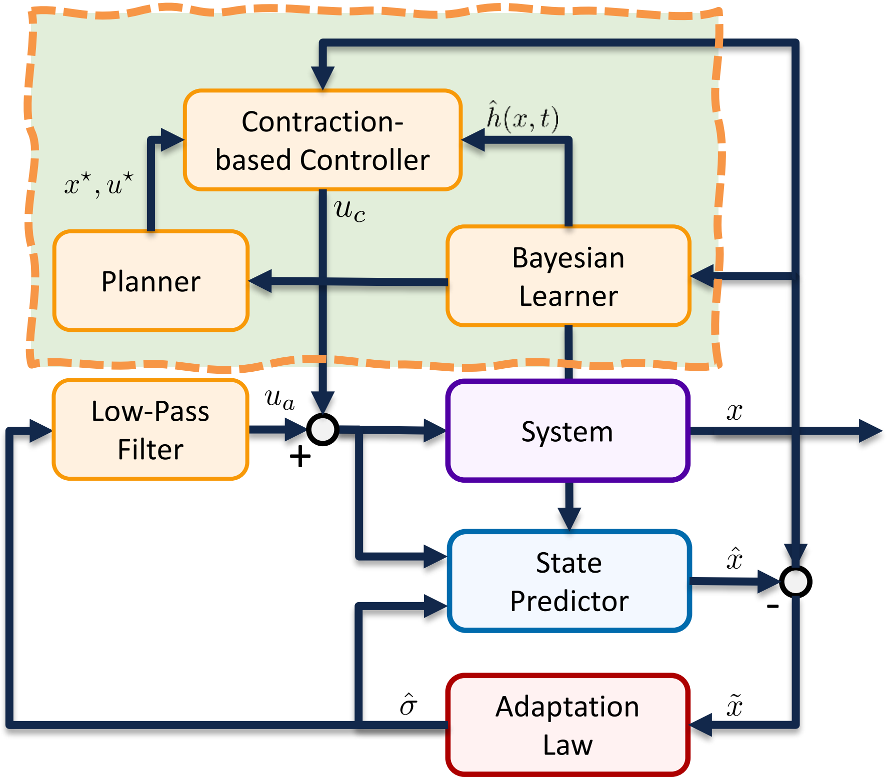
Robustness: Filter bandwidth ω

L1 Adaptive Control Architecture for Safe Learning

- **Safety certificates** in the form of tubes from the $C\mathcal{L}_1$- $\mathcal{GP}$ framework which **enables safety during learning**
- Natural framework for learning using $\mathcal{GP}$:
  - **Guaranteed performance** during the learning transients
  - Improved performance of the $\mathcal{L}_1$ adaptive controller, i.e., **smaller tubes**
  - **Improved quality** of the planned trajectory



$C\mathcal{L}_1$-$\mathcal{GP}$ Architecture



Gahlawat, Zhao, Patterson, Hovakimyan, Theodorou. $\mathcal{L}_1$-$\mathcal{GP}$: $\mathcal{L}_1$-*Adaptive Control with Bayesian Learning*, L4DC, 2020.

Intelligent Contingency Management – Fundamental Building Blocks

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  - **Optimal Control (PDDP)**
- Mission execution under off-nominal conditions
- *Collision avoidance*
- *Flight under failures*

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Autonomous Flight - Fail-operational stability → Planner

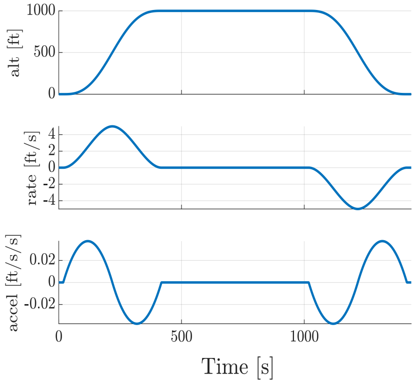
Planner challenges:

- Principled solutions/guarantees
- Accurate trajectory planning & replanning
- Epistemic uncertainty in model
- Multiple operational modes and flight regimes
- Transferability to different vehicles
- Replanning and collision avoidance for VTOL vehicles with highly nonlinear dynamics are slow and computationally costly

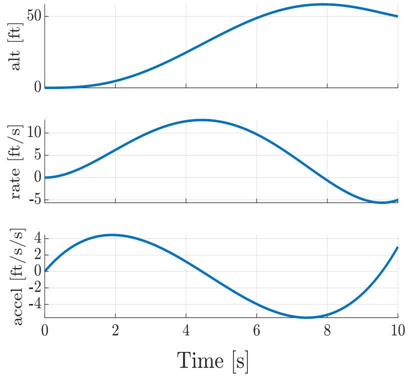
Trajectory Generation Dynamic Complexity Proposed Levels

(Less) < Dynamic Complexity -> (More)

Strategic
Pre-determined velocity and acceleration profiles



Tactical
Arbitrary derivative profiles



Full State Dynamic
Vehicle specific dynamic behavior

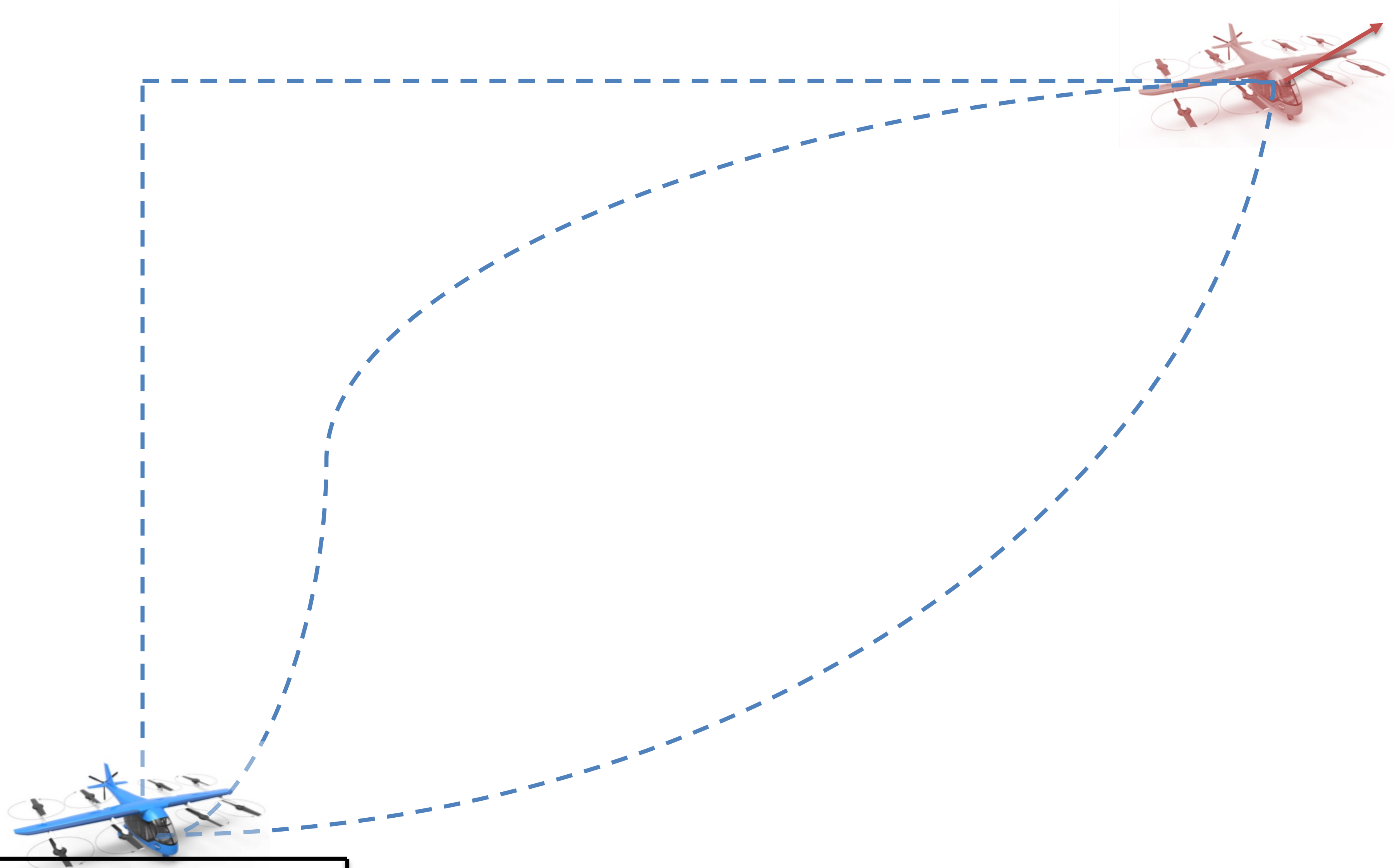
$$\dot{p} = \mathbf{v},$$
$$\dot{\eta} = S\omega,$$
$$\dot{\bar{\mathbf{v}}} = -\dot{\psi} e_3 \times \bar{\mathbf{v}} + g + m^{-1} \bar{F}\left(\bar{\mathbf{v}}, \omega, \bar{R}, u\right),$$
$$J\dot{\omega} = -\omega \times J\omega + \tau\left(\bar{\mathbf{v}}, \omega, \bar{R}, u\right),$$

- ➢ All of these levels must be **compatible** – something learned or constructed at one level can be transferred to the others since overall **algorithm spans complexity**
- ➢ Provides freedom to design at highest level and automatically generate something flyable, only need to interact with different levels of detail as needed.

Autonomous Flight – Planner Improvements for eVTOL Vehicles

Two unique challenges:

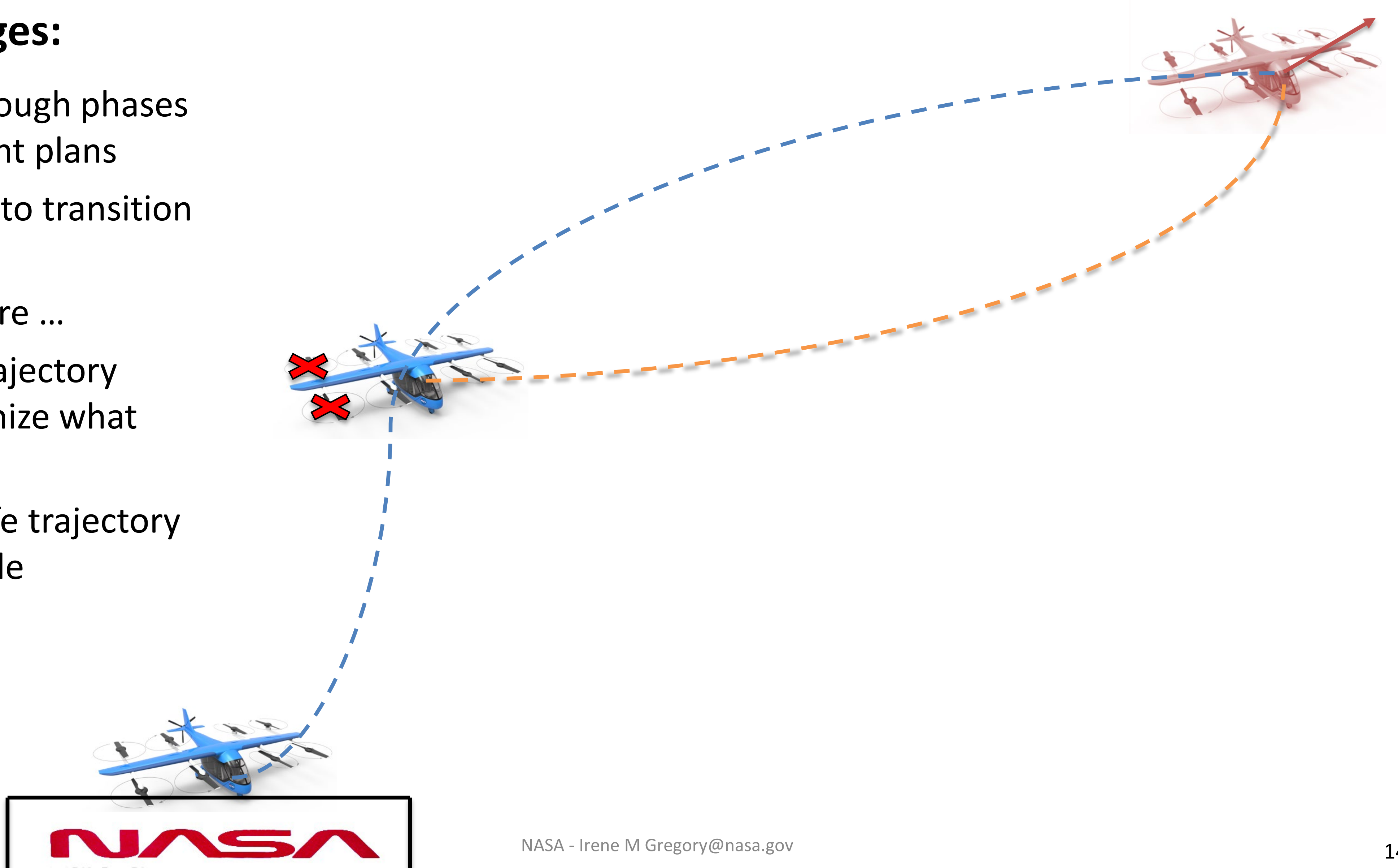
- eVTOL will switch through phases of flight in a typical flight plan
- What is the best way to transition between them?



Autonomous Flight – Planner Improvements for eVTOL Vehicles

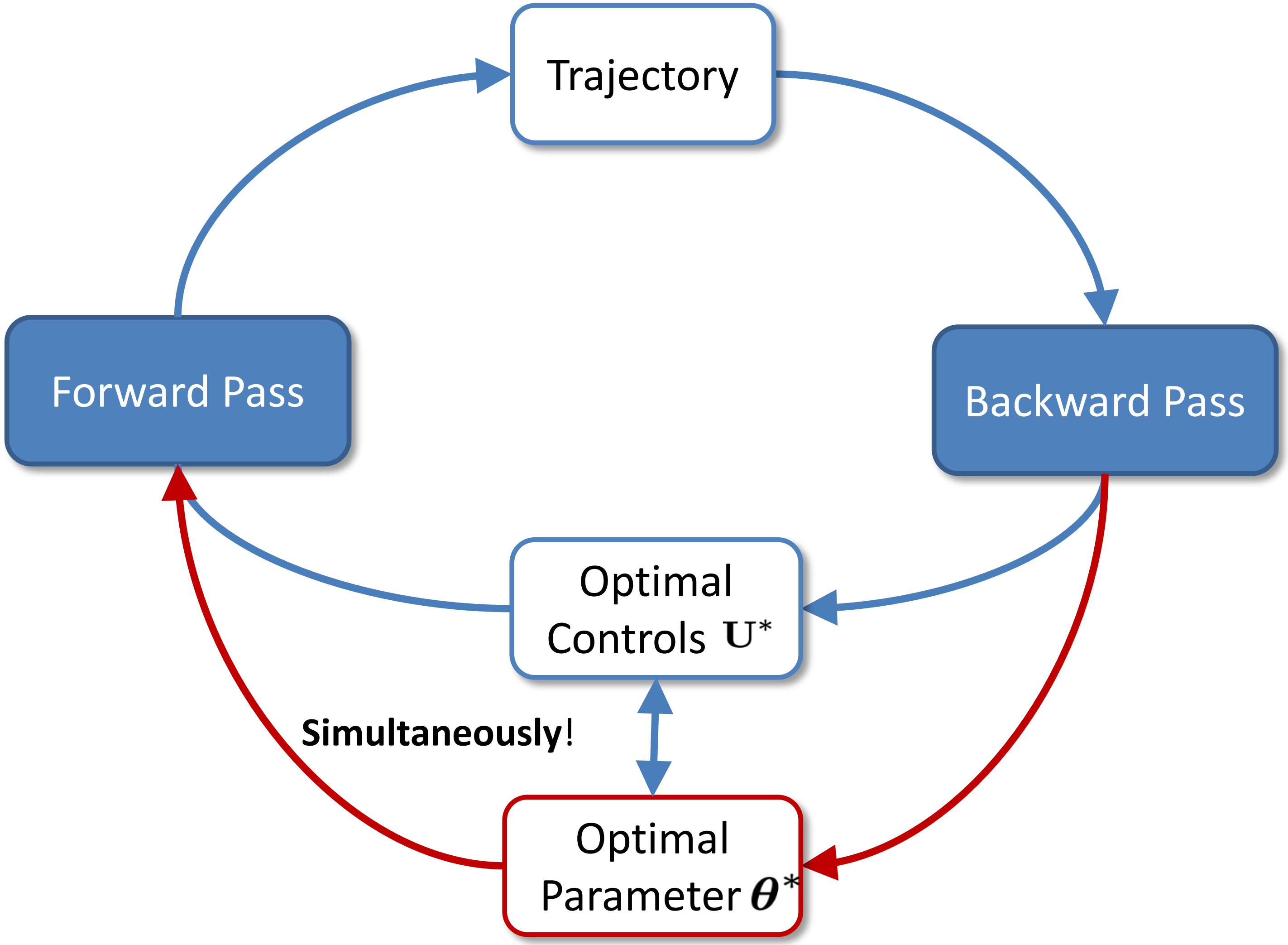
Two unique challenges:

- eVTOL will switch through phases of flight in typical flight plans
- What is the best way to transition between them?
- In the event of a failure …
- Are we able to use trajectory information to recognize what failed?
- Can we still plan a safe trajectory with these new vehicle dynamics?



Planner - Parameterized Differential Dynamic Programming*

- Motivation - Multiple operational modes and flight regimes
- Second-order algorithm derived by extending classical optimal control (DDP)
- **Convergence guarantees** independent of initialization
- **Co-optimizes** for controls and parameters simultaneously
- **Generalizes** to multiple tasks, including adaptive MPC and switching time optimization
- Enables time-optimal trajectory planning for multimodal systems, including **eVTOL vehicles**

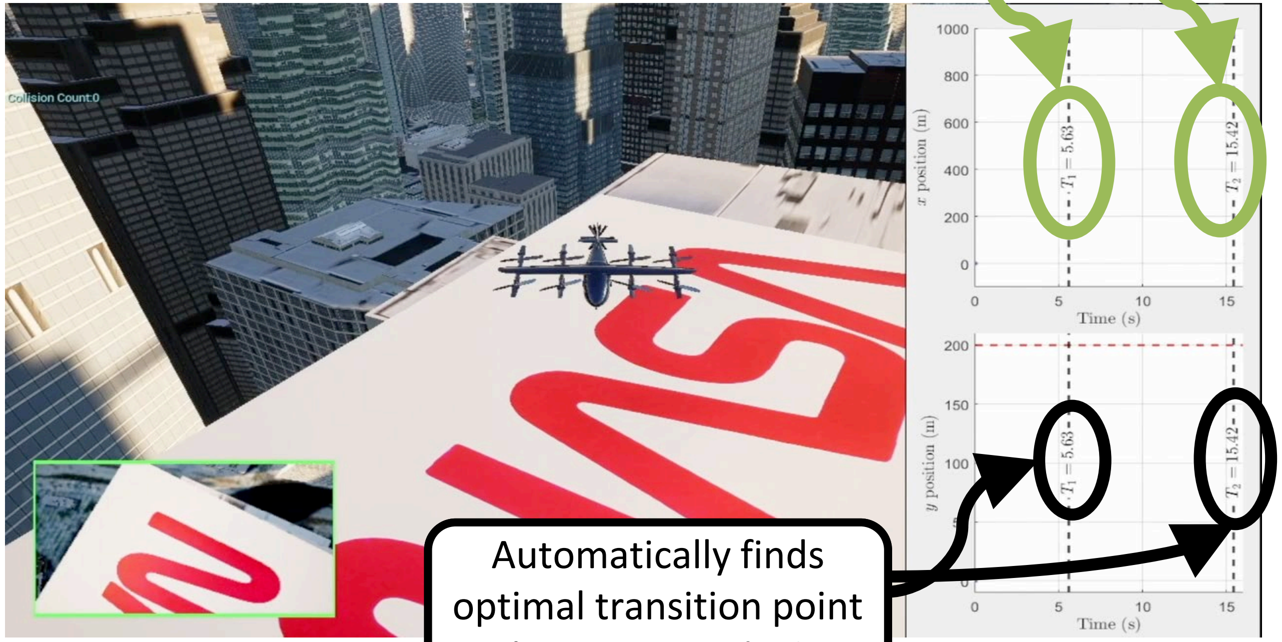


* Oshin, A., Houghton, M., Acheson, M., Gregory, I., and Theodorou, E., "Parameterized Differential Dynamic Programming," *Proceedings of Robotics: Science and Systems*, New York City, NY, USA, 2022. https://doi.org/10.15607/RSS.2022.XVIII.046.

Autonomous Flight Planner - PDDP Applications

Switching Time Optimization

Avoids manual tuning of terminal times!

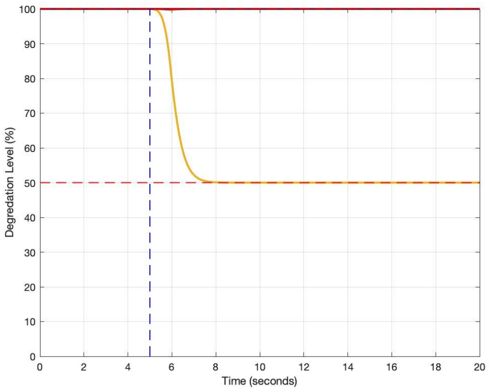


Automatically finds optimal transition point between modes!

Adaptive Model Predictive Control

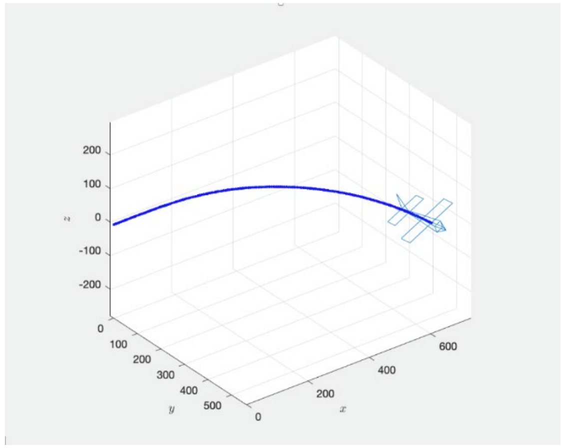
Moving Horizon Estimation

Maximize likelihood of observed states



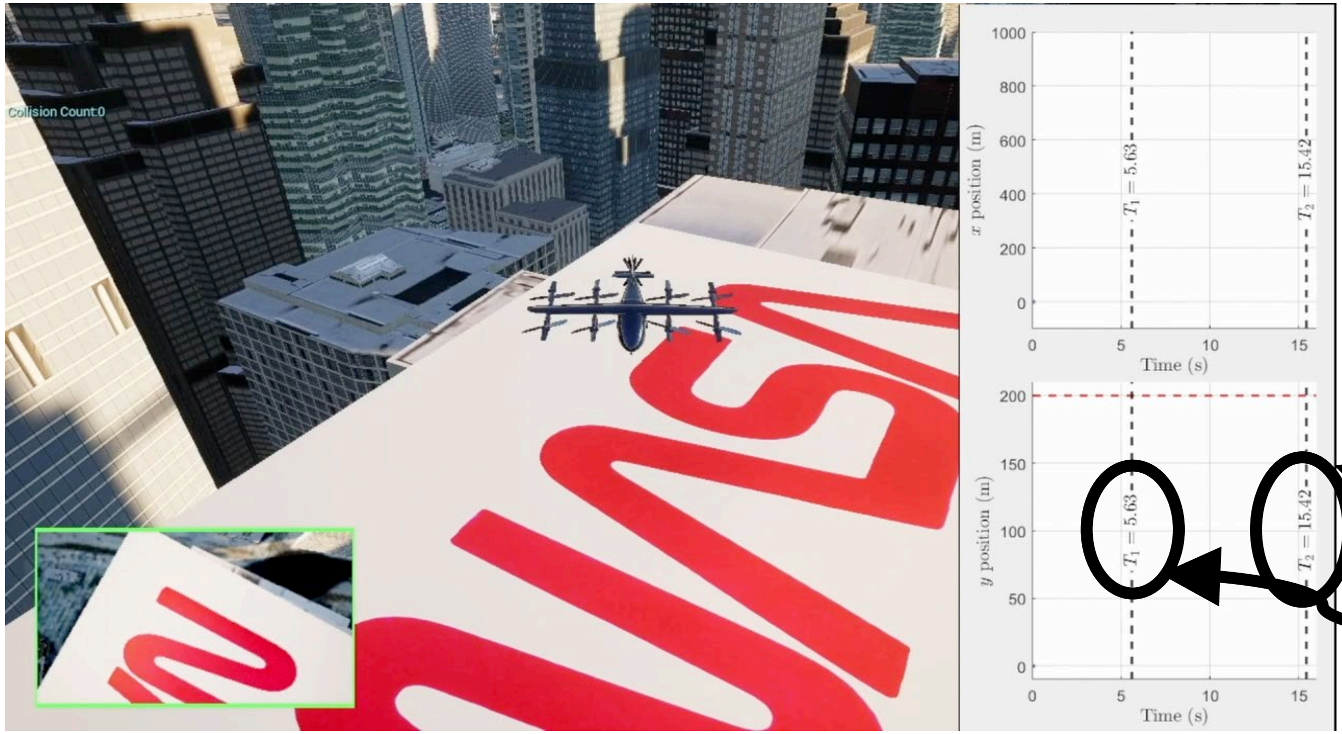
Model Predictive Control

Plan future trajectory



Autonomous Flight Planner - PDDP Transition Optimization

- Long-term planning → change operating modes from hover to forward flight
  - Classical trajectory planning methods struggle with determining how to transition between modes
- PDDP experiment → **vertical takeoff** into **cruise transition** with multiple target states
- Switching Time Optimization selects the **optimal transition** times between targets and flight regimes (without direct input from researchers)



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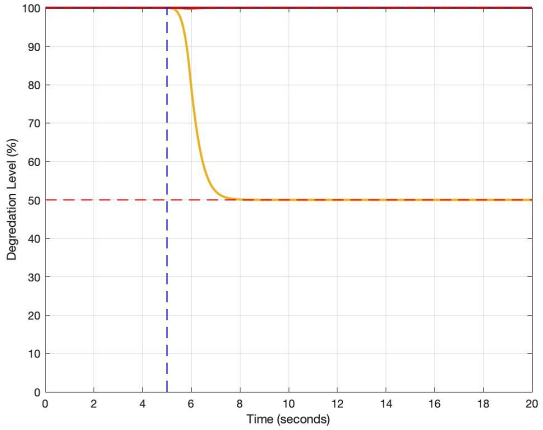
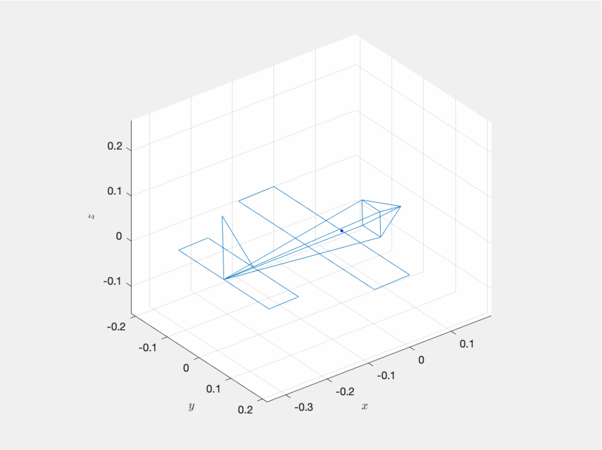


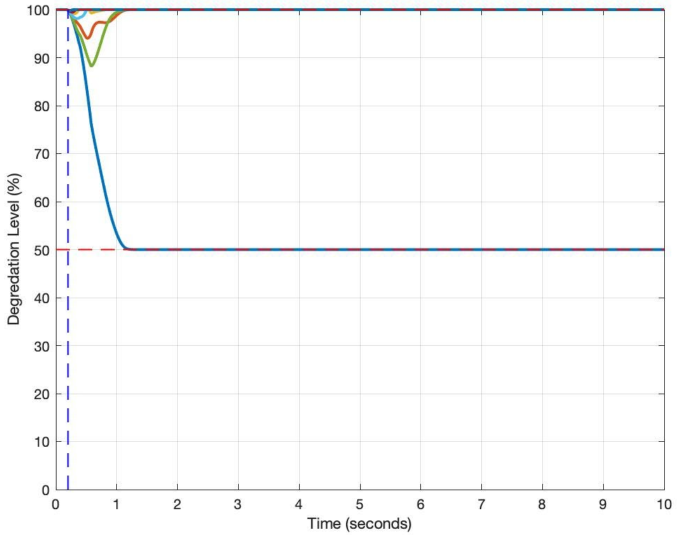


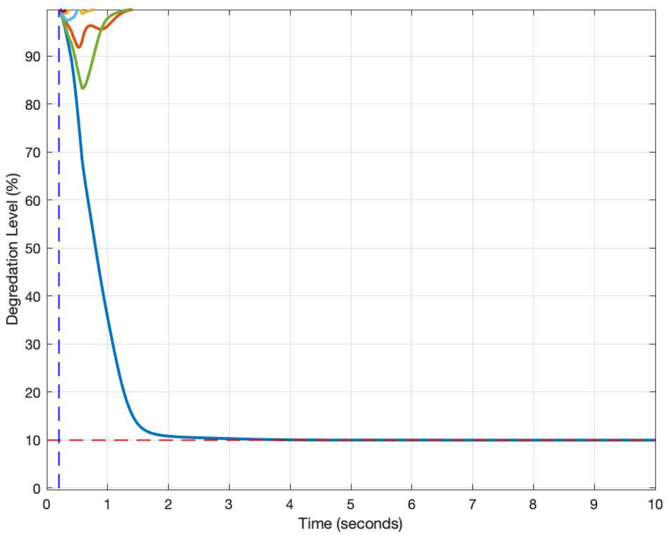
Capability Assessment - Fault Detection: Rotor Failure

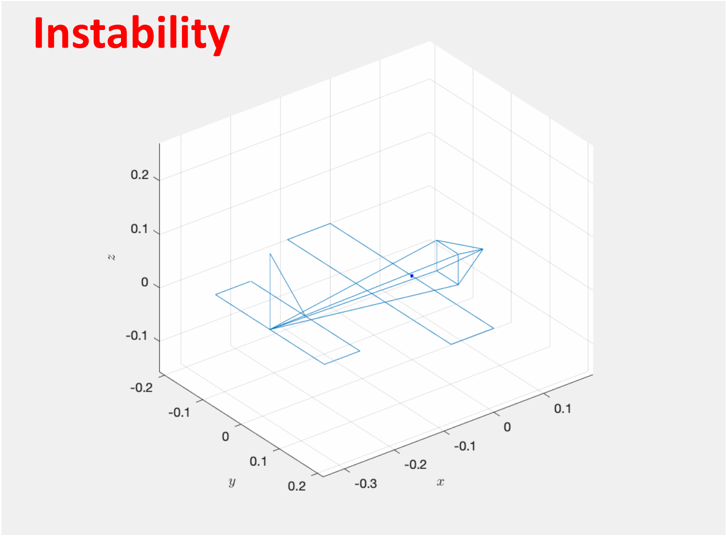
PDDP extends to Fault Detection of vehicle states (rotors and effectors)

<u>Experiment 1: Vertical Takeoff</u>

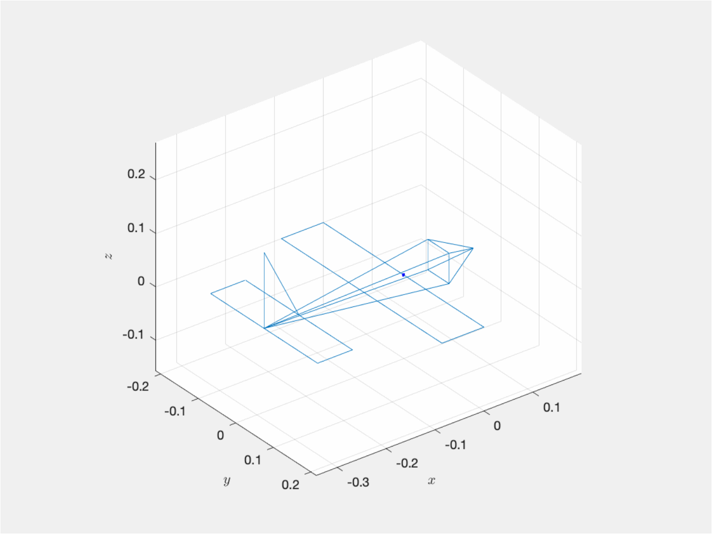
- Begin in hover
- Ascent to 200 ft
- Heavily utilizes rotors in VTOL flight regime
- Early Failure/Degradation



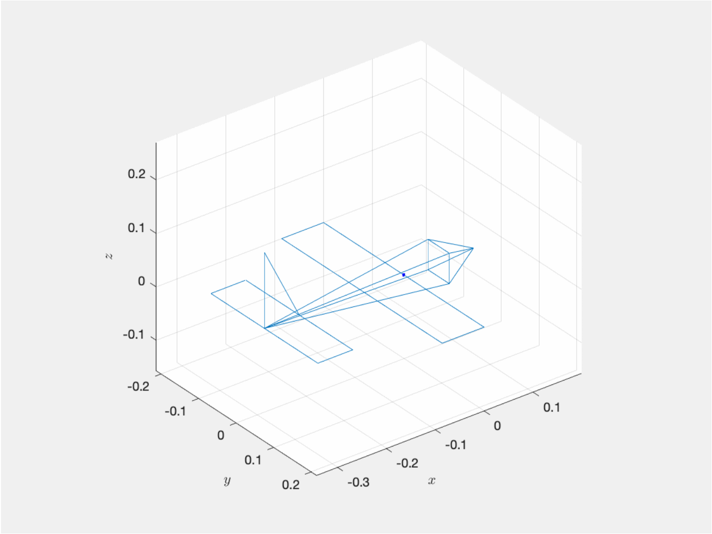




Takeoff Failure Without PDDP



50 % Rotor 1 Degradation



90 % Rotor 1 Degradation

NASA - Irene M Gregory@nasa.gov

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(CO)mbined (B)ernstein Polynomial, Optimal (R)eciprocal Collision (A)voidance DDP

Trajectory Re-planner Requirements:

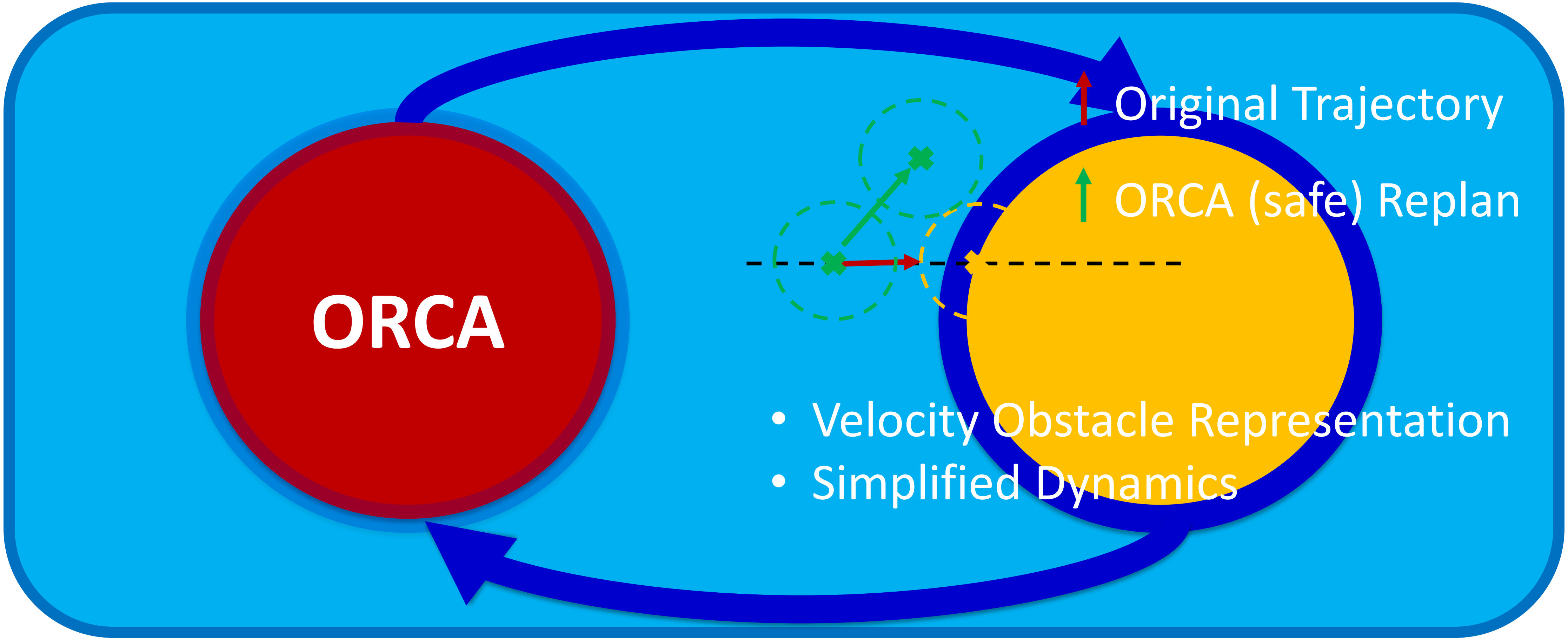
- "Real-time" **dynamically feasible** trajectories for eVTOL (transitioning) vehicles with **separation** assurances
- Dynamic planning for large number of (stationary & moving) cooperative/uncooperative obstacles

COBRA-DDP

COBRA-DDP Breakdown

Optimal Reciprocal Collision Avoidance (ORCA):

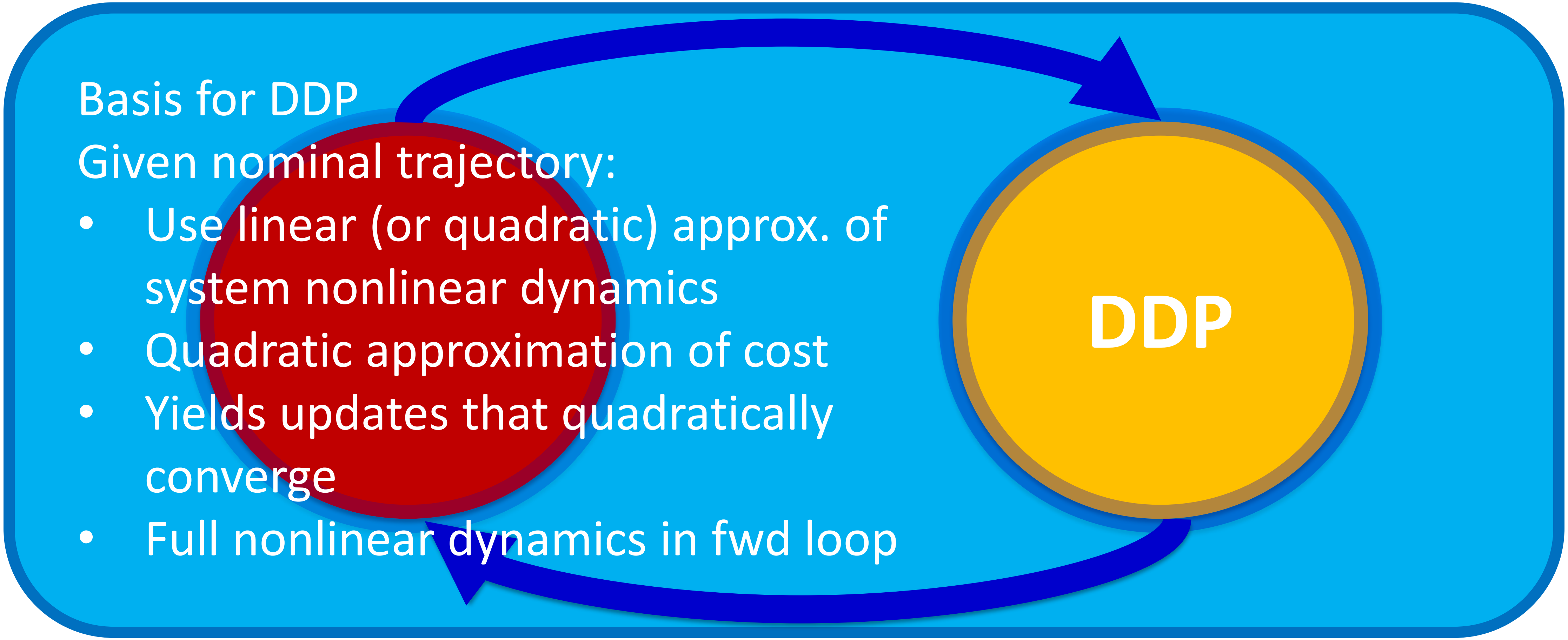
- *Advantages*: Fast computation for large number of cooperative/non-cooperative with separation assurances
- *Disadvantages*: No assurance of dynamic feasibility



COBRA-DDP Breakdown

Differential Dynamic Programming (DDP):

- *Advantages*: Fast computation of dynamically feasible optimal trajectories
- *Disadvantages*: Degraded computation speed for incorporation of state constraints (e.g., obstacles)



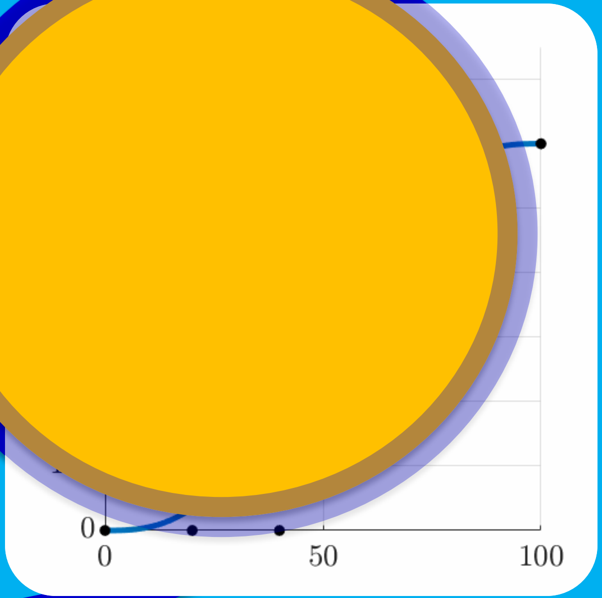
COBRA-DDP Breakdown

Piecewise Bernstein Polynomial (BP) Curves:

- *Advantages*: Fast and compact trajectory representation, smooth derivatives (position, velocity & acceleration)
- *Disadvantages*: One piece-wise segment cannot represent all curves exactly (e.g., circular arcs)

BP Curves

- Can g n control points from multiplication)
- Can trary times for DDP
- Serves a bone of the algorithm



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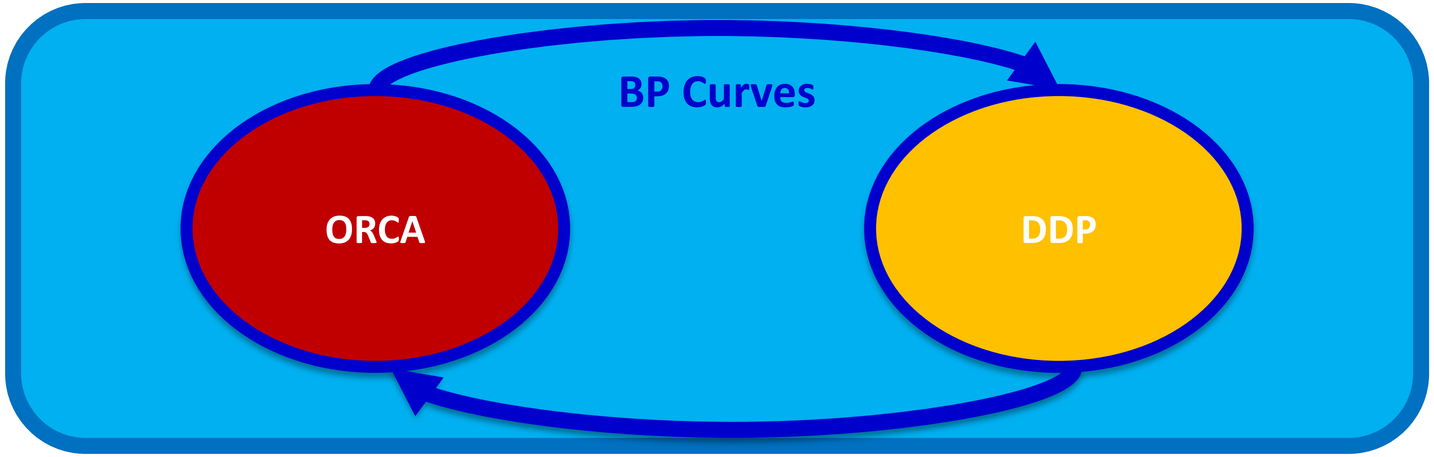


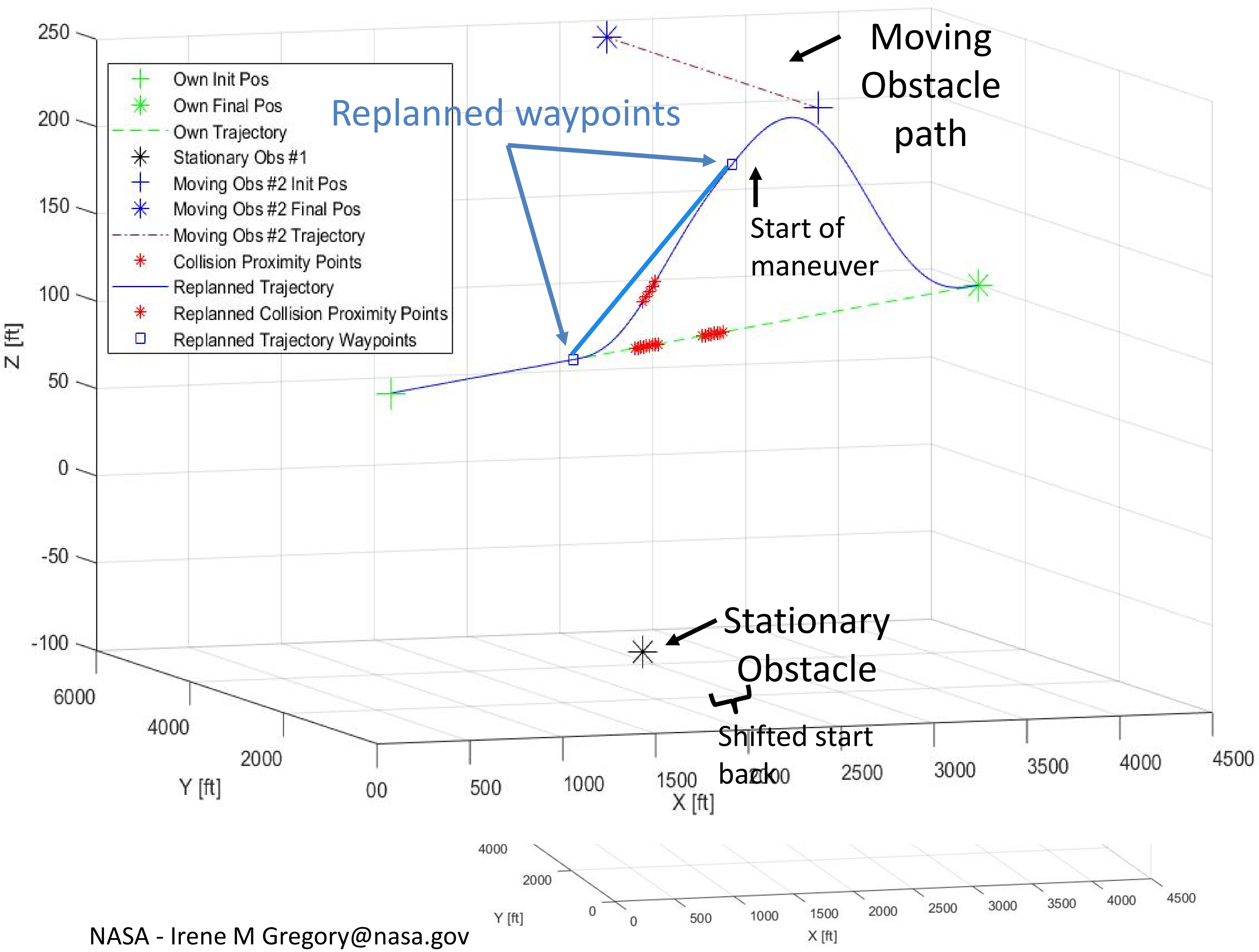
Combine to get best of each algorithm!

*M.D. Houghton, *et.al.*, “Combined Bernstein Polynomial, Optimal Reciprocal Collision Avoidance, Differential Dynamic Programming for Trajectory Replanning and Collision Avoidance for UAM Vehicles” AIAA SciTech Forum, 2023.

Autonomous Flight – Collision Avoidance Planner COBRA-DDP

- ORCA collision detection Δt steps along own-ship trajectory
- Initial trajectory collides with safety radii of both stationary obstacle below and moving obstacle above
- ORCA replans points to avoid obstacle using simplified dynamics - output velocity to create new waypoints, converted into BP curve
- BP curve integrated with trim knowledge and passed to DDP
- BP/DDP curve - more dynamically viable trajectory - causes new collision
- ORCA detects collision, replans
  - Initiates maneuver earlier

Moving vehicle + Stationary obstacle

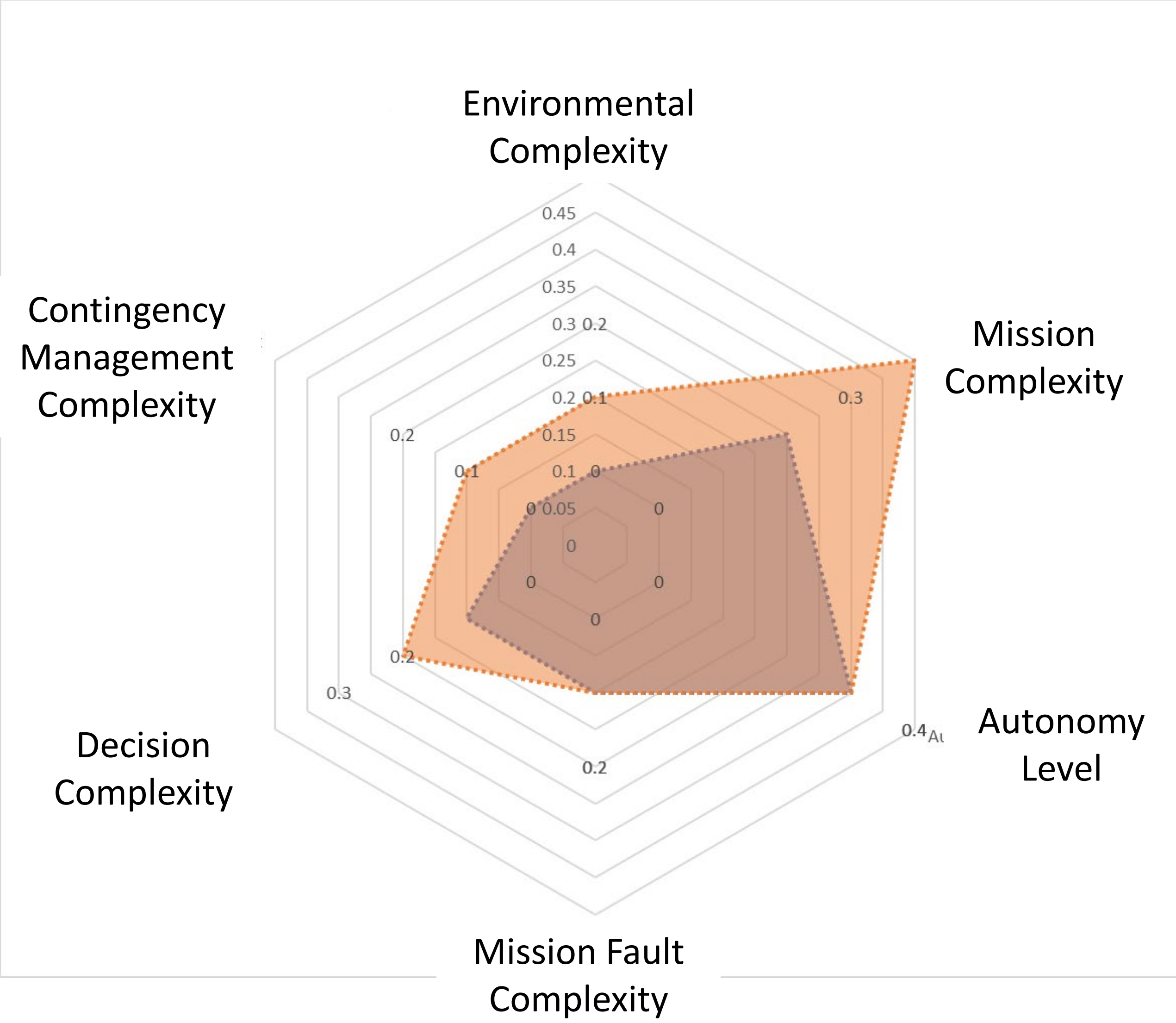


Autonomous Flight - How do we measure progress?

- How do you distinguish between progress made for small UAS vs. Cessna cargo delivery in Alaska vs. air taxi in Tokyo?
- Is there a common language that can be used to communicate among different sectors of autonomy applications? Needs to capture the nuances and challenges along multiple vectors required for full instantiation of autonomy.
- Initial considerations of a framework to evaluate progress towards fully autonomous flight with focus on Advanced Air Mobility application.
  - To be published at the 2024 AIAA SciTech Forum
- As this framework develops and is assessed by the community for relevance, will it also become useful outside the aviation domain?

Autonomous Flight – Measure of Progress Framework

- Complexity of environment
  - Structured/unstructured, static/dynamic, known/unknown
- Complexity of Mission
  - Simple/complex flight plan, normal/off-nominal operations, recoverable/unrecoverable failure (in current mission sense)
- Complexity (level) of Autonomy
  - No automation to full autonomy; 1-5 similar to SAE
- Complexity of decision
  - Immediate system to mission level
- Mission fault complexity
  - External/internal, correctable/uncorrectable
- Complexity of contingency management
  - Evaluates the potential hazards and consequences of the vehicle in case of a failure or emergency
  - Contingency risk assessment - level of risk posed by a specific contingency action



Autonomous Flight for Advanced Air Mobility - Summary

Within the context of multi-modal vehicles with narrow performance margins operating in complex unstructured environments, in increasingly autonomous fashion

Research opportunities:

- Resilient safety-critical mission management architecture – robustness to any single algorithmic failure
- Formal assurance of L1 adaptive control for fail-safe stability and within the learning framework
- Tightly integrated multi-time scale trajectory planners
  - COBRA-DDP plans dynamically feasible collision avoiding trajectories and can select preferential avoidance direction

- Need for a common language/framework to assess progress in enabling autonomous operations across variable complexity of environments, missions, contingency actions and associated risks
- Establish common benchmark problems

Questions?

Contact Information:

Irene.M.Gregory@nasa.gov

Abstract

- This talk discusses the challenges associated with autonomous flight and potential approaches to contingency management. We cover the autonomy drivers, what we consider fundamental building blocks for successful autonomous flight with success defined as safe completion of assigned mission. Any realistic operations have to deal with anticipated and unanticipated off-nominal events, i.e. contingencies. Contingency management is one of the most difficult challenges of autonomous flight. We introduce a high-level architecture and provide some examples from our work of integrating different algorithms to deal with contingencies that arise in flight. We also discuss a potential need to assess progress to autonomy across various aviation niches and evolving sectors and propose a framework to do so.

Why Autonomy in Aviation?

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- **Autonomy changes** the nature of
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    - Regional cargo delivery competing in cost with trucking
  - Maintenance logistics and safety well beyond traditional aerospace
    - Oil platforms, pipelines, power lines, wind turbines, infrastructure inspection and maintenance
  - Agriculture, land management, 1st responders (e.g., rapid response to inaccessible disaster areas)
- **Long Term** Aviation Revolution/Autonomy **Impacts**:
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  - Maintains and enhances **safety** as density of heterogeneous fleet of vehicles and operations increases

Autonomy is a REQUIRED GAME CHANGER to enable revolution in the aerospace industry
Autonomy must be implemented in a safe, efficient, scalable, certifiable way

Why NASA?

- NASA has been a valued partner in **accelerating** maturation and adoption of advanced **technologies** for U.S. industry (industry view)
- NASA serves as a bridge between academia's fundamental research and industry's limited time horizon
- NASA's role should be to **accelerate** and **enable** autonomy in aerospace industry

NASA and key partners can **collectively** consider the **most difficult mission challenges**, **ambitious operations** and help mature required technologies to **enable** US industrial competitiveness and leadership

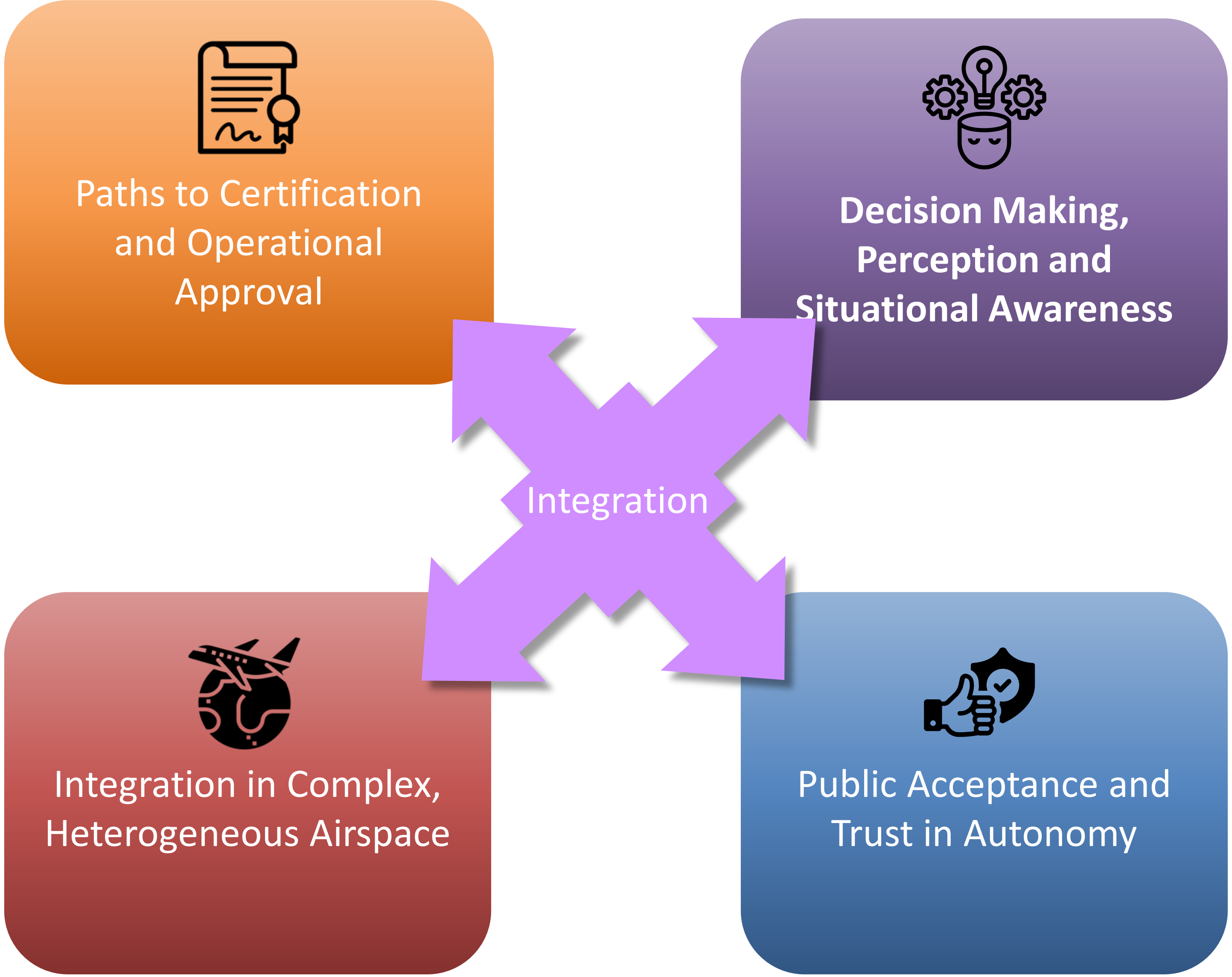
NASA can **accelerate U.S. development and deployment** by

- Providing the data and confidence regulators need to certify and approve
- Tackling system-of-systems integration issues
- Openly sharing knowledge and unifying community around remaining challenges
- Taking **higher technical risk** and focus beyond immediate time horizon

Key Barriers for Increasingly Autonomous Aerospace

- Industry is making great strides, but many barriers remain
  - Industry focus on developing and certifying *individual systems*
  - Industry focus on the *near-term* operational horizon
  - Many integration questions remain (between systems and operations)

- Different sectors have different paths to autonomy
- Deployment paths consider cost, risk, ROI
- Different paths have different challenges, crosscutting ones



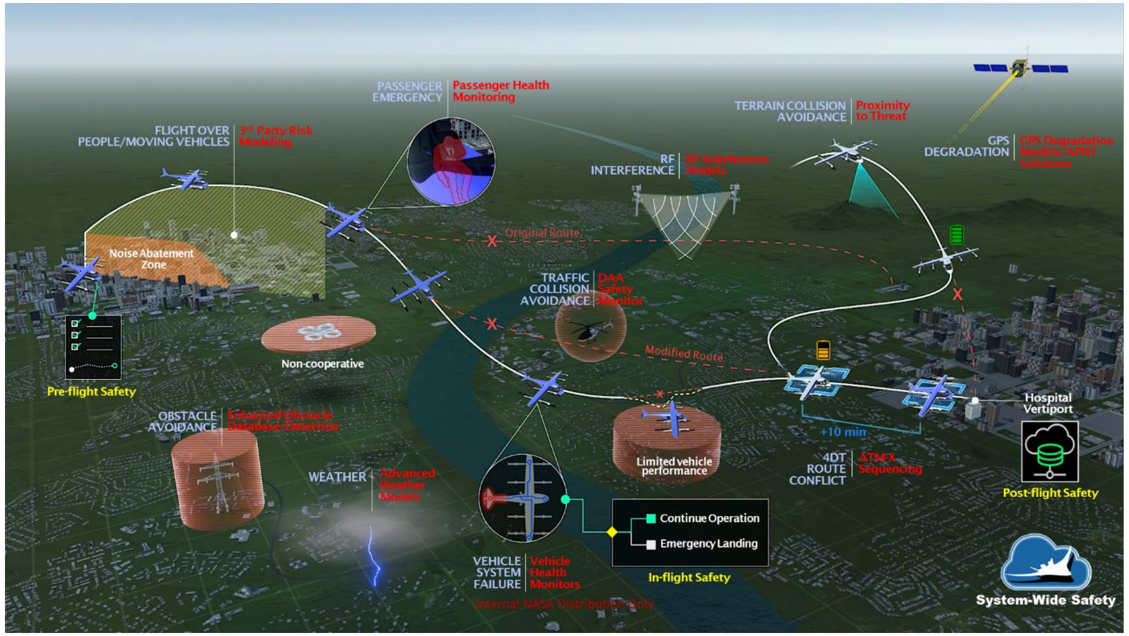
Motivation for Intelligent Contingency Management

Emerging aerospace sectors – missions and vehicles

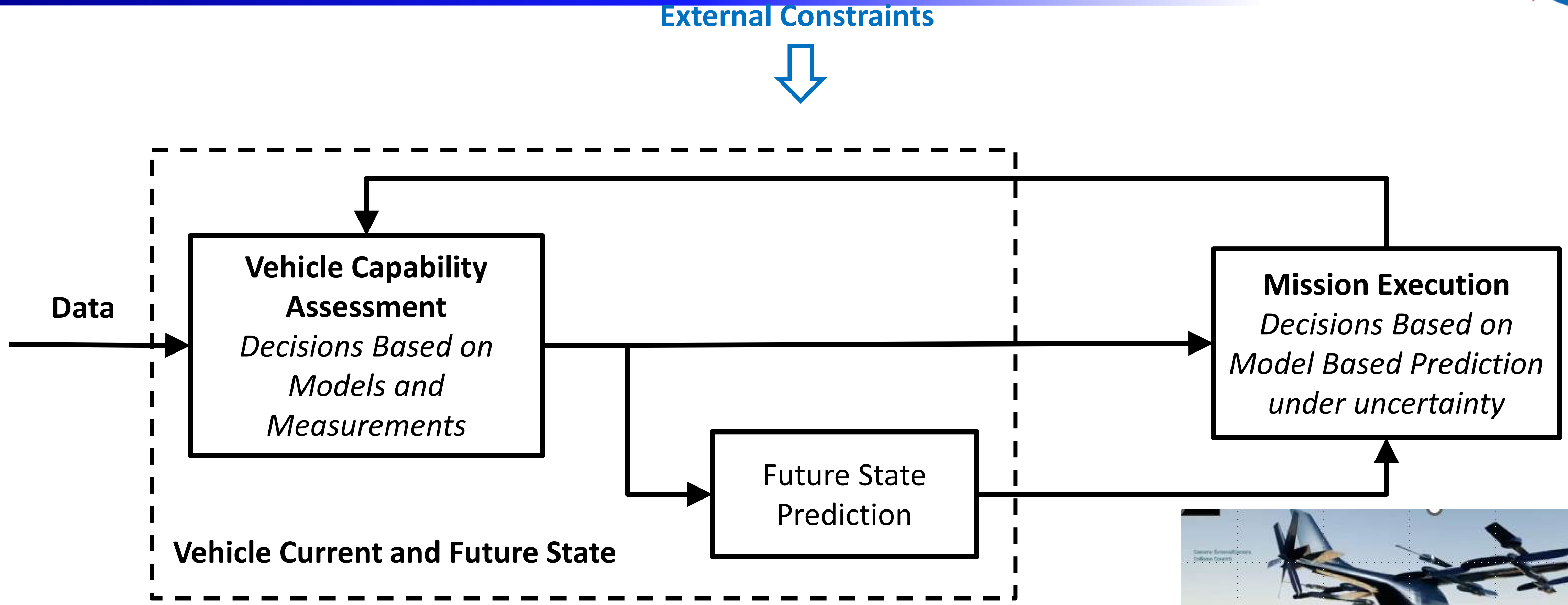
- Autonomous cargo delivery
- Urban Air Mobility (UAM)
- Complexity of the environment
- Unconventional configurations with **multi-modal dynamics**
- **Highly nonlinear flight dynamics**
- **Autonomous** flight for scalability

Challenges:

- **New technology** – more likely performance degradation/failures
- **Narrow performance margins** – can't afford conservatism
- **Accurate trajectory following** in the face of system uncertainty and atmospheric disturbances
- **Safe control** while learning elements are engaged



Overview



High level architecture

* I. M. Gregory *et al.*, “Intelligent contingency management for urban air mobility,” in *AIAA Scitech 2021 Forum*, 2021.

Overview

External Constraints

- Planning/replanning for mission
- Collision avoidance
- Mission execution under off-nominal conditions
- Flight under failures

Data

Vehicle Capability Assessment
Decisions Based on Models and Measurements

Decision making

Mission Execution
Decisions *Based on Prediction under uncertainty*

Future State Prediction

Vehicle Current and Future State

- System Identification
- Machine Learning methods
- Optimal Control (PDDP)

Motivation for L1 Adaptive Control for System Safety & Performance

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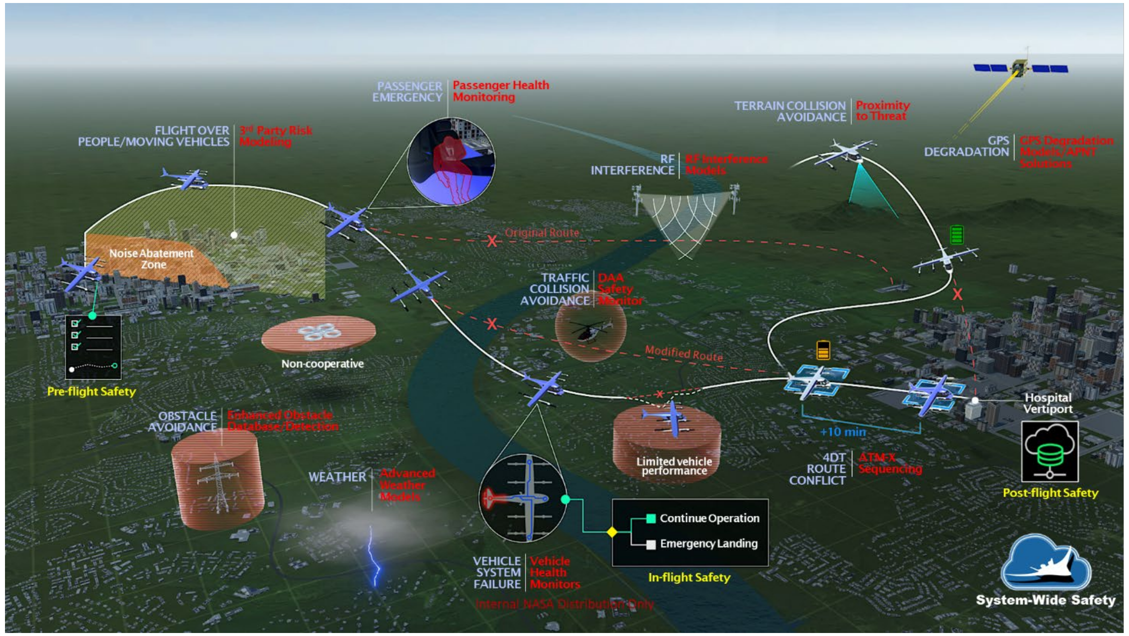

Adaptive Optimization for System Performance: Parameterized Differential Dynamic Programming

Alex Oshin*#, Matthew D. Houghton*, Michael J. Acheson*, Irene M. Gregory* and Evangelos Theodorou#

*NASA Langley Research Center**

Georgia Institute of Technology#

AIAA SciTech Forum and Exposition

23-27 January 2023

National Harbor, MD

Motivation for Adaptive Optimization for System Performance

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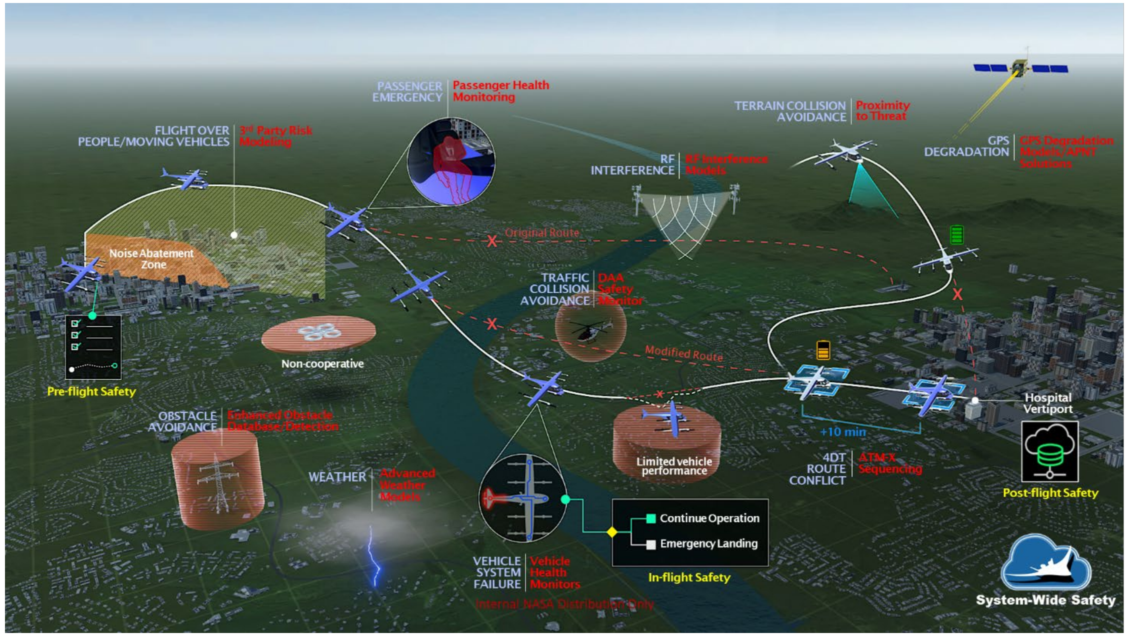
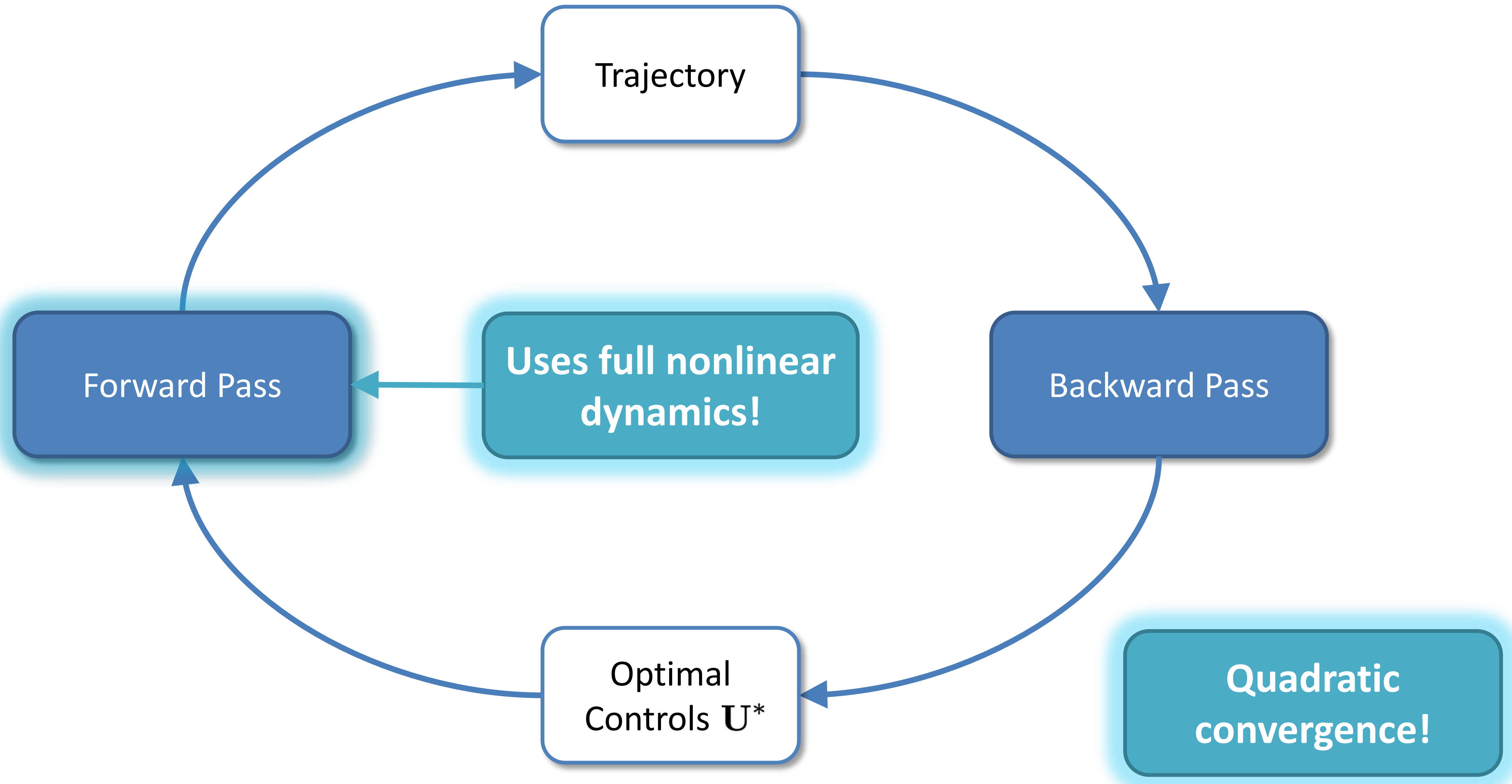
Planner challenges:

- Principled solutions/guarantees
- Accurate trajectory planning & replanning
- Epistemic uncertainty in model
- Multiple operational modes and flight regimes
- Transferability to different vehicles

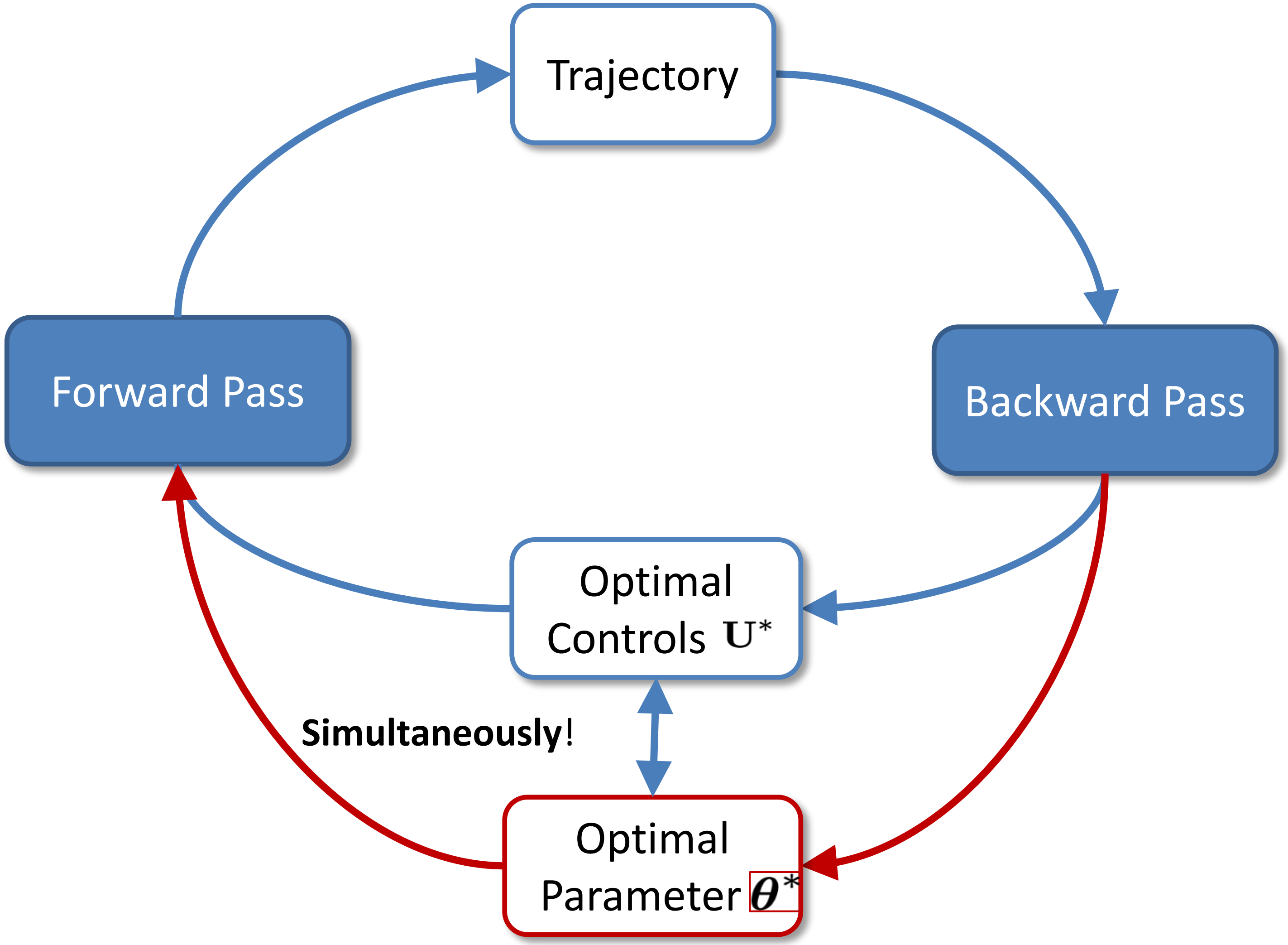


Differential Dynamic Programming (DDP)



Parameterized Differential Dynamic Programming (PDDP)*

- Second-order algorithm derived by extending classical optimal control (DDP)
- **Convergence guarantees** independent of initialization
- **Co-optimizes** for controls and parameters simultaneously
- **Generalizes** to multiple tasks, including adaptive MPC and switching time optimization
- Enables time-optimal trajectory planning for multimodal systems, including **UAM vehicles**

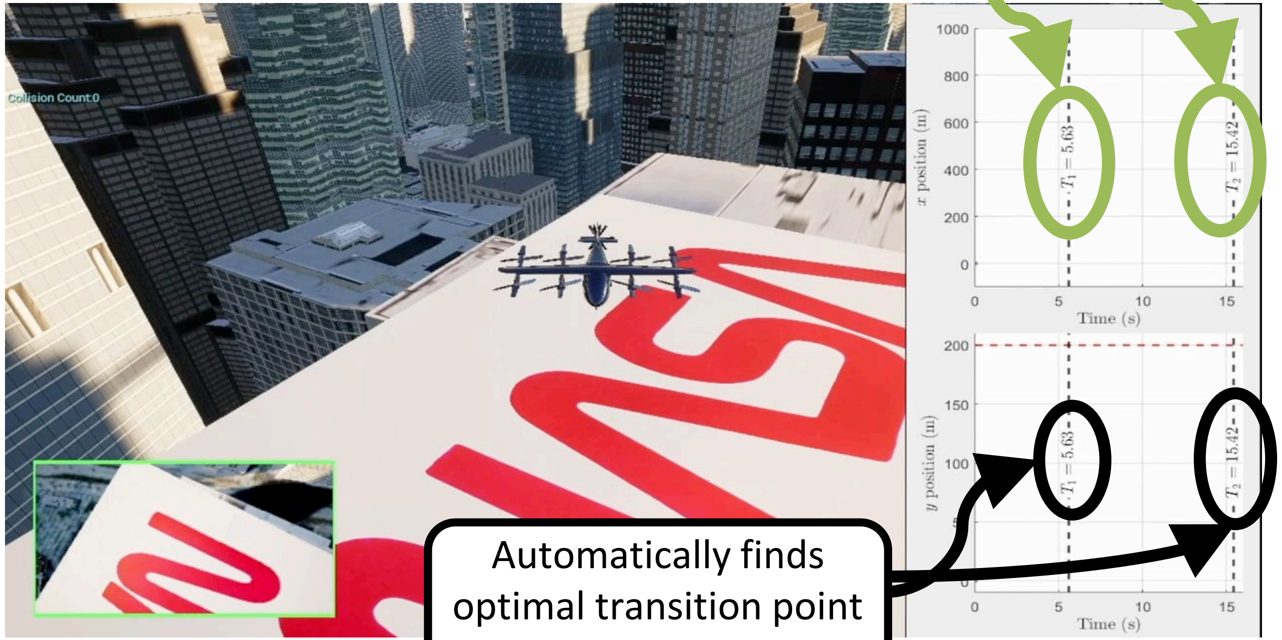


* Oshin, A., Houghton, M., Acheson, M., Gregory, I., and Theodorou, E., “Parameterized Differential Dynamic Programming,” *Proceedings of Robotics: Science and Systems*, New York City, NY, USA, 2022. https://doi.org/10.15607/RSS.2022.XVIII.046.

PDDP Applications

Switching Time Optimization

Avoids manual tuning of terminal times!

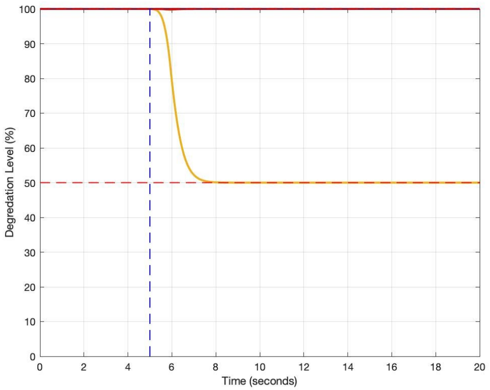


Automatically finds optimal transition point between modes!

Adaptive Model Predictive Control

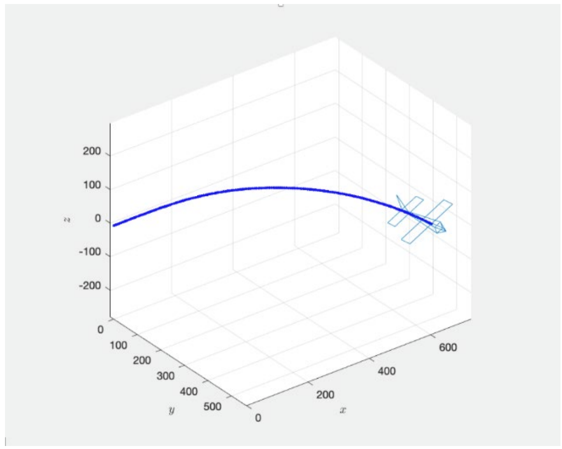
Moving Horizon Estimation

Maximize likelihood of observed states



Model Predictive Control

Plan future trajectory



PDDP Transition Optimization

- Long-term planning requires the L+C vehicle to change operating modes from hover to forward flight. Classical trajectory planning methods struggle with determining how to transition between modes.
- PDDP L+C experiment involves vertical takeoff into cruise transition with multiple target states
- Switching Time Optimization selects the **optimal transition** times between targets and flight regimes (without direct input from researchers)

Multimodal System

$$\dot{\mathbf{x}}(t) = \mathbf{f}^{(i)}(\mathbf{x}(t), \mathbf{u}(t))$$

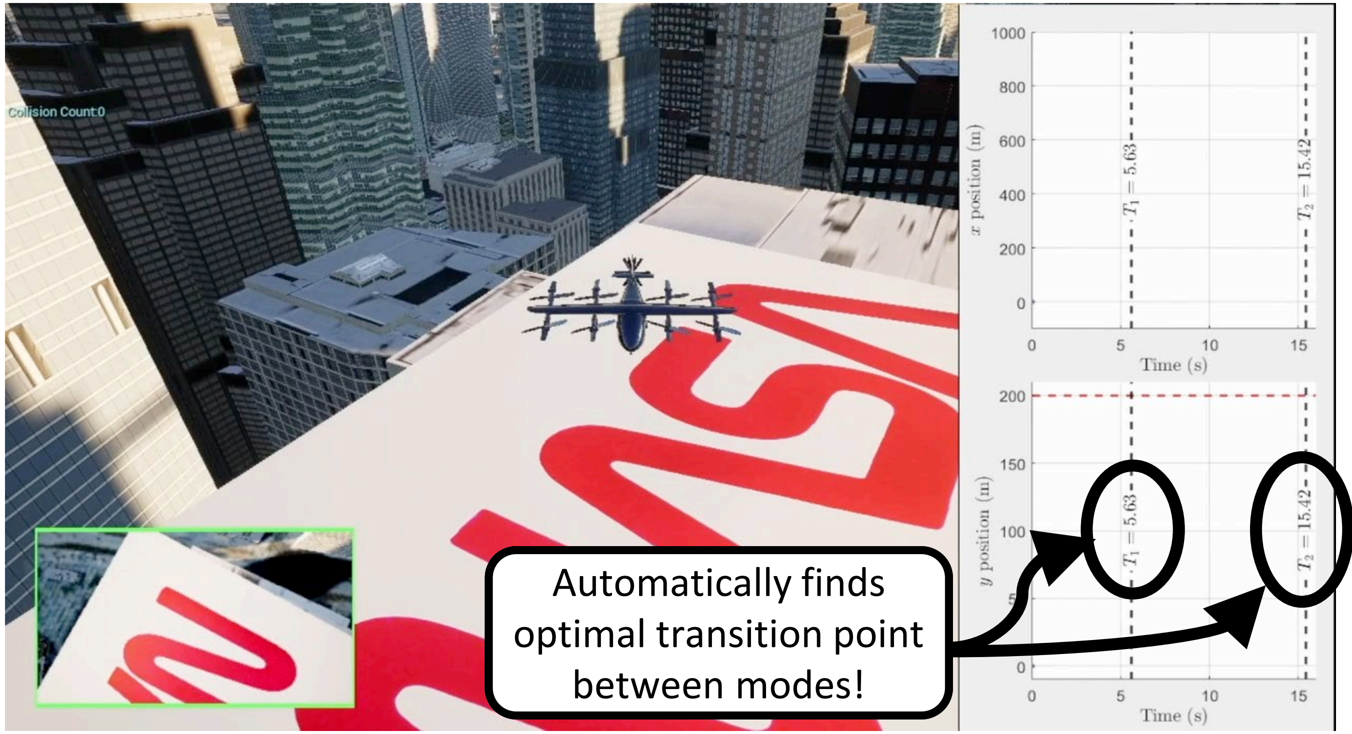
$i = 1, 2, \ldots, N$

Switching Time System

$$\mathbf{x}_{t+1} = \mathbf{x}_t + \theta_i \mathbf{f}^{(i)}(\mathbf{x}_t, \mathbf{u}_t)\Delta t$$

$$\sum_{t=T_{i-1}+1}^{T_i} \theta_i \mathcal{L}^{(i)}(\mathbf{x}_t, \mathbf{u}_t) + \phi^{(i)}(\mathbf{x}_{T_i+1})$$

$i = 1, 2, \ldots, N$



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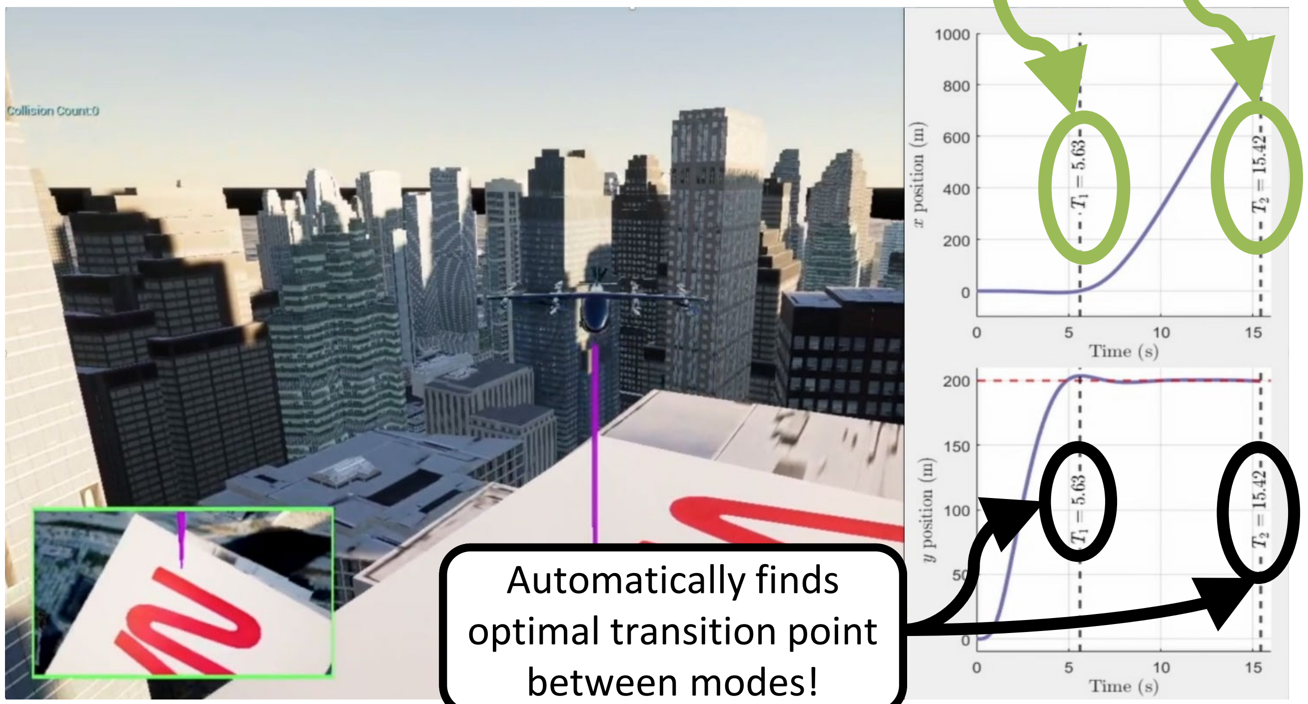

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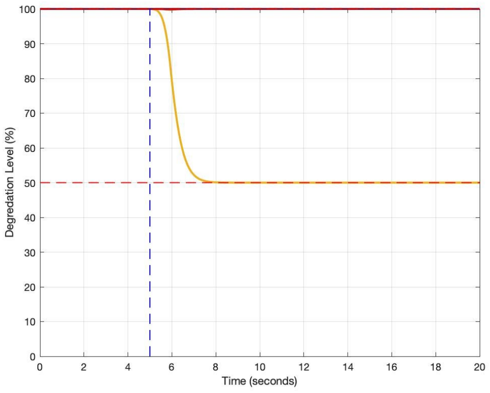

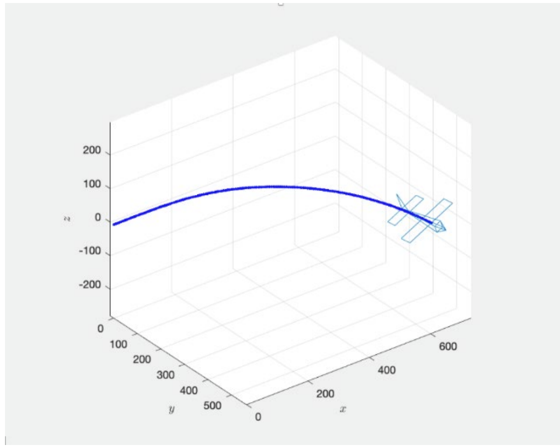

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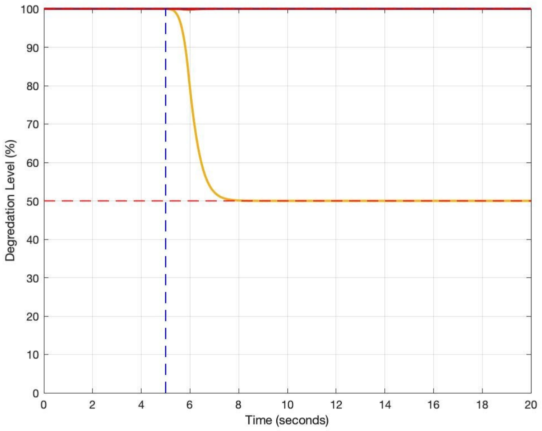
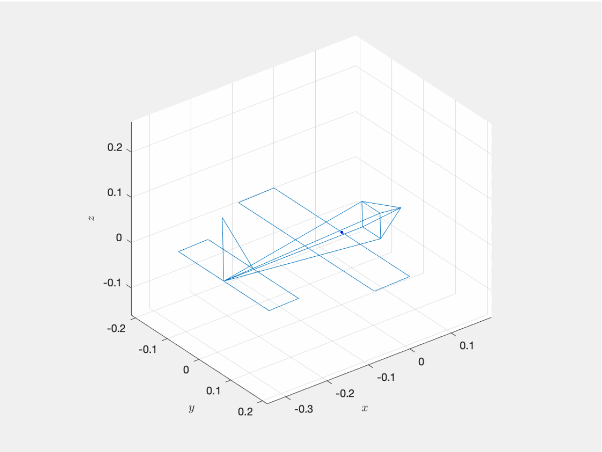
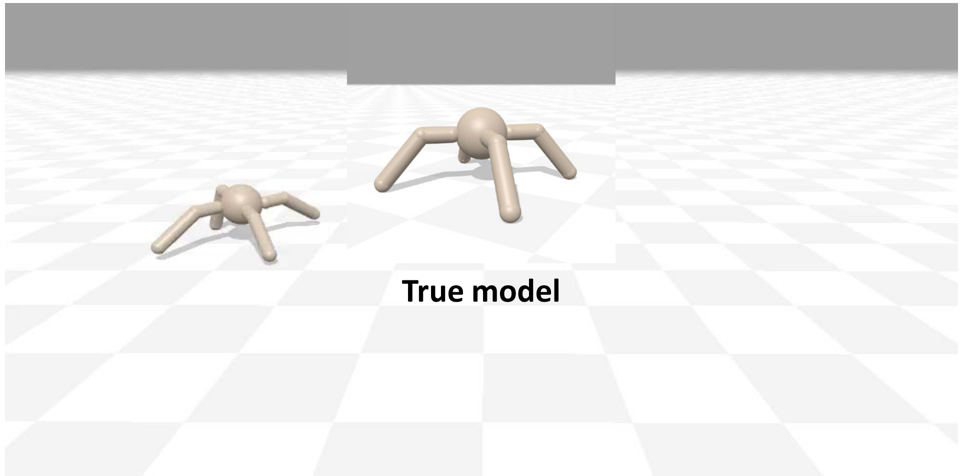




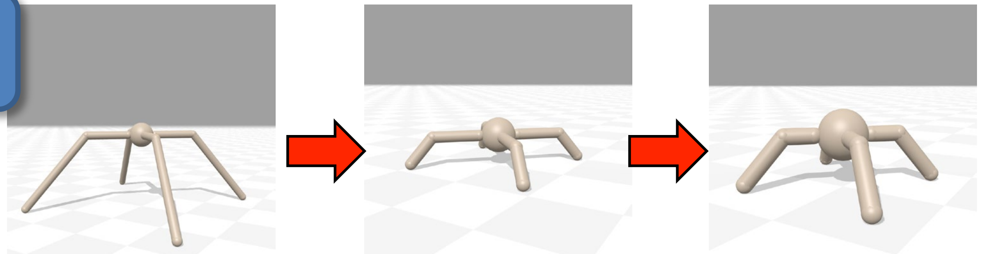
PDDP: Adaptive MPC

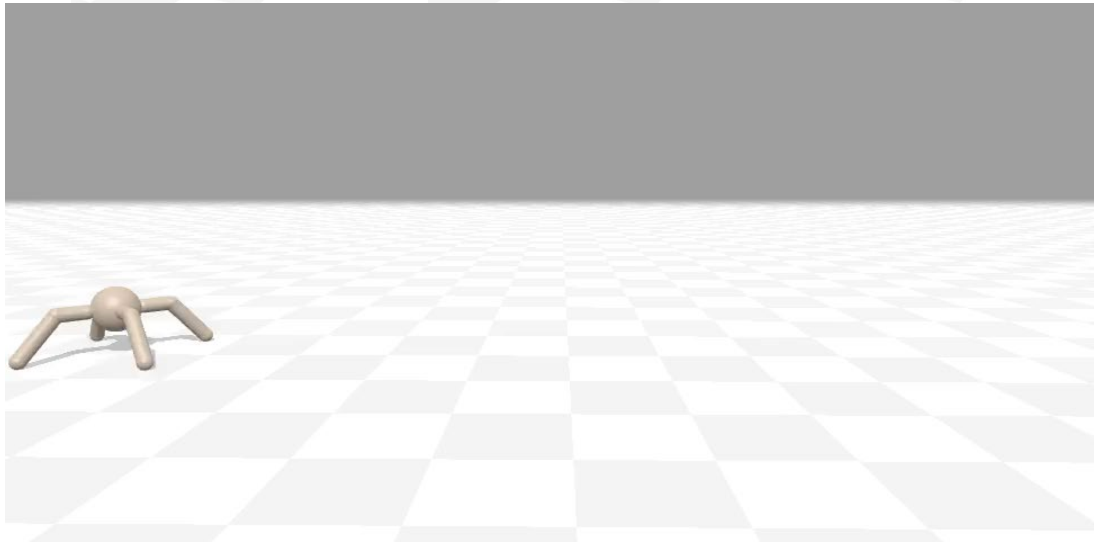
Ant

DDP planning on model with incorrect parameters

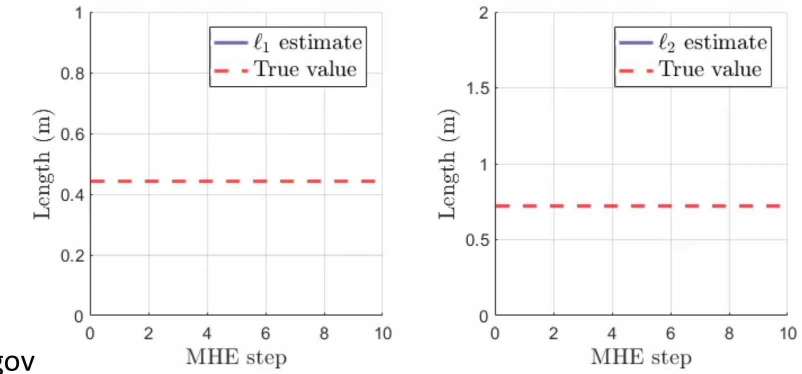


Executing plan on true model: Failure





PDDP with adaptive control: Success



Parameterized Differential Dynamic Programming (PDDP)

PDDP is a trajectory optimization algorithm that builds upon DDP

- Enables the **co-optimization** of a **trajectory** and time invariant **parameters** in the same process.
- Parameters can be extremely diverse and goal specific
- Experiments tested PDDP's ability to successfully **estimate vehicle dynamic parameters** while implementing **optimal trajectories**, resulting in Adaptive Model Predictive Control

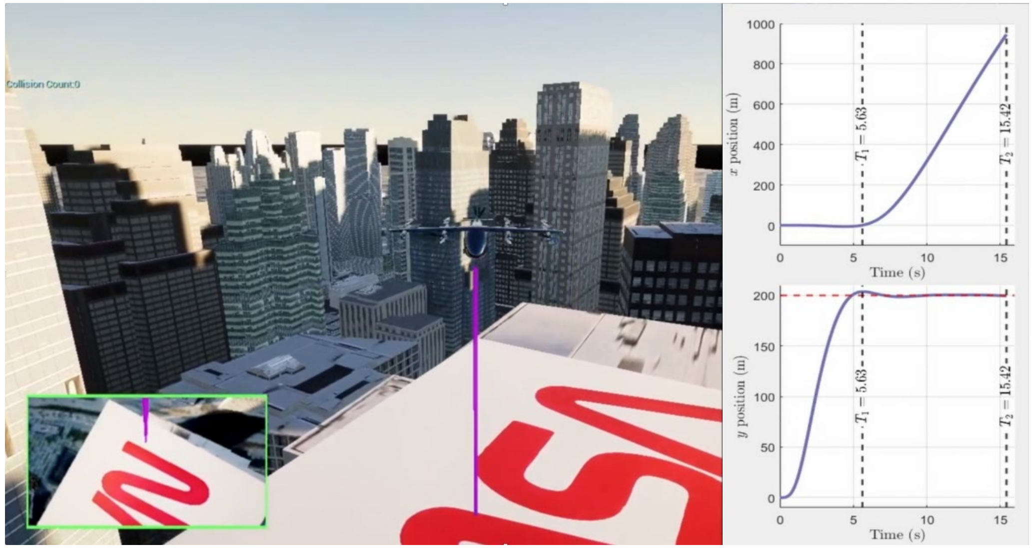
Fault Detection

- Online estimation of vehicle **dynamic** parameters
- **Online estimation** of **degradation** level for effectors + rotors
- **Replan trajectory** based on new estimation of vehicle parameters
- Deviations in estimation from norms can alert system ID of vehicle to run further diagnostics of vehicle health

PDDP Applications

Switching Time Optimization

Avoids manual tuning of terminal times!



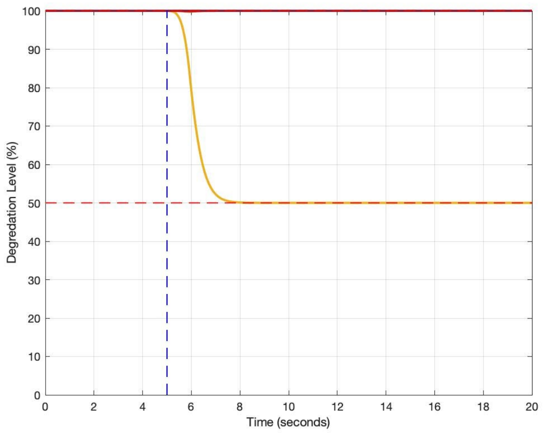
Adaptive Model Predictive Control

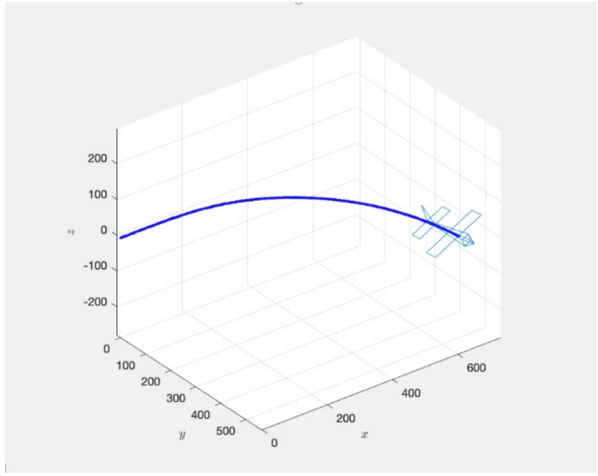
Moving Horizon Estimation

Maximize likelihood of observed states

Model Predictive Control

Plan future trajectory



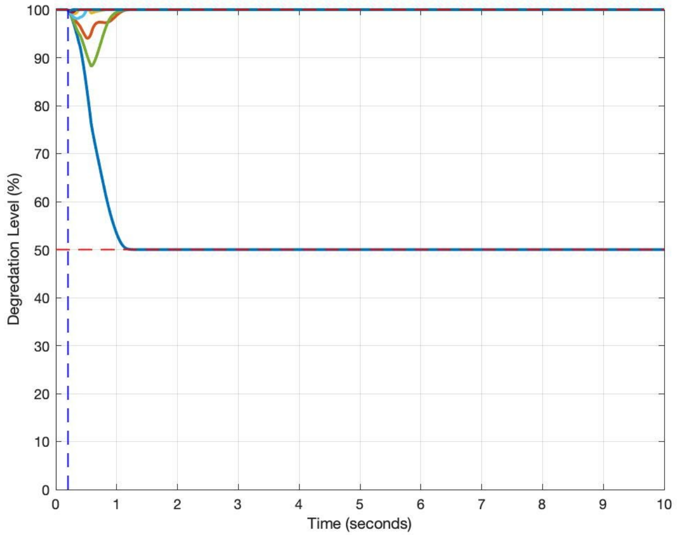


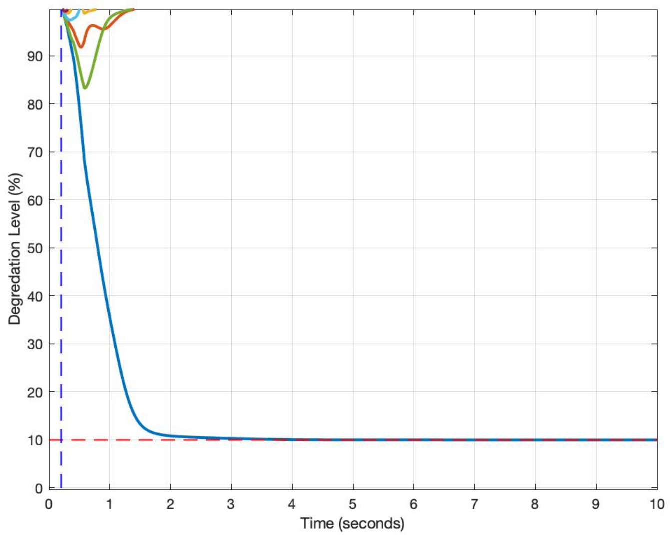
Fault Detection: Rotor Failure

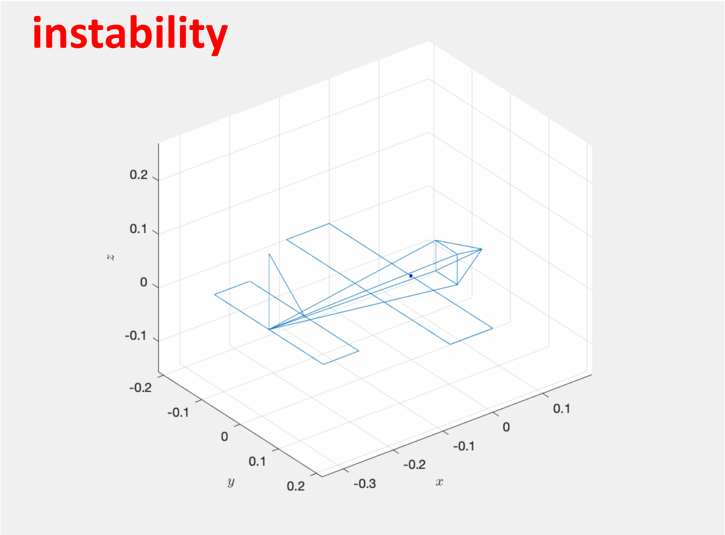
PDDP extends to Fault Detection of vehicle states (rotors and effectors)

<u>Experiment 1: Vertical Takeoff</u>

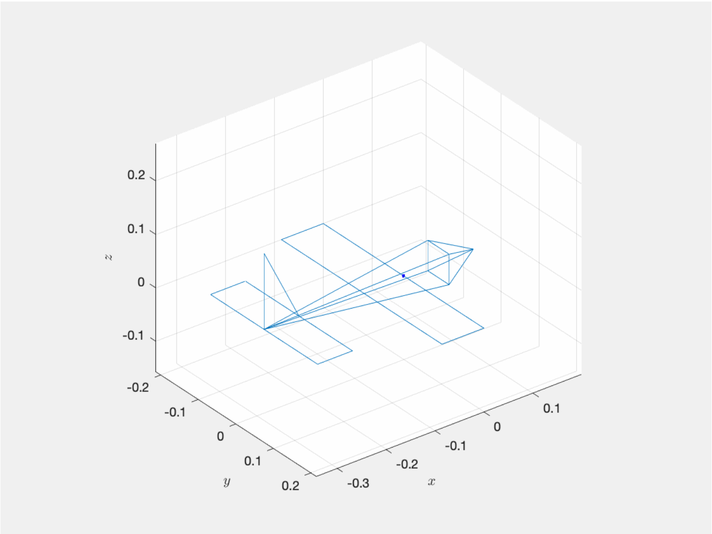
- Begin in hover
- Early Failure/Degradation
- Ascent to 200 ft
- Heavily utilizes rotors in VTOL flight regime



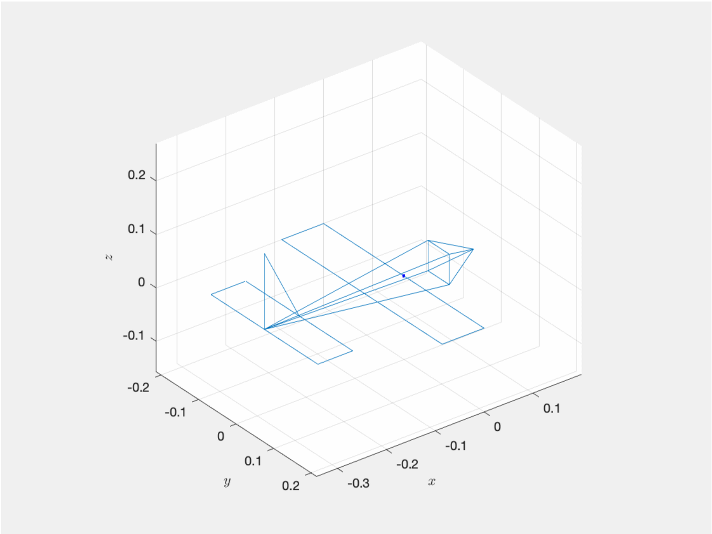




Takeoff Failure Without PDDP



50 % Rotor 1 Degradation

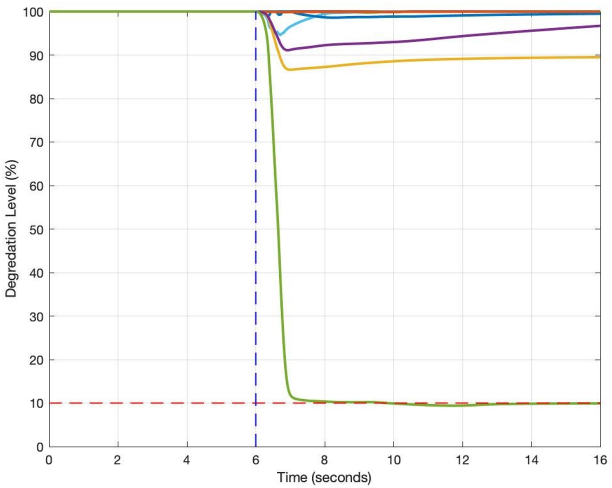


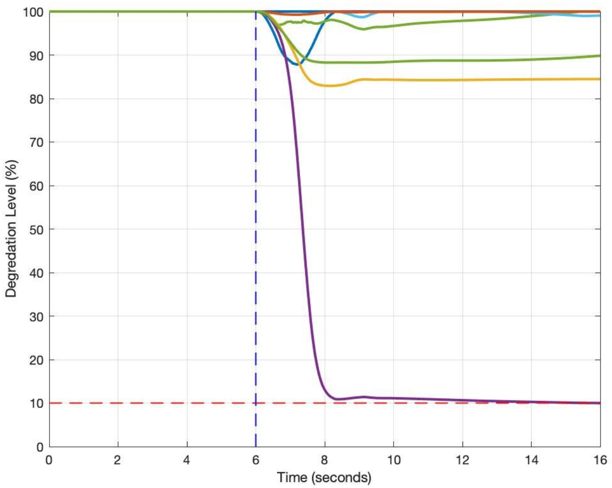
90 % Rotor 1 Degradation

Fault Detection: Effectors

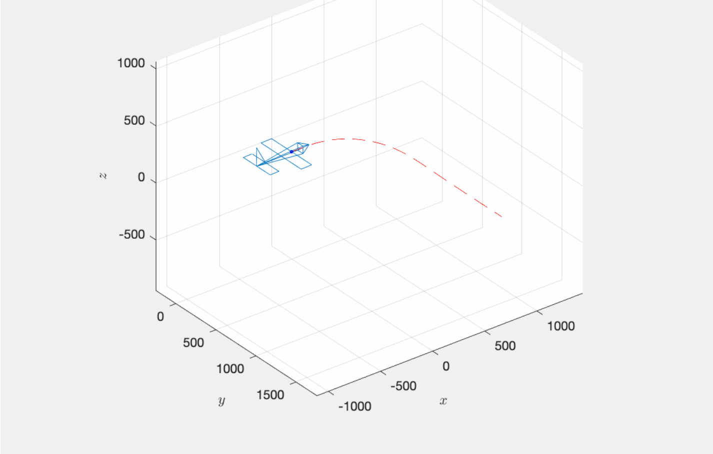
Experiment 2: Bank Right Turn

- Begin in fixed-wing cruise
- Failure/Degrad at 6 seconds
- Perform a right bank turn
- Heavily utilizes effectors in fixed-wing flight regime

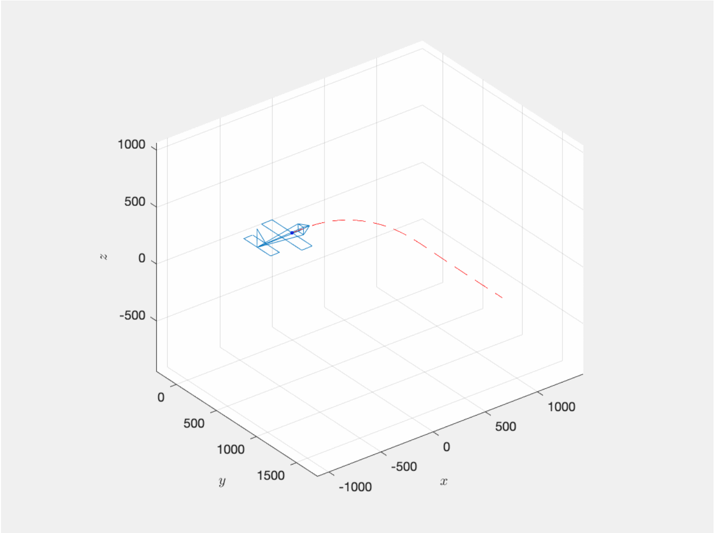




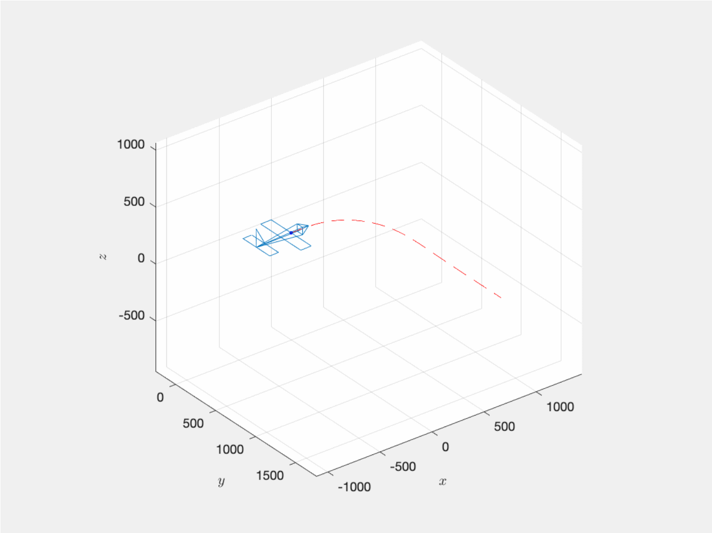
Vehicle discontinues turn after failure



Failure Mid Bank Turn No PDDP



90 % Rudder Degradation



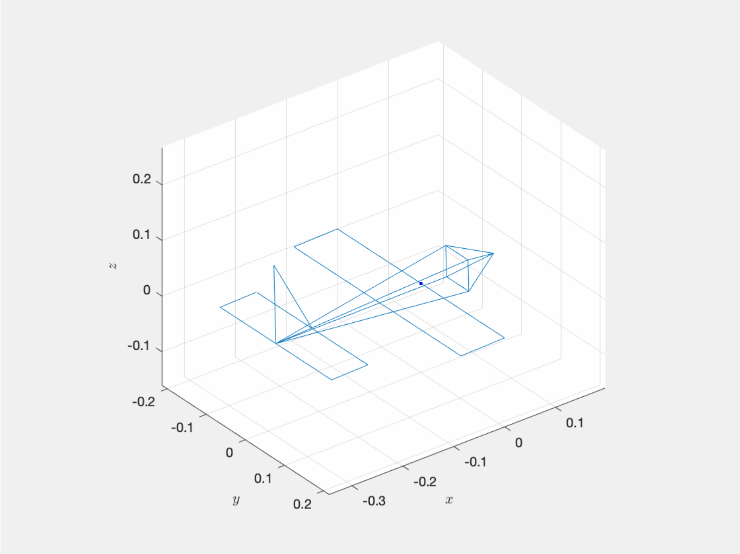
90 % Aileron Degradation

Fault Detection: Split Effector Failure

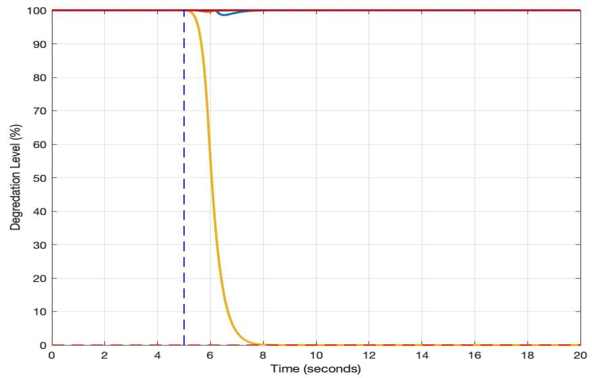
Experiment 3: Split Effector Bank Right

- Previous state configuration for L+C has used ganged effectors
- This experiment added state values of both the LEFT and RIGHT Ailerons
- Added states found to reduce the uncertainty of PDDP's parameter estimation even at small degradation values
- Failure/Degradation of Left Aileron ONLY at 5 seconds for bank right turn experiment
- All experiments capable of replanning a similar trajectory post failure

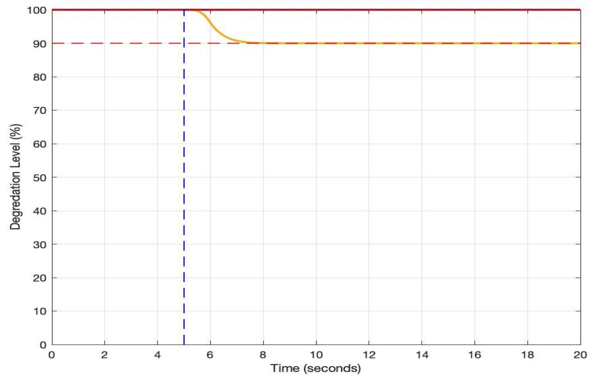
Left Aileron failure Bank Right



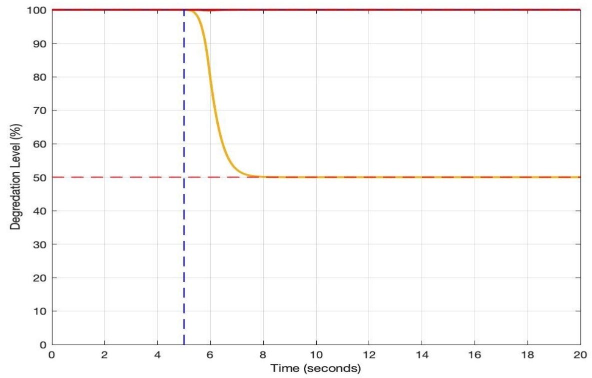
100% Degradation



10% Degradation



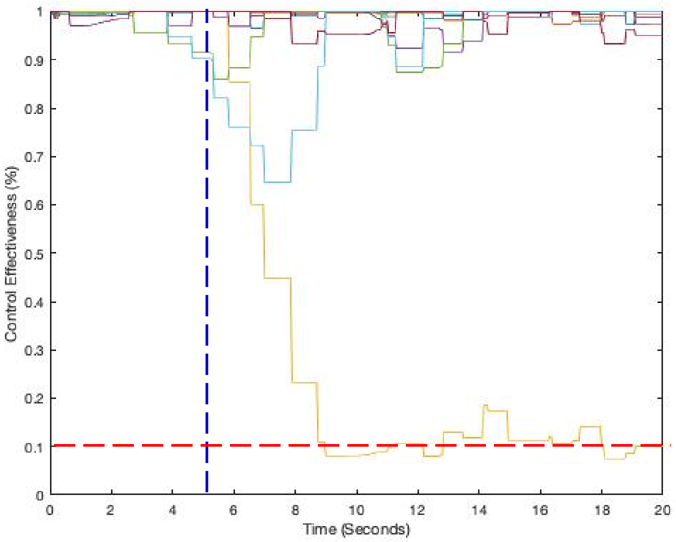
50% Degradation

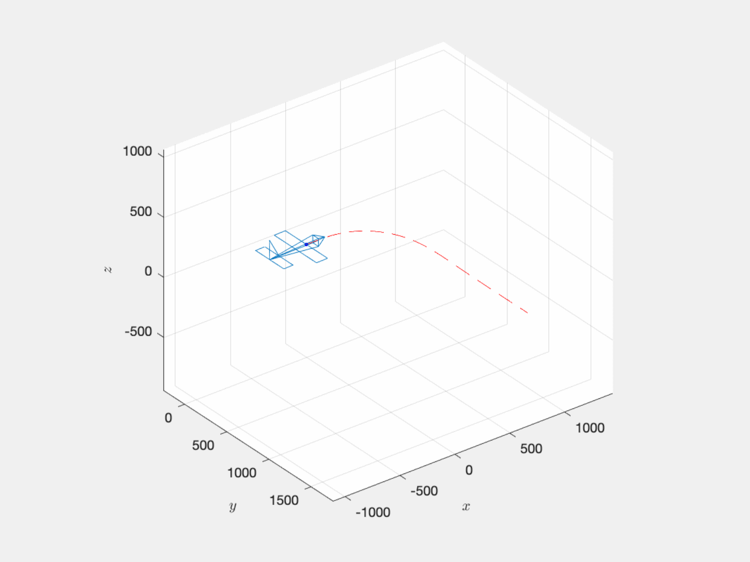


Fault Detection: Estimation with Noise

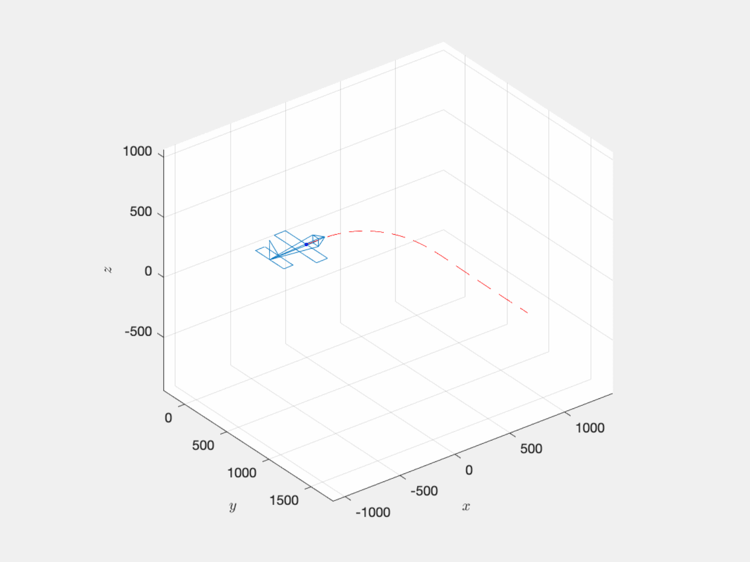
Experiment 3: Bank Right Turn

- Inclusion of process and measurement noise causes non-PDDP informed case to fail
- PDDP successfully maintains vehicle stability and plans trajectory using modified dynamics





90 % Split Aileron Degradation no PDDP



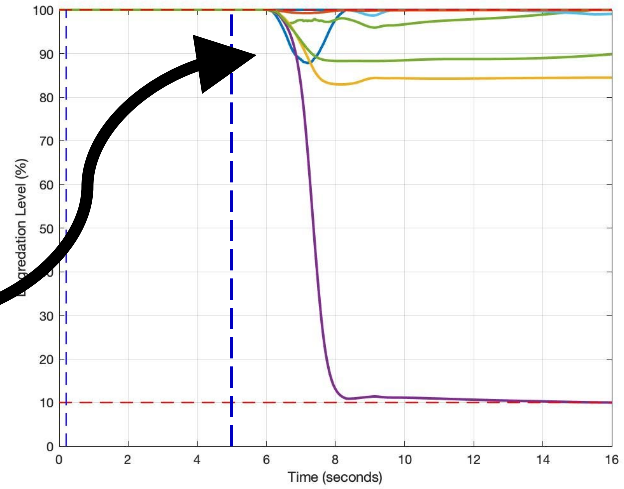
90 % Split Aileron Degradation

Fault Detection: Effect of Split Effector Failure

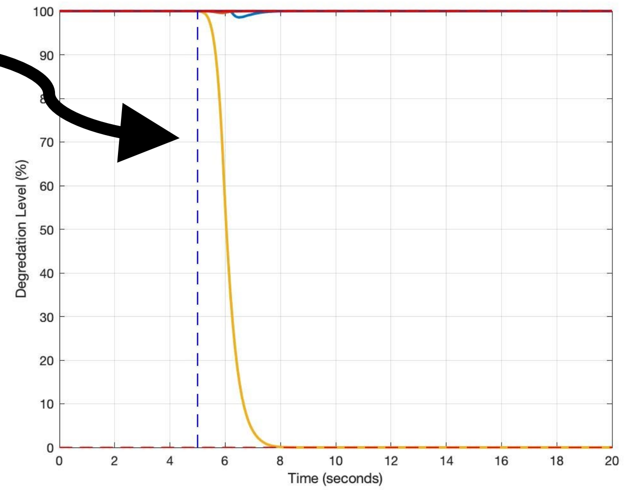
Results

- PDDP effectively utilizes state information to estimate both severe and minimal failures
- PDDP can replan using updated parameters in MPC fashion
- PDDP estimates are improved by utilization of state and the specificity of state information
- PDDP is sensitive enough to inform system ID to minor and major degradation/failures

Note:
Giving PDDP greater access to specific vehicle states improves the distinguishability of fault estimation



90 % Ganged Aileron Degradation



100 % Split Aileron Degradation

Summary - Parameterized Differential Dynamic Programming (PDDP)

- Second-order algorithm derived by extending classical optimal control
- **Convergence guarantees** independent of initialization
- **Co-optimizes** for controls and parameters simultaneously
- **Generalizes** to multiple tasks, including adaptive MPC and switching time optimization
- Enables time-optimal trajectory planning for multimodal systems, including **UAM vehicles**

Application of PDDP – Current experimentation and directions

- **Fault detection** (parameter estimation)
  - Can run both as a full optimal control or strictly in the backward path to identify dynamic degradation
- **Adaptive MPC** - Replanning trajectory to accommodate new identified dynamics
  - Even when vehicle is incapable of following original trajectory new trajectory is planned to attain the original goal as closely as dynamically feasible
- **Switching Time Optimization**
  - **Optimal transition time** between flight regimes (difficult for highly nonlinear vehicles like L+C)
  - **Decreases tuning** work for engineers when planning for common maneuvers that transition between flight regimes
  - Allows for the input and optimization of multiple target states for **long-term planning** and replanning

Questions?

Contact Information:

Irene.M.Gregory@nasa.gov

Adaptive Optimization for System Performance
and
Combined Bernstein Polynomial, Optimal Reciprocal Collision Avoidance, Differential Dynamic Programming for Trajectory Replanning and Collision Avoidance for UAM Vehicles

Matthew Houghton, Michael Acheson, Andrew Patterson, Alex Oshin, Kasey Ackerman, Irene Gregory

NASA Langley Research Center

AIAA Hampton Roads Section Technical Seminar

16 March 2023

Adaptive Optimization for System Performance: Parameterized Differential Dynamic Programming*

Alex Oshin*#, Matthew D. Houghton*, Michael J. Acheson*, Irene M. Gregory* and Evangelos Theodorou#

*NASA Langley Research Center**

Georgia Institute of Technology#

*Oshin, Alexander B., Houghton, Matthew D., Acheson, Michael J., Gregory, Irene M., Theodorou, Evangelos A., "Parameterized Differential Dynamic Programming," In the Proceedings of Robotics: Science and Systems, June 27-July1, 2022, New York, USA.

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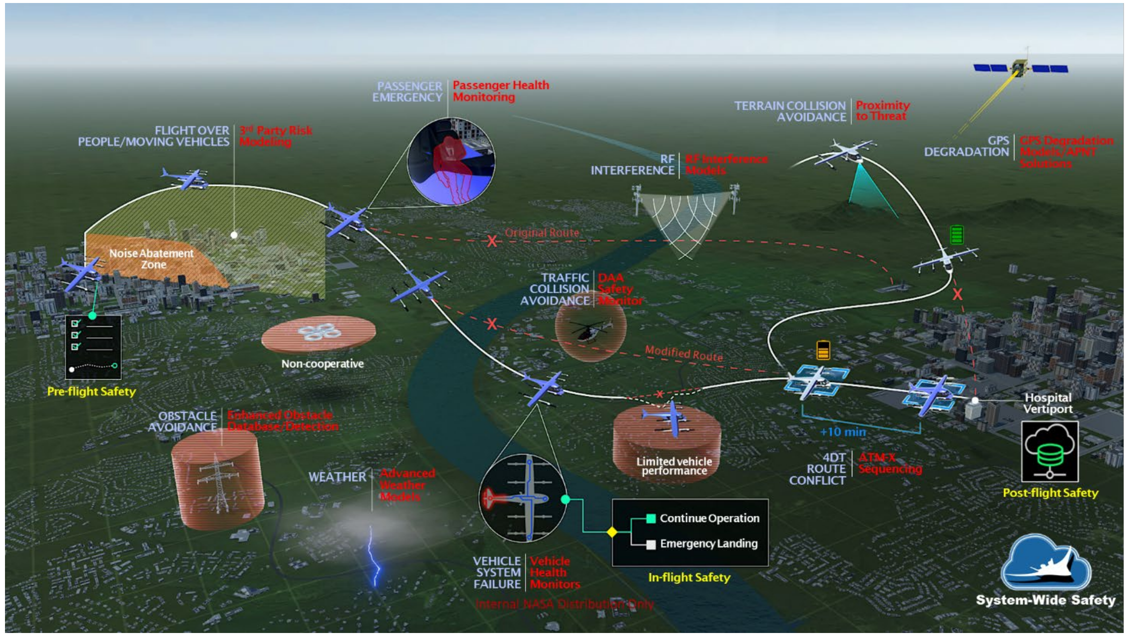

Planner challenges:

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- Accurate trajectory planning & replanning
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- Multiple operational modes and flight regimes
- Transferability to different vehicles

Optimal Trajectory Problem

Problem: Find optimal control (and states) to achieve a desired end state while minimizing cost

Discrete system nonlinear dynamics

$$\mathbf{x}_{t+1} = \mathbf{f}(\mathbf{x}_t, \mathbf{u}_t)$$

State Vector

$$\mathbf{x}_t \in \mathbb{R}^n$$

Control Vector

$$\mathbf{u}_t \in \mathbb{R}^m$$

Cost Function

$$\mathcal{J}(\mathbf{U}) = \sum_{t=1}^{T-1} \mathcal{L}(\mathbf{x}_t, \mathbf{u}_t) + \phi(\mathbf{x}_T)$$

Running Cost

$$\mathcal{L}(\mathbf{x}_t, \mathbf{u}_t)$$

Terminal Cost

$$\phi(\mathbf{x}_T)$$

State Trajectory

$$\mathbf{X} := \{\mathbf{x}_1, \ldots, \mathbf{x}_T\}$$

Control Trajectory

$$\mathbf{U} := \{\mathbf{u}_1, \ldots \mathbf{u}_{T-1}\}$$

Finite Time

$$T \in \mathbb{N}^+$$

Differential Dynamic Programming

DDP: Given nominal trajectory, use linear (or quadratic) approx. of system nonlinear dynamics and quadratic approx. of cost to yield updates to optimal controls that quadratically converge

Cost Function

$$\mathcal{J}_i(\mathbf{x}_i, \mathbf{U}_i) := \sum_{t=i}^{T-1} \mathcal{L}(\mathbf{x}_t, \mathbf{u}_t) + \phi(\mathbf{x}_T)$$

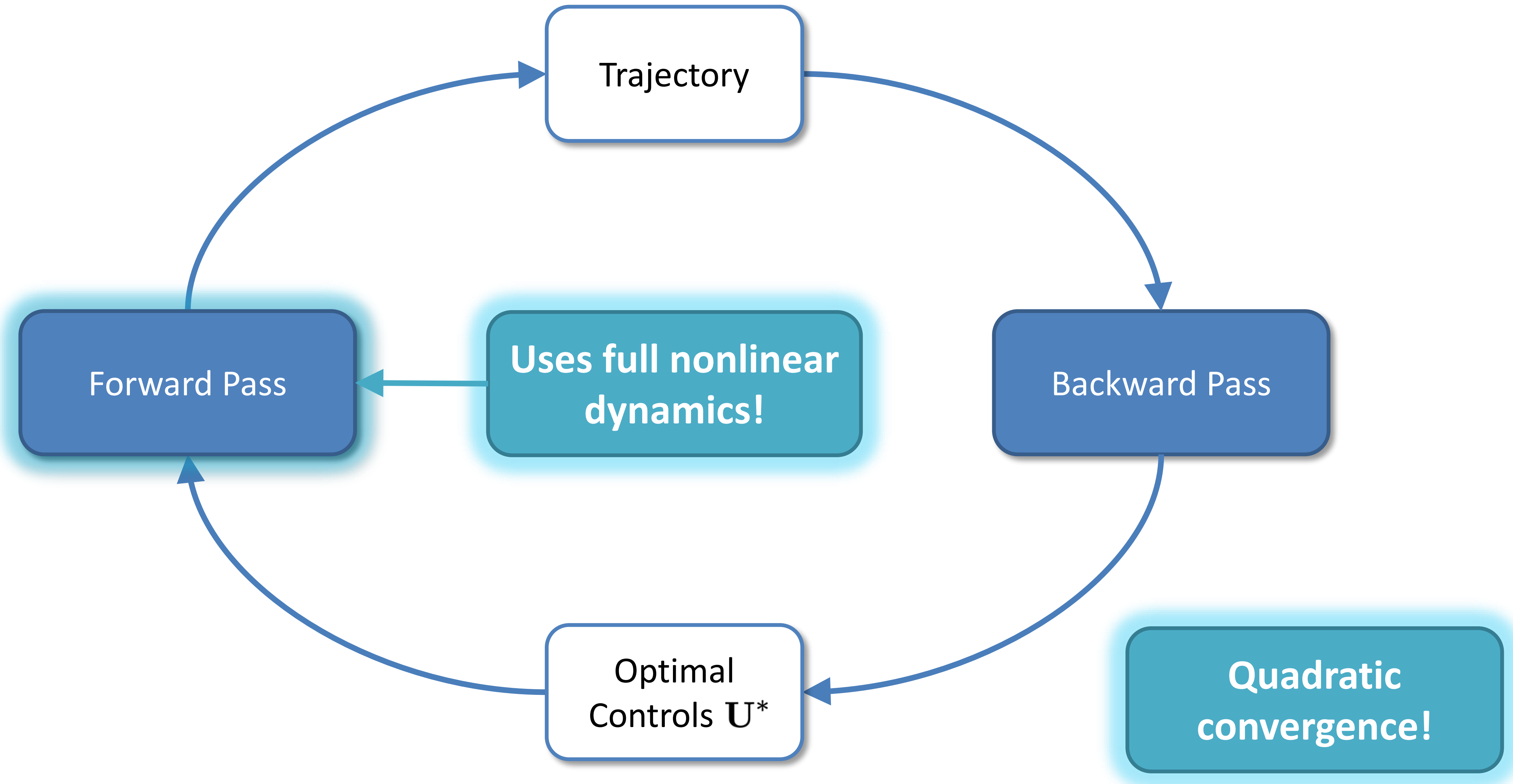
Truncated Control Sequence

$$\mathbf{U}_i := \{\mathbf{u}_i, \ldots, \mathbf{u}_{T-1}\}$$

Bellman's Principle of Optimality: find overall optimal control as sequence minimization for each truncated control sequence backwards in time (cost-to-go)

$$V(\mathbf{x}_i) = \min_{\mathbf{u}_i} \Big[\underbrace{\mathcal{L}(\mathbf{x}_i, \mathbf{u}_i) + V(\mathbf{x}_{i+1})}_{Q(\mathbf{x}_i, \mathbf{u}_i)} \Big]$$

Differential Dynamic Programming (DDP)



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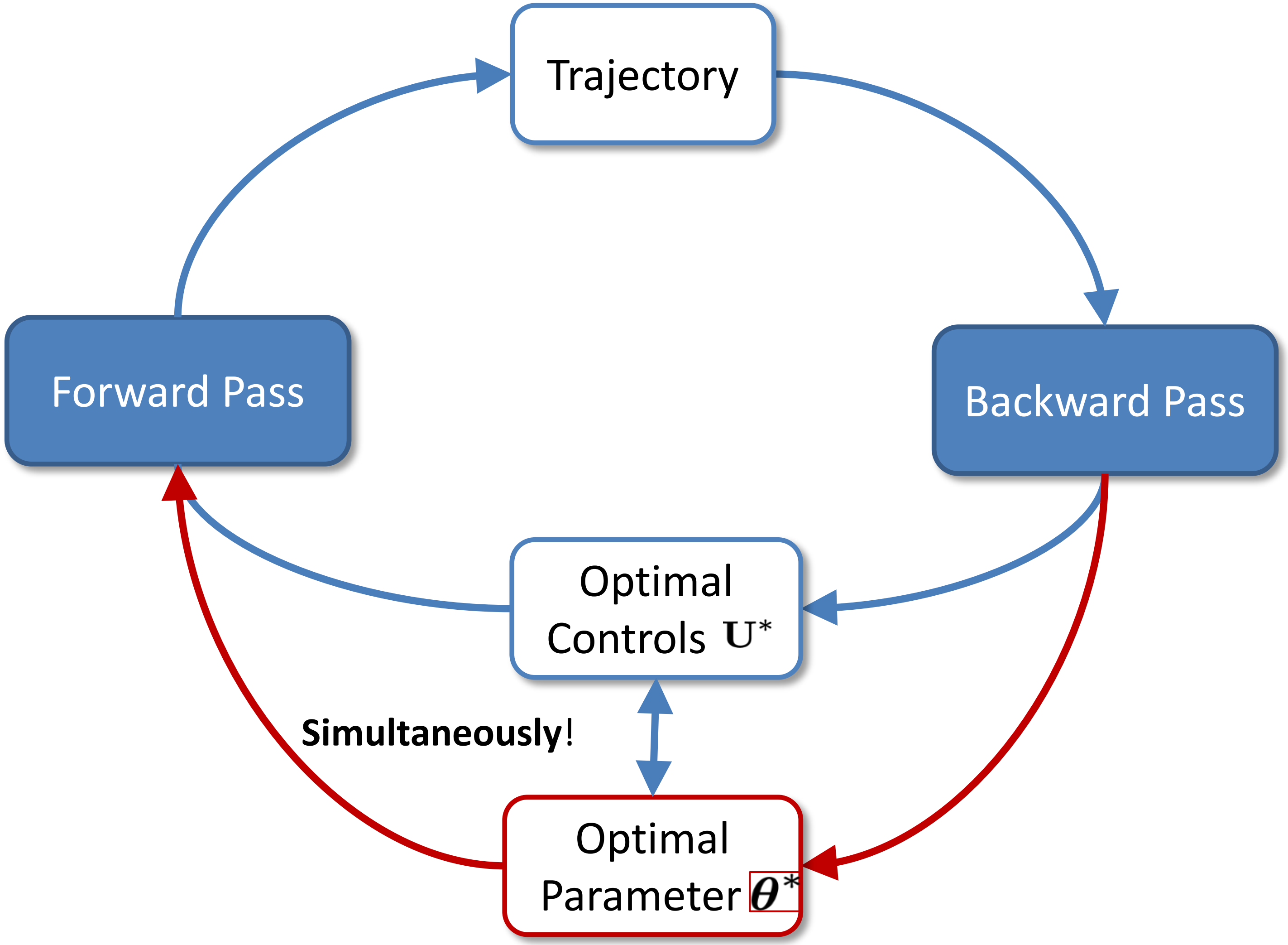
- **Generalizes** to multiple tasks, including adaptive MPC and switching time optimization
- Enables time-optimal trajectory planning for multimodal systems, including **UAM vehicles**

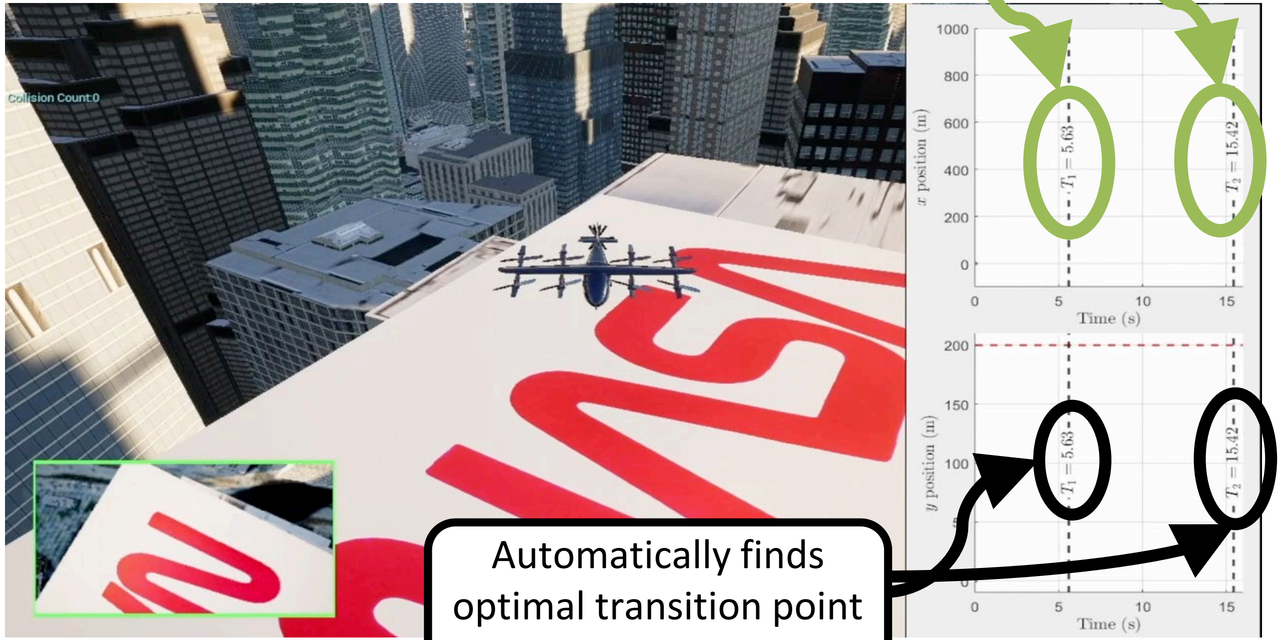


* Oshin, A., Houghton, M., Acheson, M., Gregory, I., and Theodorou, E., "Parameterized Differential Dynamic Programming," *Proceedings of Robotics: Science and Systems*, New York City, NY, USA, 2022. https://doi.org/10.15607/RSS.2022.XVIII.046.

PDDP Applications

Switching Time Optimization

Avoids manual tuning of terminal times!

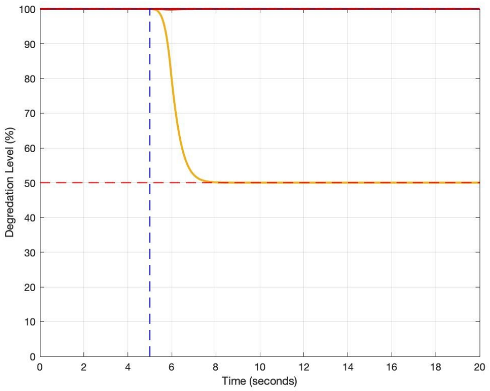


Automatically finds optimal transition point between modes!

Adaptive Model Predictive Control

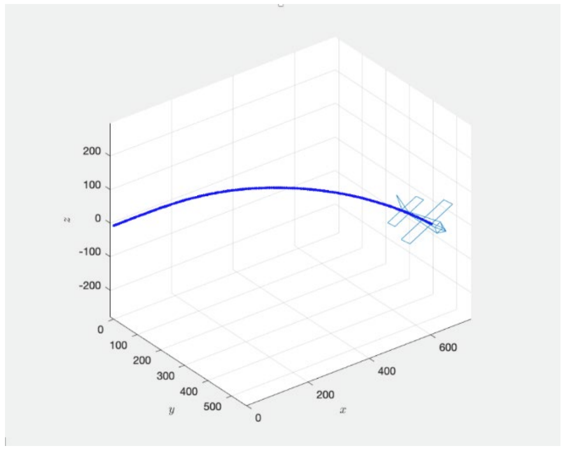
Moving Horizon Estimation

Maximize likelihood of observed states



Model Predictive Control

Plan future trajectory



PDDP Transition Optimization

- Long-term planning requires the L+C vehicle to change operating modes from hover to forward flight. Classical trajectory planning methods struggle with determining how to transition between modes.
- PDDP L+C experiment involves vertical takeoff into cruise transition with multiple target states.
- Switching Time Optimization selects the **optimal transition** times between targets and flight regimes (without direct input from researchers).

Multimodal System

$$\dot{\mathbf{x}}(t) = \mathbf{f}^{(i)}(\mathbf{x}(t), \mathbf{u}(t))$$

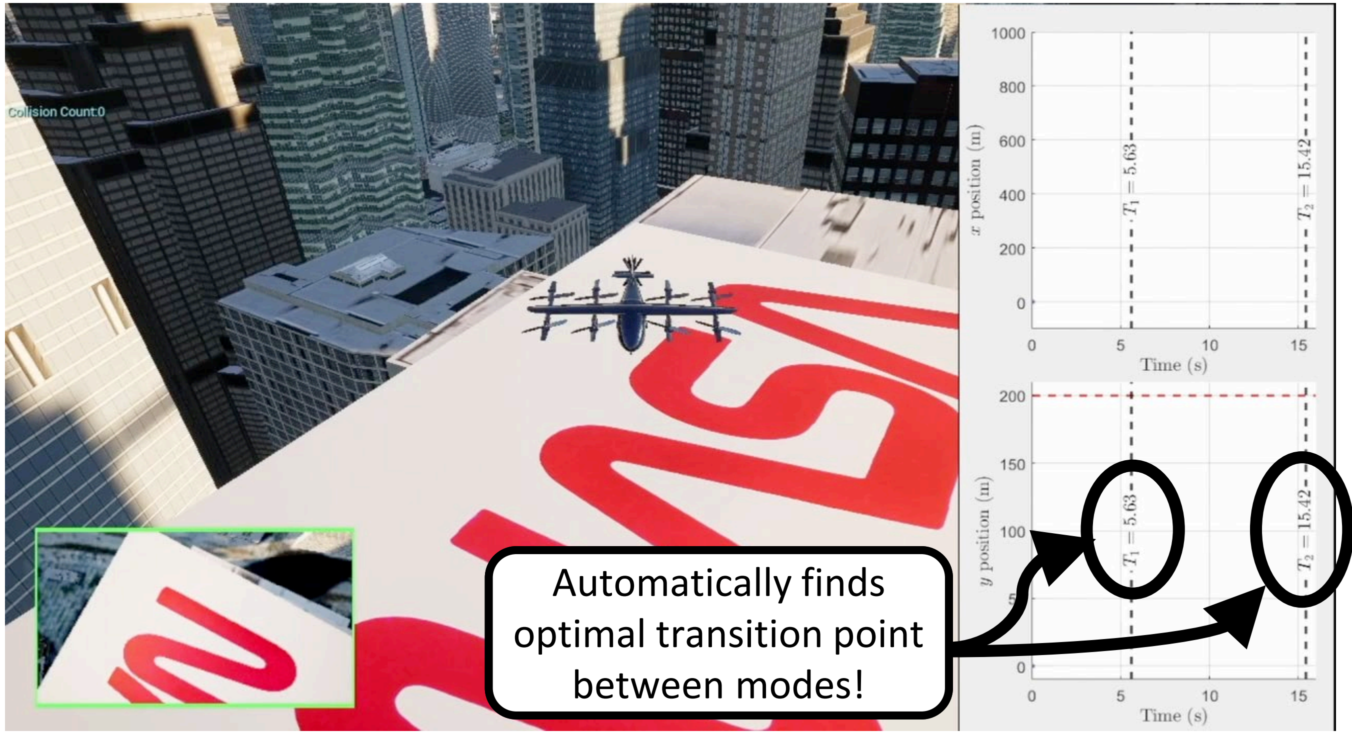
$$i = 1, 2, \ldots, N$$

Switching Time System

$$\mathbf{x}_{t+1} = \mathbf{x}_t + \theta_i \mathbf{f}^{(i)}(\mathbf{x}_t, \mathbf{u}_t)\Delta t$$

$$\sum_{t=T_{i-1}+1}^{T_i} \theta_i \mathcal{L}^{(i)}(\mathbf{x}_t, \mathbf{u}_t) + \phi^{(i)}(\mathbf{x}_{T_i+1})$$

$$i = 1, 2, \ldots, N$$



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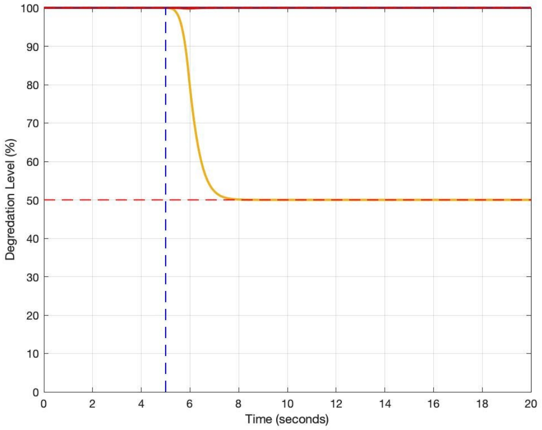

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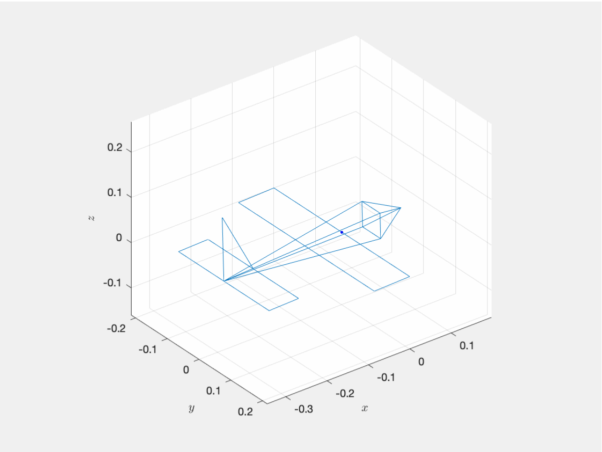
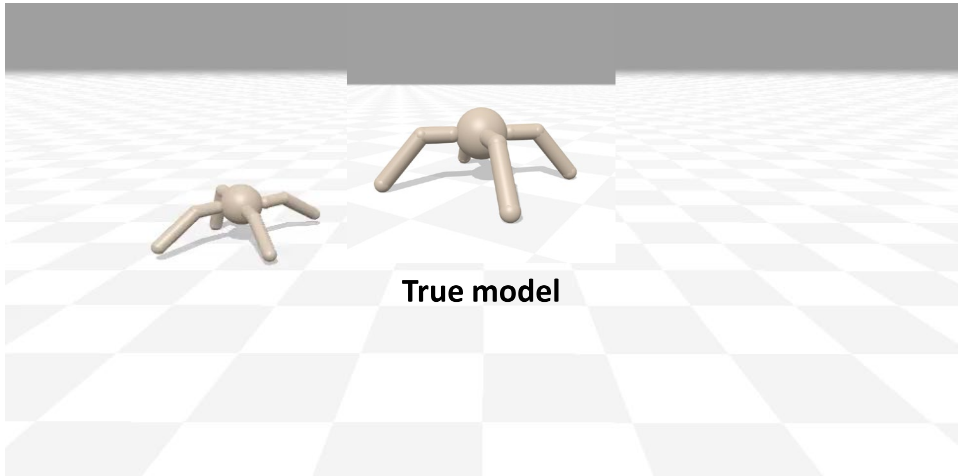


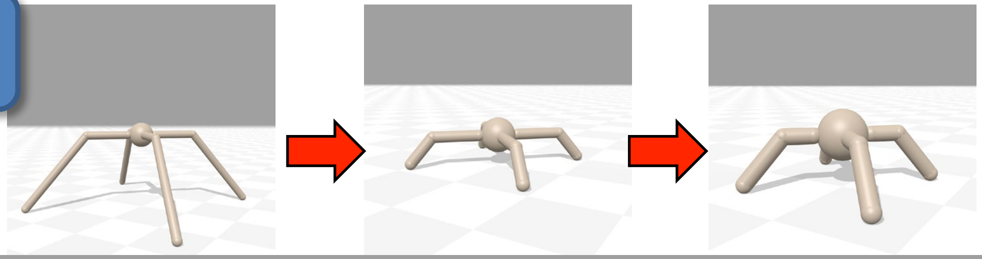
PDDP: Adaptive MPC

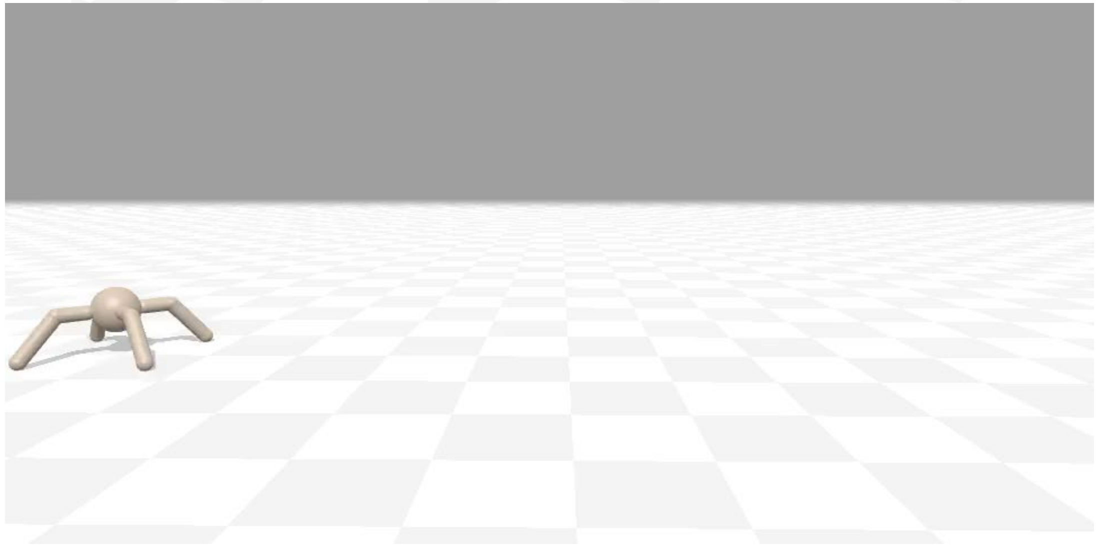
DDP planning on model with incorrect parameters



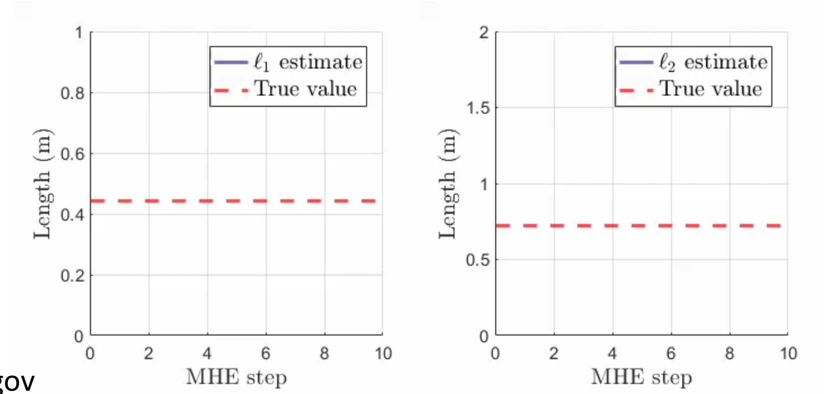
Executing plan on true model: Failure

Ant





PDDP with adaptive control: Success



Parameterized Differential Dynamic Programming (PDDP)

PDDP is a trajectory optimization algorithm that builds upon DDP

- Enables the **co-optimization** of a **trajectory** and time invariant **parameters** in the same process.
- Parameters can be extremely diverse and goal specific
- Experiments tested PDDP's ability to successfully **estimate vehicle dynamic parameters** while implementing **optimal trajectories**, resulting in Adaptive Model Predictive Control

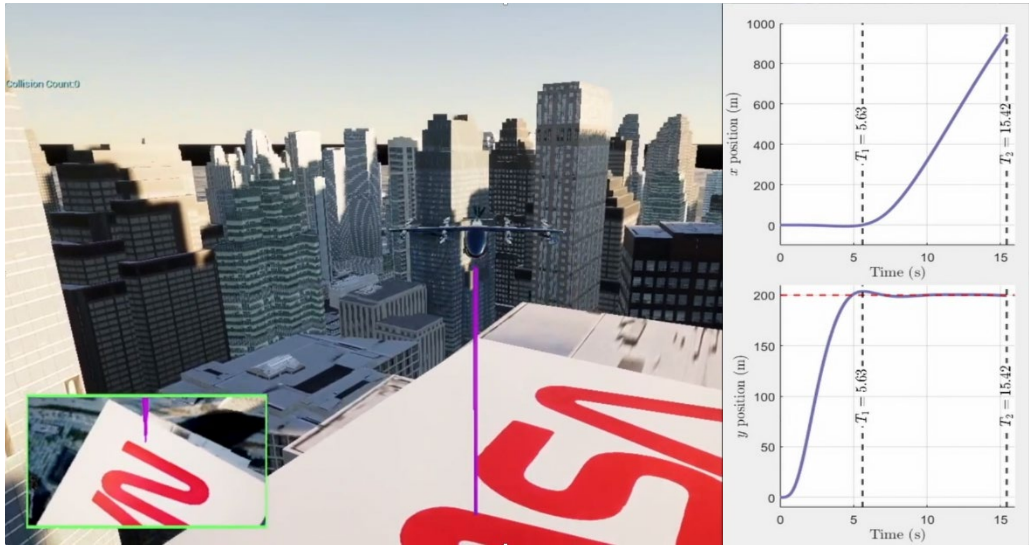
Fault Detection

- Online estimation of vehicle **dynamic** parameters
- **Online estimation** of **degradation** level for effectors + rotors
- **Replan trajectory** based on new estimation of vehicle parameters
- Deviations in estimation from norms can alert system ID of vehicle to run further diagnostics of vehicle health

PDDP Applications

Switching Time Optimization

Avoids manual tuning of terminal times!



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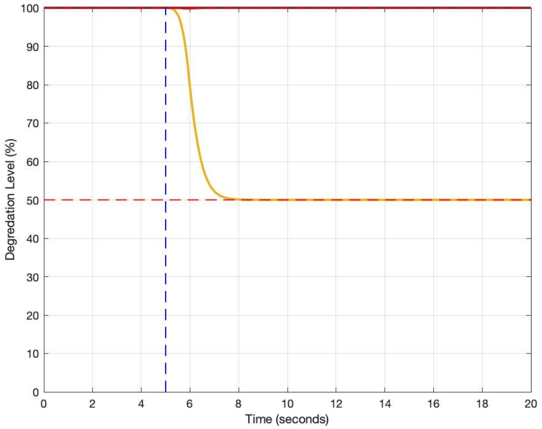
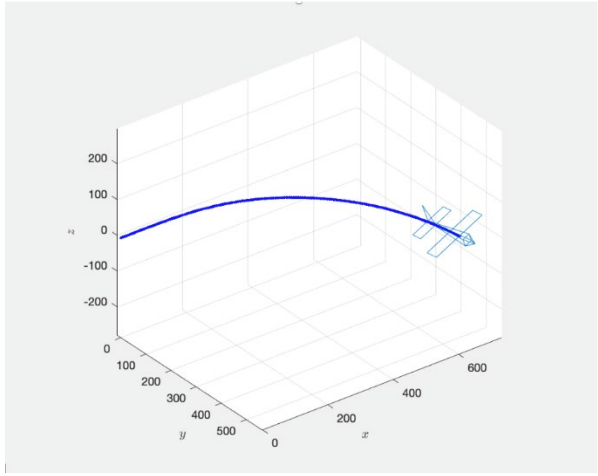


Model Predictive Control

Plan future trajectory

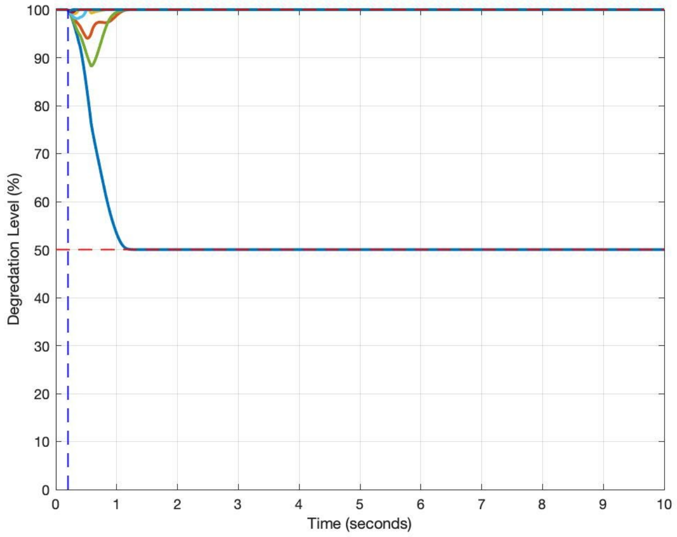


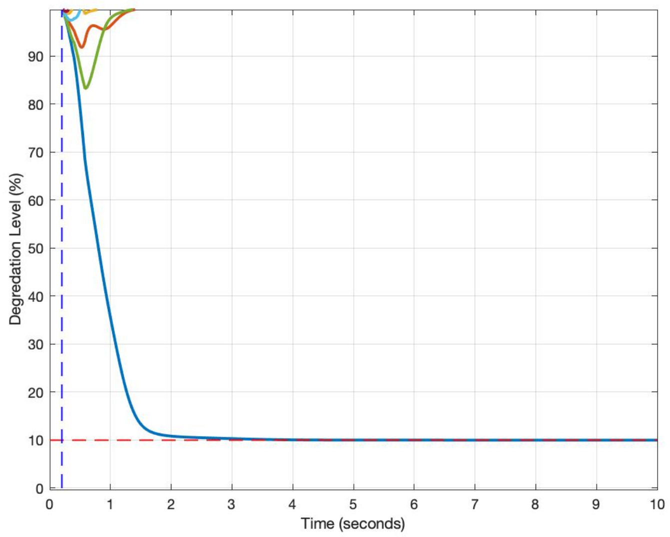
Fault Detection: Rotor Failure

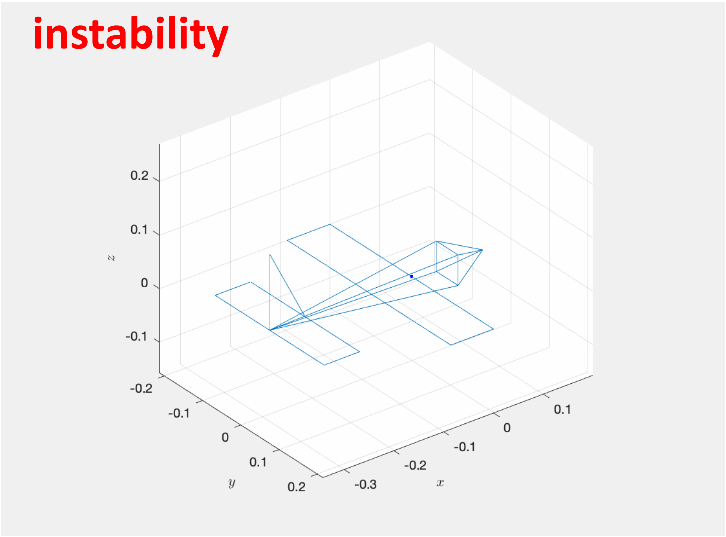
PDDP extends to Fault Detection of vehicle states (rotors and effectors)

<u>Experiment 1: Vertical Takeoff</u>

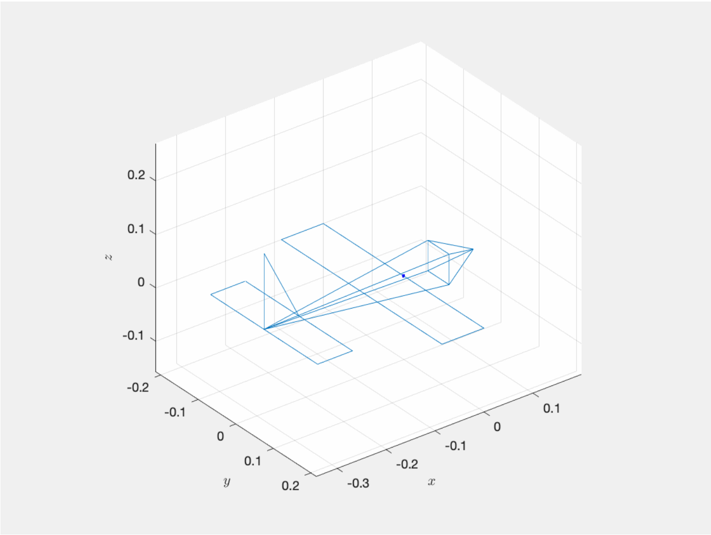
- Begin in hover
- Early Failure/Degradation
- Ascent to 200 ft
- Heavily utilizes rotors in VTOL flight regime



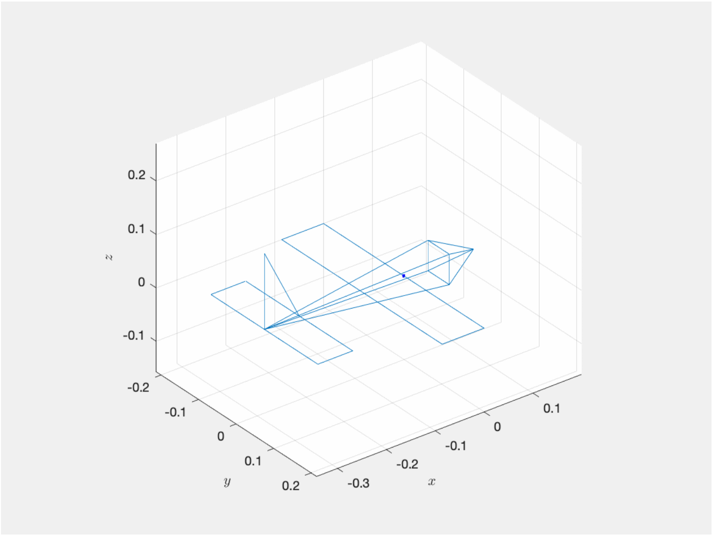




Takeoff Failure Without PDDP



50 % Rotor 1 Degradation



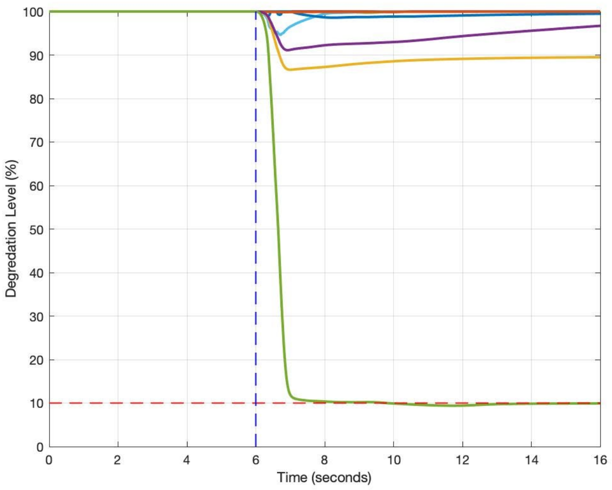
90 % Rotor 1 Degradation

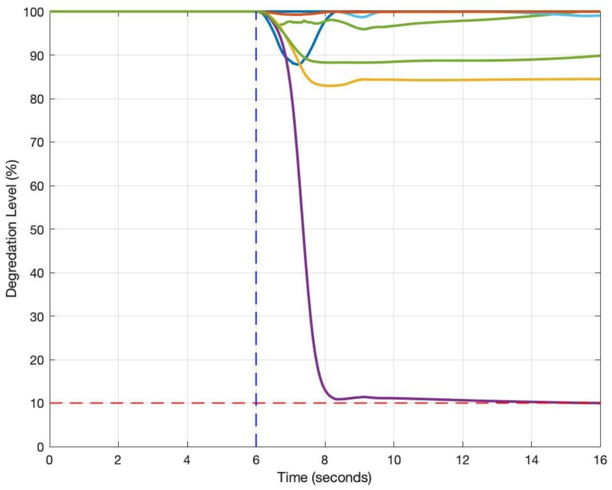
NASA - Irene M Gregory@nasa.gov

Fault Detection: Effectors

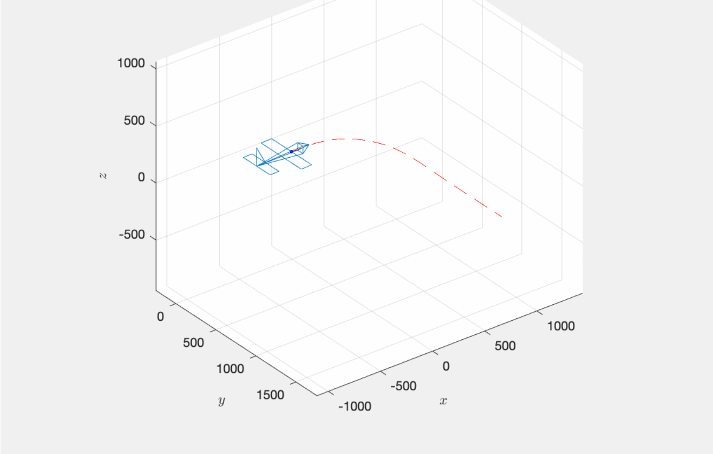
Experiment 2: Bank Right Turn

- Begin in fixed-wing cruise
- Failure/Degradation at 6 seconds
- Perform a right bank turn
- Heavily utilizes effectors in fixed-wing flight regime

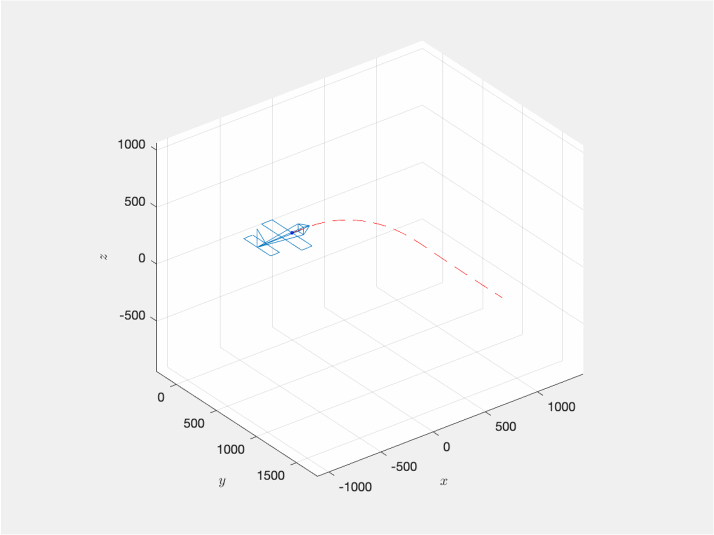




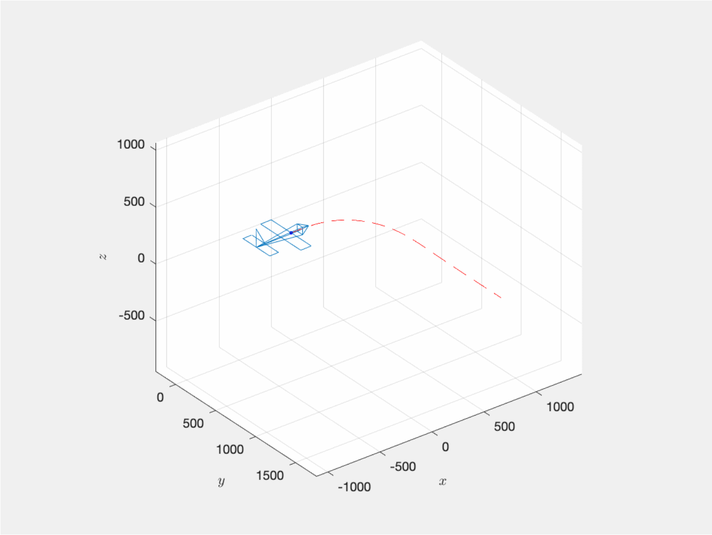
Vehicle discontinues turn after failure



Failure Mid Bank Turn No PDDP



90 % Rudder Degradation



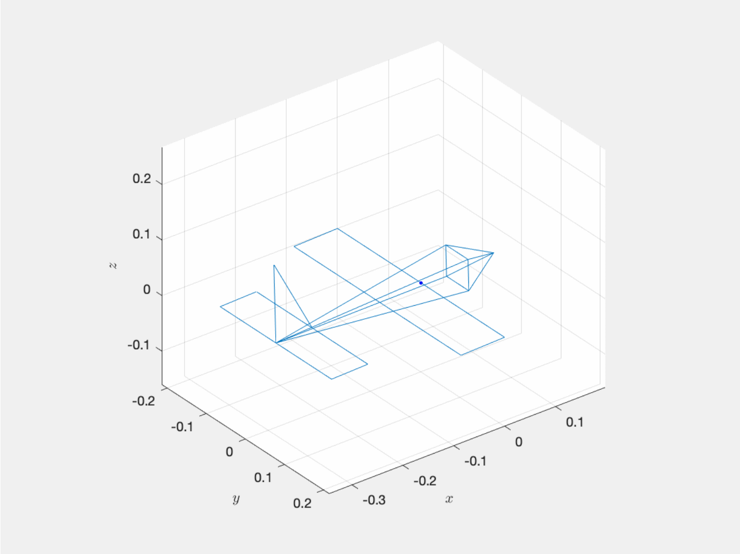
90 % Aileron Degradation

Fault Detection: Split Effector Failure

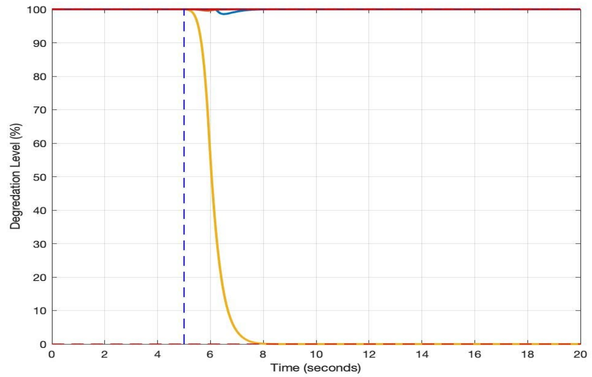
Experiment 3: Split Effector Bank Right

- Previous state configuration for L+C has used ganged effectors
- This experiment added state values of both the LEFT and RIGHT Ailerons
- Added states found to reduce the uncertainty of PDDP's parameter estimation even at small degradation values
- Failure/Degradation of Left Aileron ONLY at 5 seconds for bank right turn experiment
- All experiments capable of replanning a similar trajectory post failure

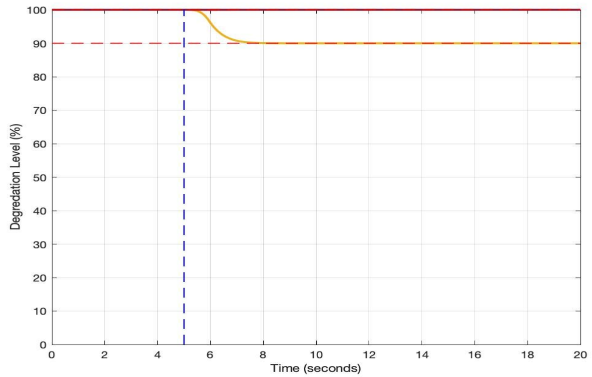
Left Aileron failure Bank Right



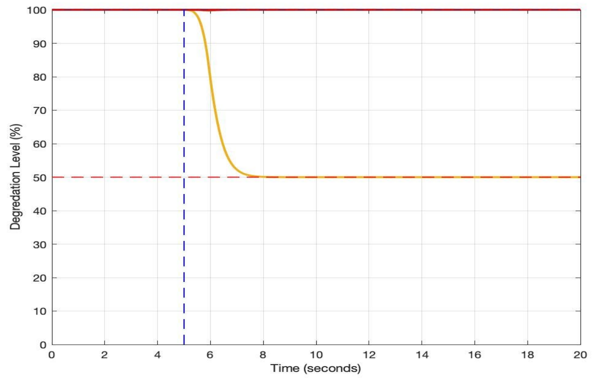
100% Degradation



10% Degradation



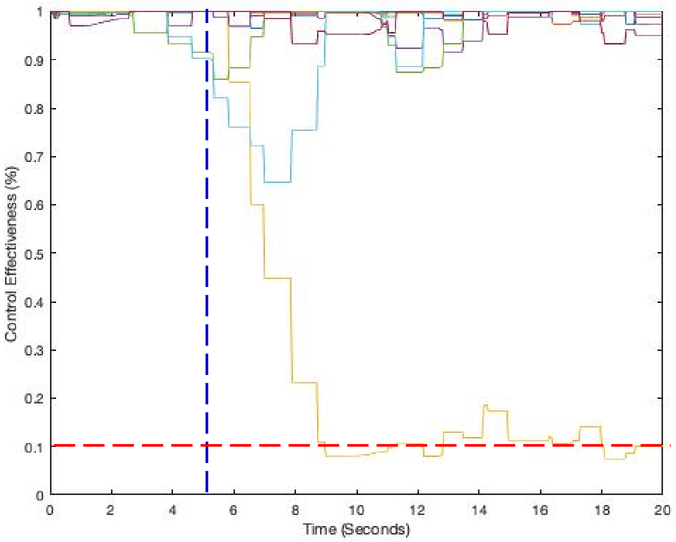
50% Degradation

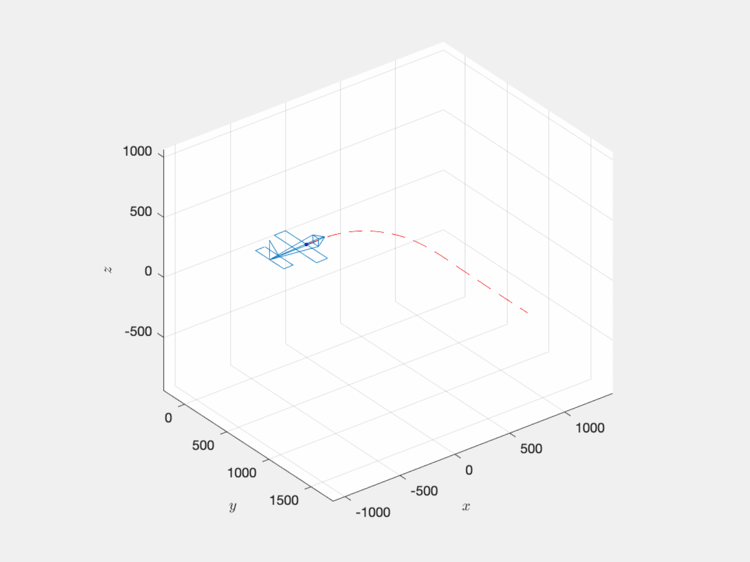


Fault Detection: Estimation with Noise

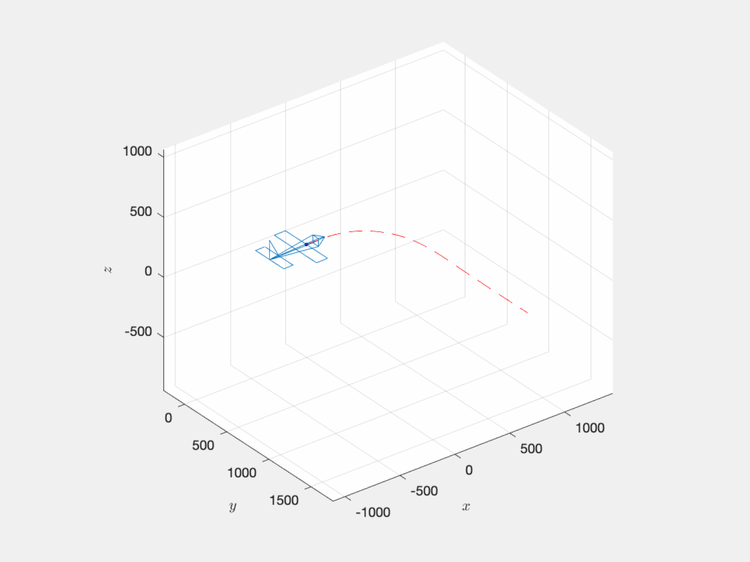
Experiment 3: Bank Right Turn

- Inclusion of process and measurement noise causes non-PDDP informed case to fail
- PDDP successfully maintains vehicle stability and plans trajectory using modified dynamics





90 % Split Aileron Degradation no PDDP



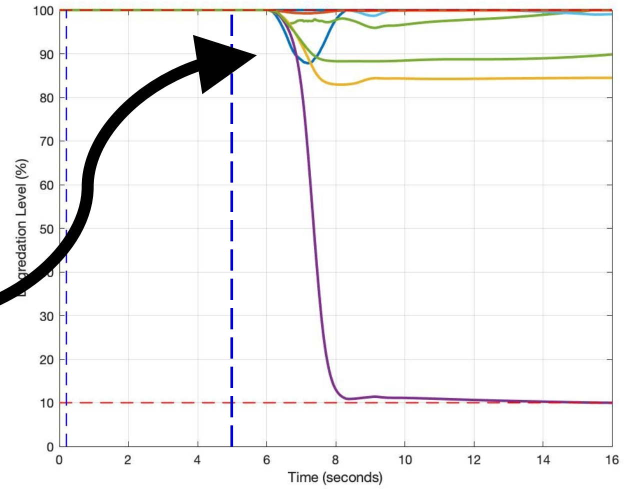
90 % Split Aileron Degradation

Fault Detection: Effect of Split Effector Failure

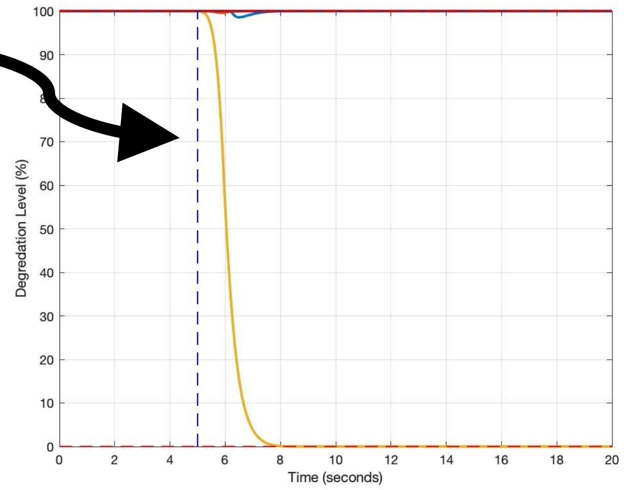
<u>Results</u>

- PDDP effectively utilizes state information to estimate both severe and minimal failures
- PDDP can replan using updated parameters in MPC fashion
- PDDP estimates are improved by utilization of state and the specificity of state information
- PDDP is sensitive enough to inform system ID to minor and major degradation/failures

Note:
Giving PDDP greater access to specific vehicle states improves the distinguishability of fault estimation



90 % Ganged Aileron Degradation



100 % Split Aileron Degradation

Summary - Parameterized Differential Dynamic Programming (PDDP)

- Second-order algorithm derived by extending classical optimal control
- **Convergence guarantees** independent of initialization
- **Co-optimizes** for controls and parameters simultaneously
- **Generalizes** to multiple tasks, including adaptive MPC and switching time optimization
- Enables time-optimal trajectory planning for multimodal systems, including **UAM vehicles**

Application of PDDP – Current experimentation and directions

- **Fault detection** (parameter estimation)
  - Can run both as a full optimal control or strictly in the backward path to identify dynamic degradation
- **Adaptive MPC** - Replanning trajectory to accommodate new identified dynamics
  - Even when vehicle is incapable of following original trajectory new trajectory is planned to attain the original goal as closely as dynamically feasible
- **Switching Time Optimization**
  - **Optimal transition time** between flight regimes (difficult for highly nonlinear vehicles like L+C)
  - **Decreases tuning** work for engineers when planning for common maneuvers that transition between flight regimes
  - Allows for the input and optimization of multiple target states for **long-term planning** and replanning

Combined Bernstein Polynomial, Optimal Reciprocal Collision Avoidance, Differential Dynamic Programming for Trajectory Replanning and Collision Avoidance for UAM Vehicles*

Matthew Houghton, Michael Acheson, Andrew Patterson, Alex Oshin, Irene Gregory

NASA Langley Research Center

*Houghton, Matthew D., Acheson, Michael A., Oshin, Patterson, Andrew P., Alexander B., Gregory, Irene M., "Combined Bernstein Polynomial, Optimal Reciprocal Collision Avoidance, Differential Dynamic Programming for Trajectory Replanning and Collision Avoidance for UAM Vehicles" 2023 AIAA SciTech Forum, National Harbor, MD, January 2023. AIAA-2023-2544

Outline

- Motivation: Trajectory Replanning and Collision Avoidance for VTOL vehicles with highly nonlinear dynamics are slow and computationally costly
- COBRA-DDP proposed
  - Bernstein Polynomials
  - Optimal Reciprocal Collision Avoidance
  - Differential Dynamic Programming
- Experiments:
  - Sample Results demonstrating the algorithm
- Conclusions and Ongoing Work

Lift + Cruise VTOL Vehicle

(CO)mbined (B)ernstein Polynomial, Optimal (R)eciprocal Collision (A)voidance DDP

Trajectory Re-planner Requirements:

- "Real-time" dynamically feasible trajectories for UAM class (transitioning) vehicles with separation assurances
- Dynamic planning for large number of (stationary & moving) cooperative/uncooperative obstacles

Piecewise Bernstein Polynomial Curves:

- Advantages: Fast and compact trajectory representation, smooth derivatives (position, velocity & acceleration)
- Disadvantages: one piece-wise segment can't represent all curves exactly (e.g., circular arcs)

Optimal Reciprocal Collision Avoidance (ORCA):

- Advantages: fast computation for large number of cooperative/non-cooperative with separation assurances
- Disadvantages: no assurance of dynamic feasibility

Differential Dynamic Programming (DDP):

- Advantages: fast computation of dynamically feasible optimal trajectories
- Disadvantages: Degraded computation speed for incorporation of state constraints (e.g., obstacles)

Combine to get best of each algorithm!

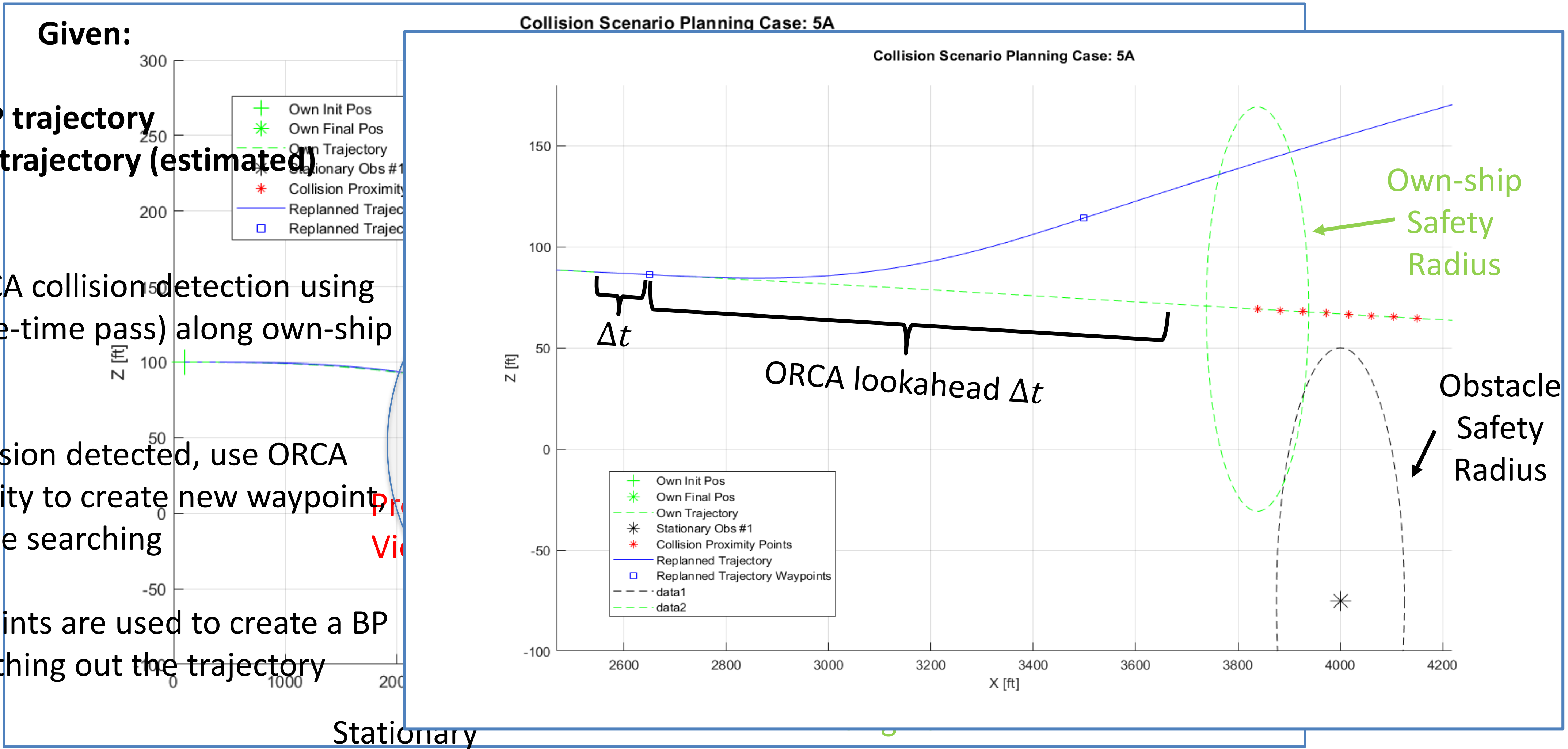
Integration: ORCA + Bernstein Polynomials

Goal: Modify own-ship BP trajectory to ensure smooth collision avoidance

Given:

- **Own-ship BP trajectory**
- **Obstacle BP trajectory (estimated)**

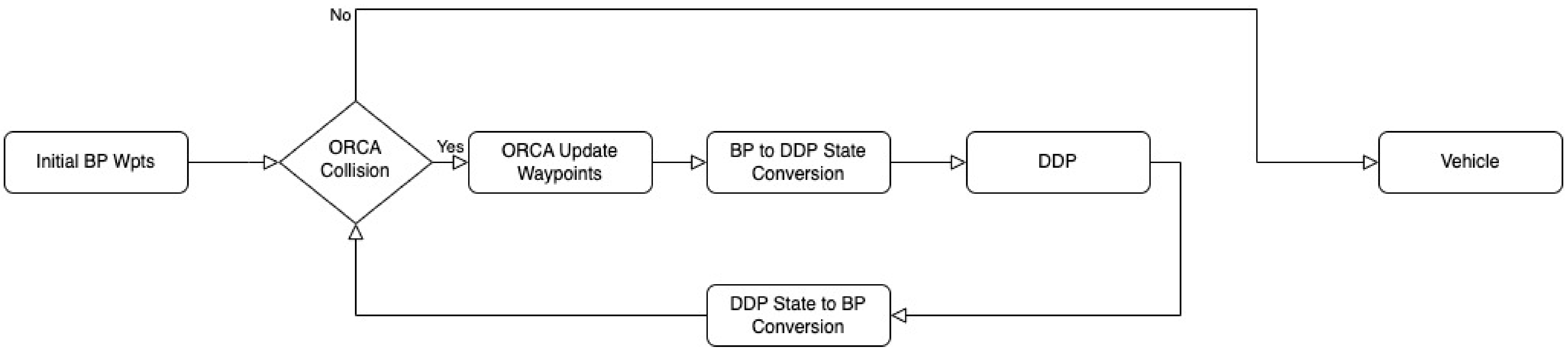
- Perform ORCA collision detection using Δt steps (one-time pass) along own-ship trajectory
- Pending collision detected, use ORCA output velocity to create new waypoint, then continue searching
- ORCA waypoints are used to create a BP curve, smoothing out the trajectory



Stationary Obstacle

Trajectory

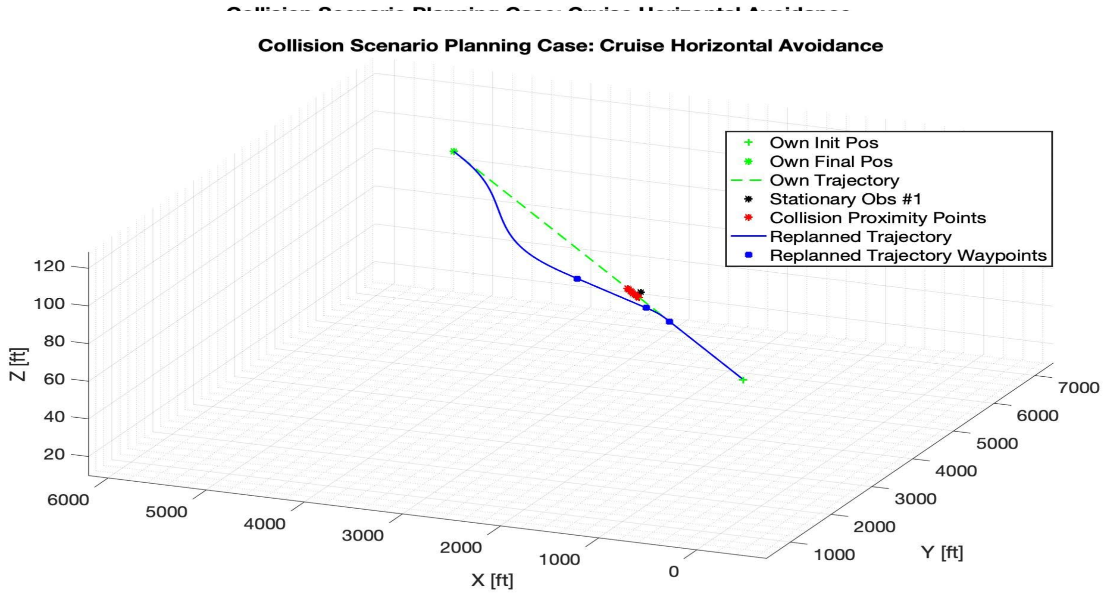
Algorithm Implementation

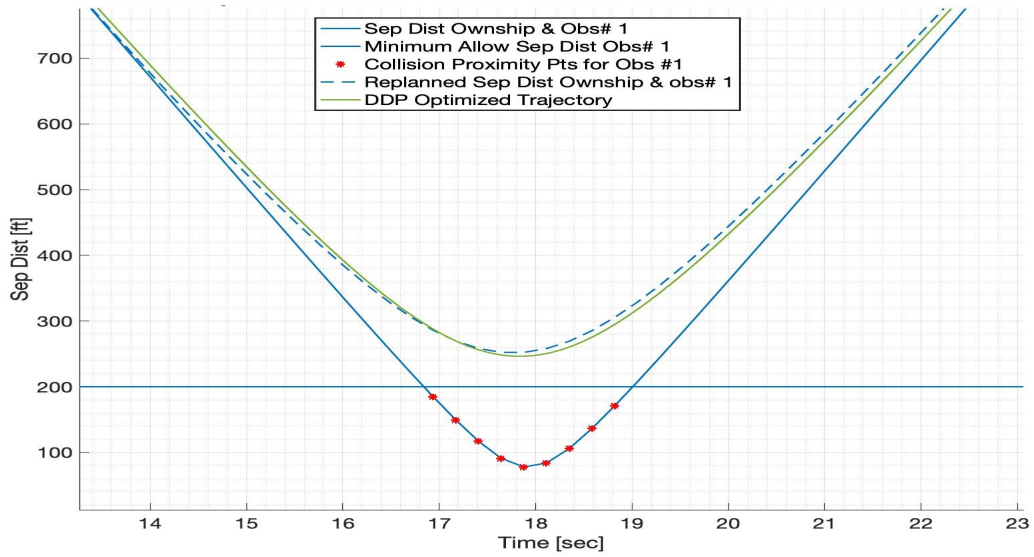


- Leverages ORCA fast collision avoidance checks and preferential avoidance direction selection
- BP's serve as compact trajectory representation between ORCA and DDP that can be quickly evaluated at any time along the curve
- DDP provides dynamically feasible optimal trajectories given simplified ORCA information

Cruise to Horizontal Maneuver

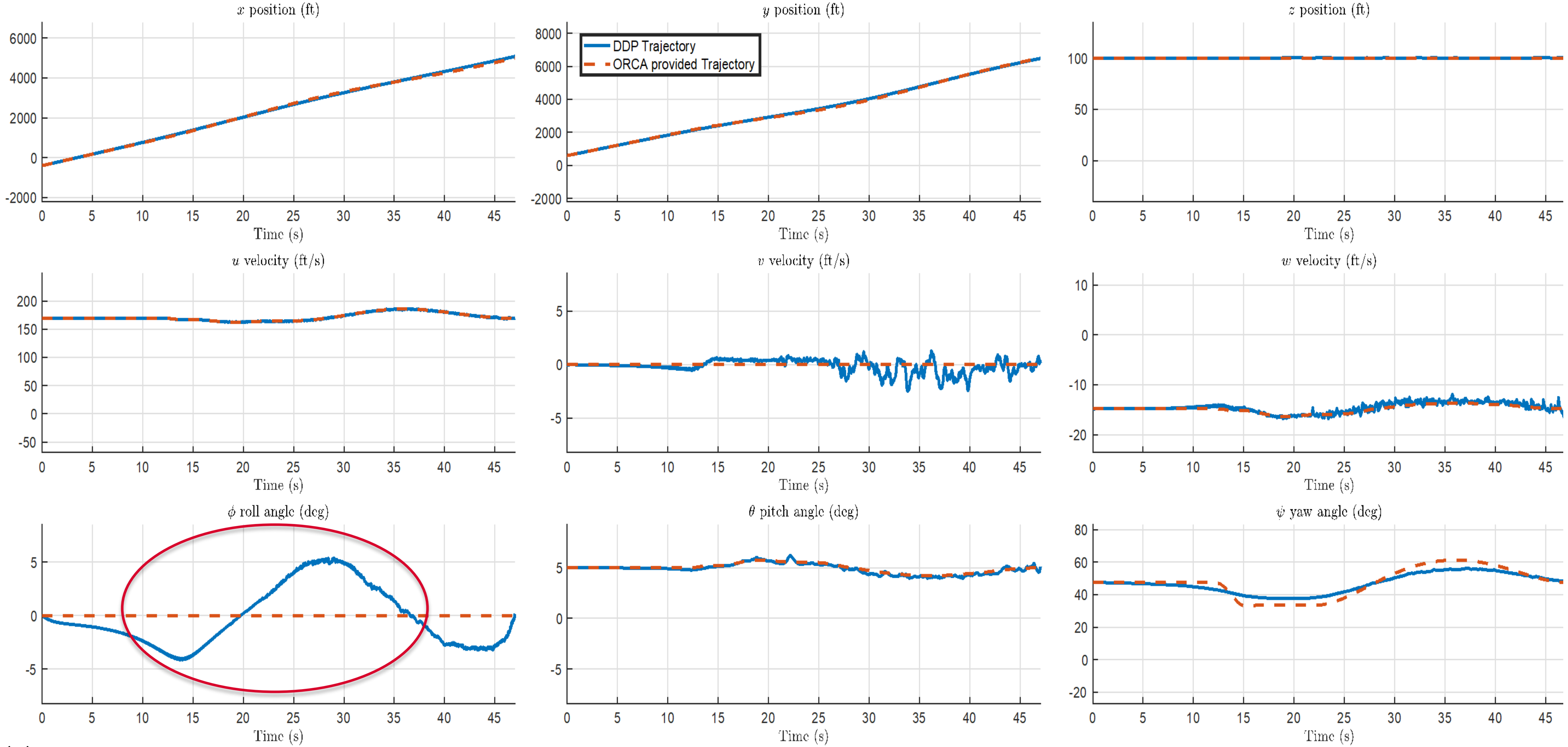
- 170 ft/s cruise with 200 ft safety radius
- Static obstacle 75 ft to the right
- Recognition of safety radius breach
- ORCA recalculates, maintains safety radius
- ORCA waypoints converted into BP curves
- BP curves integrated with trim knowledge and passed to DDP
- DDP optimized new trajectory avoids obstacle





Cruise to Horizontal Maneuver

DDP was provided wing-level cruise trim values for suggested trajectory



Conclusions and Ongoing Work:

- BP curves serve as an effective transfer of trajectory information between ORCA and DDP
- COBRA-DDP plans dynamically feasible collision avoiding trajectories and can select preferential avoidance direction
- COBRA-DDP can enhance the optimization of other state-constrained optimizers

Comparison of Acoustic Models and Trajectory Generation Methods for an Acoustically-Aware Aircraft*

Kasey A. Ackerman and Irene M. Gregory

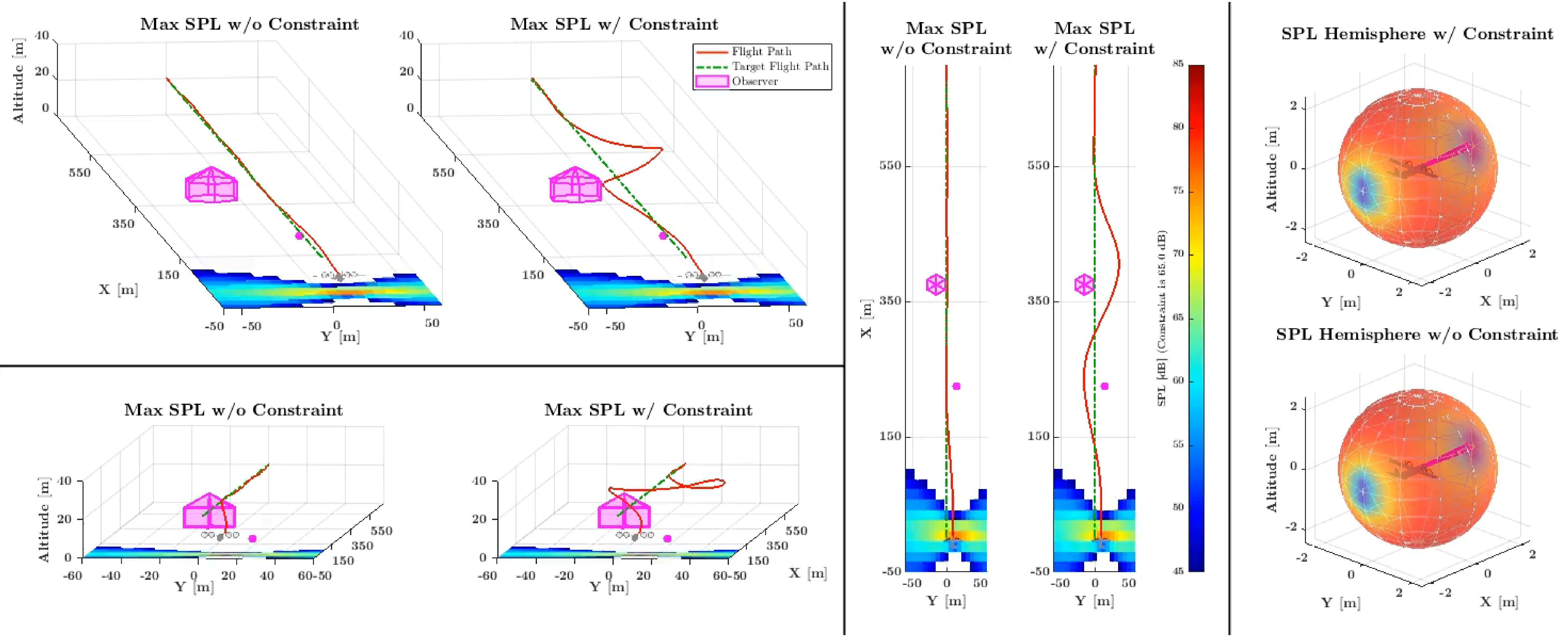
NASA Langley Research Center

Hampton, VA 23681

*Ackerman, Kasey J., Gregory, Irene M., "Comparison of Acoustic Models and Trajectory Generation Methods for an Acoustically-Aware Aircraft," 2023 AIAA SciTech Forum, National Harbor, MD, January 2023. AIAA-2023-2543

Noise Model Comparison

- Hemisphere model



Questions?

Contact Information:

Irene.M.Gregory@nasa.gov

matthew.d.houghton@nasa.gov

kasey.a.ackerman@nasa.gov

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  Revolutionary Air Mobility / Autonomous Systems / Intelligent Contingency Management (ICM)
- Revolutionary Vertical Lift Technologies (RVLT) project

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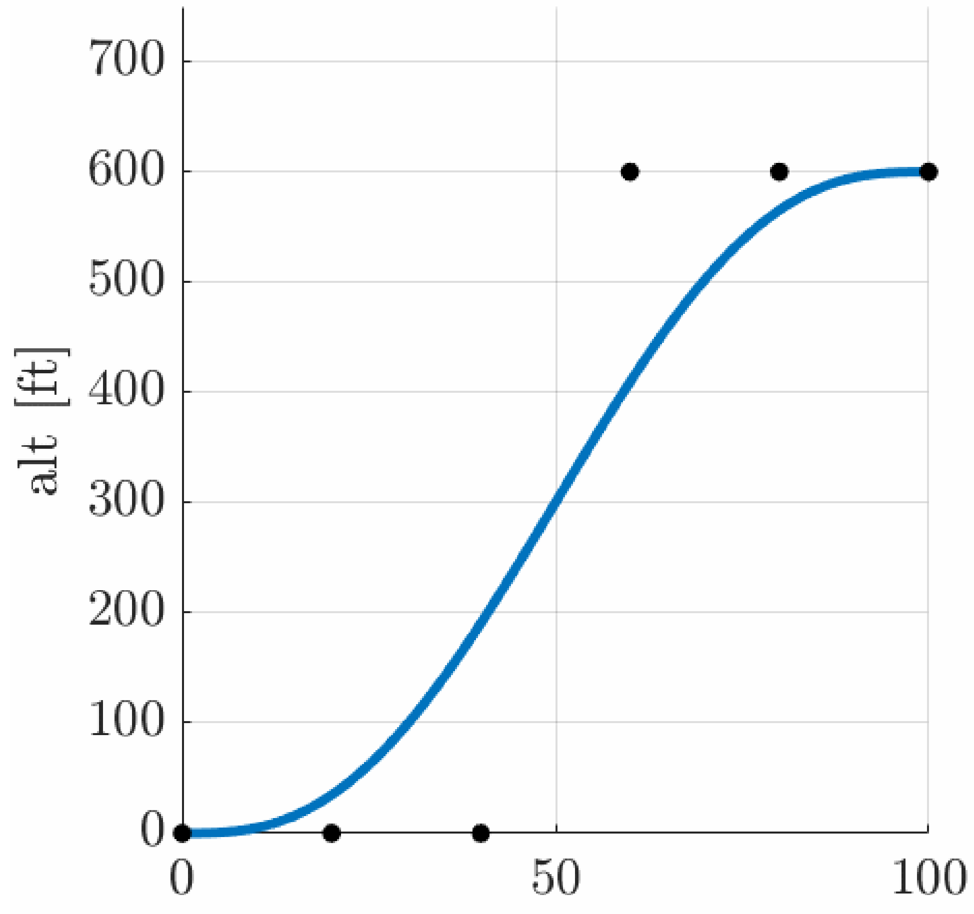
Bernstein Polynomials

- Original Emphasis was mathematical



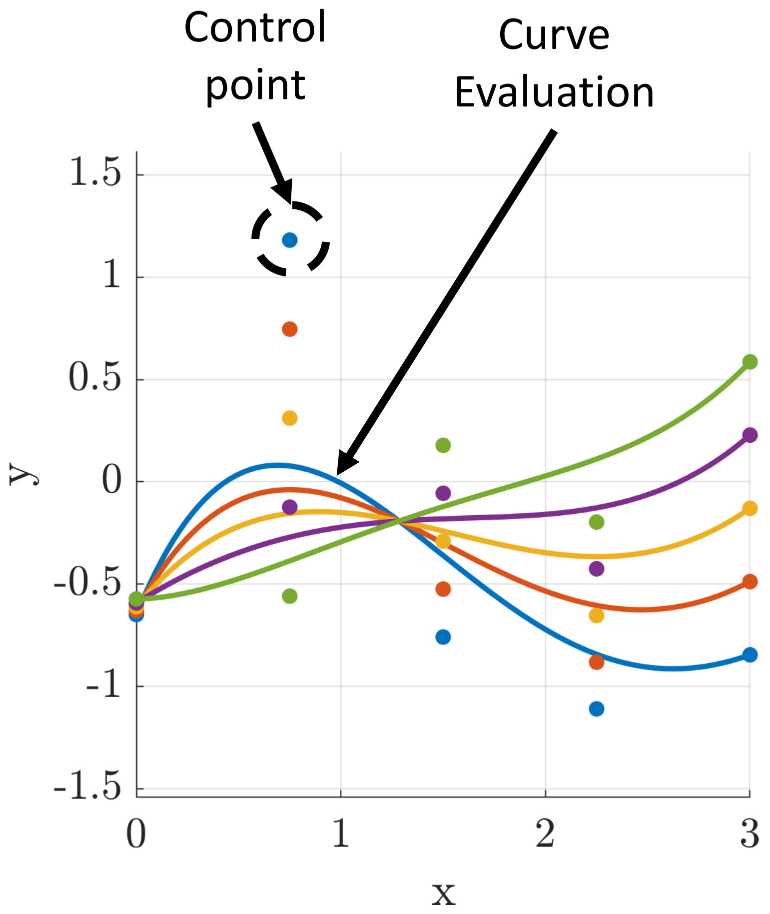
Bernstein Polynomials

Basics

- Polynomial curves using Bernstein basis (rather than monomial basis)
- Polynomial coefficients become control points

Benefits of Bernstein Form

- Control points have physical interpretation
  - Curve connected to end points
  - Curve contained inside control points
- Fast collision and constraint checking algorithms
  - Dynamic feasibility checks
- Differentiation yields Bernstein curve



Bernstein Polynomial control points and evaluations.

Dynamic Waypoints

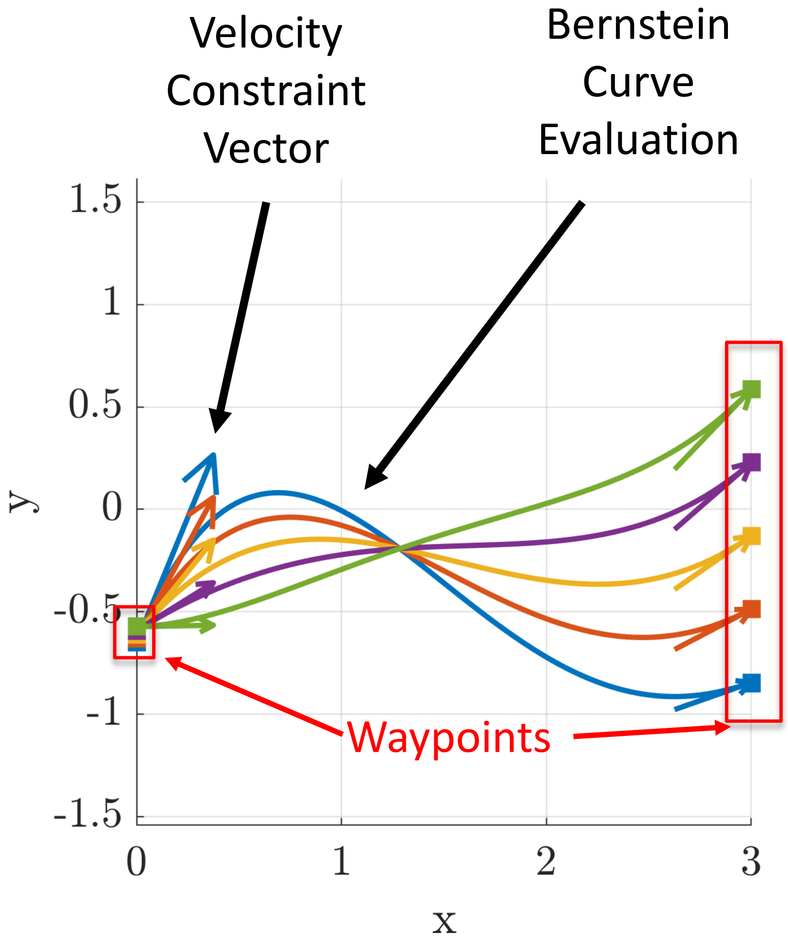
- Waypoints allow specification of spatial/dynamic initial/terminal constraints.
- *e.g. climb from 100 to 200 ft and accelerate from 0 fps to 4 fps.*

Conversion

- Generate Bernstein control points from waypoints (matrix multiplication)
- Bernstein polynomials are the back-end

Use

- ORCA waypoints are expressed as terminal constraints on time, position, velocity
- DDP samples Bernstein polynomial at arbitrary times



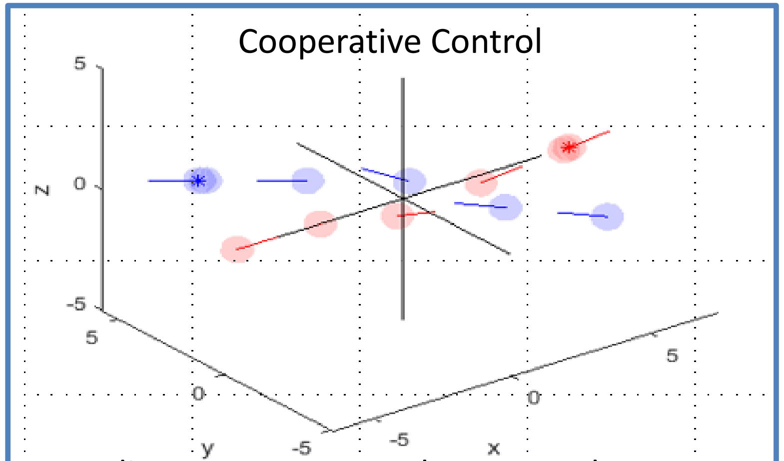
Waypoints connected by polynomial curve evaluations (Only position and velocity constraints shown)

Optimal Reciprocal Collision Avoidance Algorithm (robotics community focused):

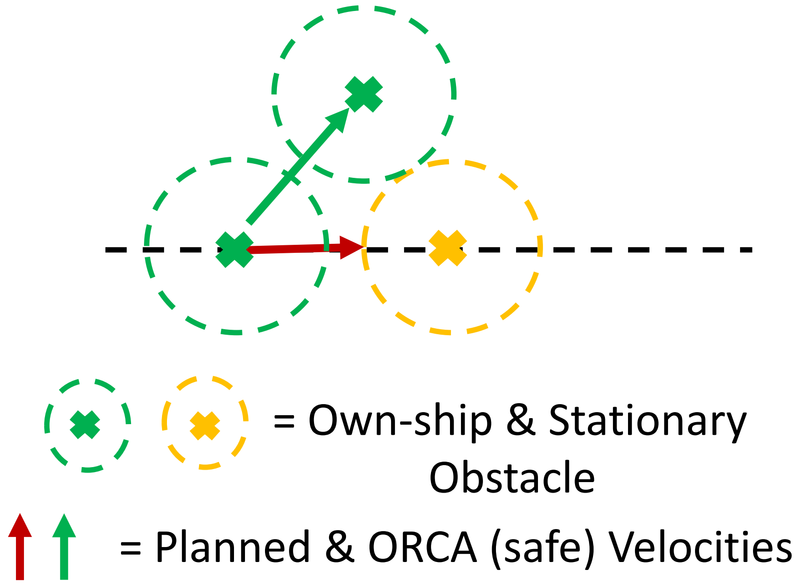
Collision Avoidance: robotics literature defines as autonomous robot navigation with fixed/moving obstacles (other intelligent vehicles)
Recurring cycle: sense/act, repeat

ORCA:

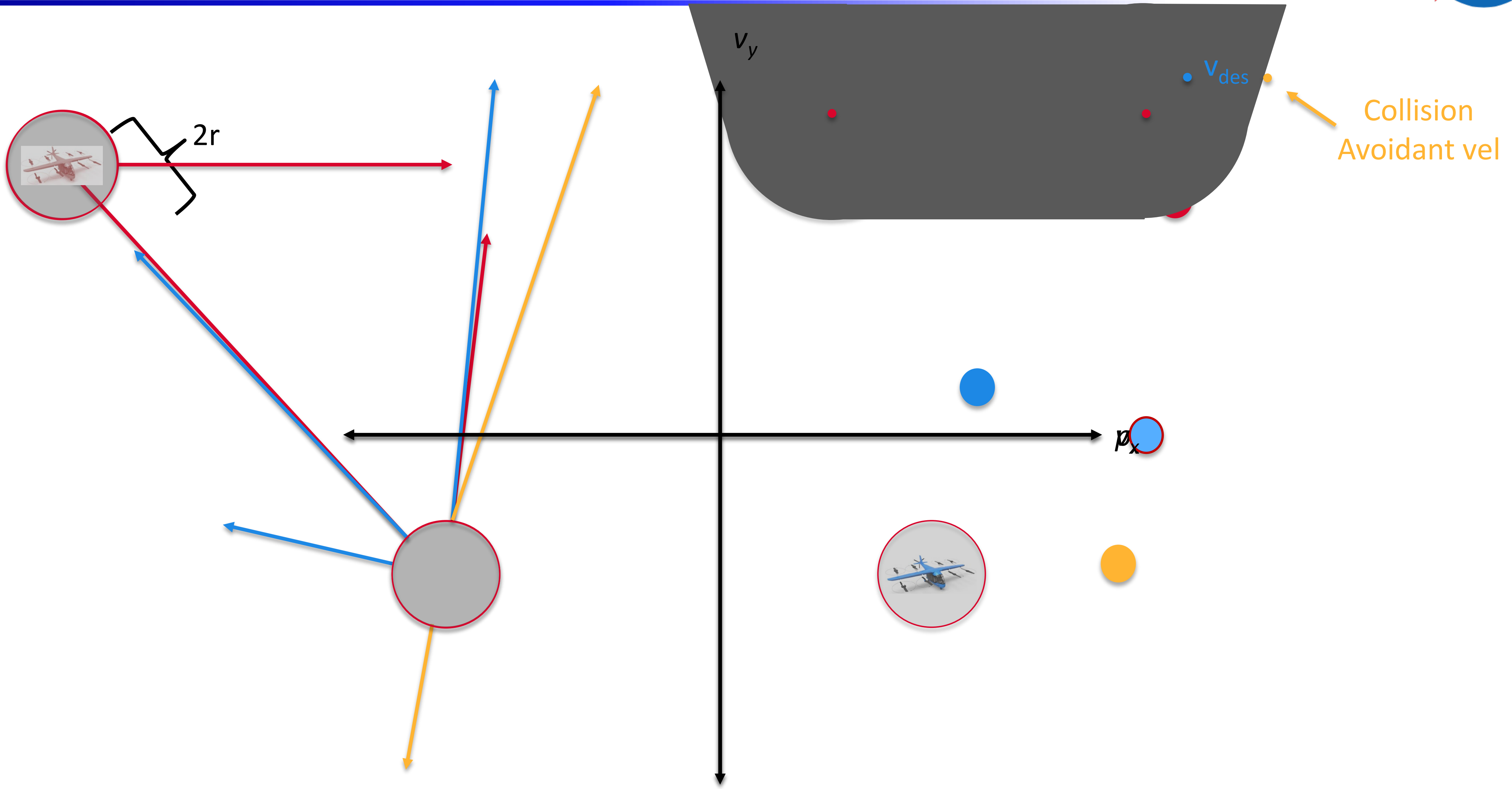
- Input: position and velocity knowledge (own-ship, obstacles/vehicles)
- Output: next own-ship velocity step (magnitude and direction)
- Point modeling (no vehicle dynamics) with safety sphere (keep-out radius)
- “Velocity object” representations, provide mathematical guarantees of collision free for look-ahead time
- Cooperative law: each vehicles applies ½ velocity correction
- Uncooperative law: own-ship takes 100% of velocity correction



Credit: Bart Bacon, Langley Research Center



ORCA + Velocity Obstacle Explanation



Optimal Trajectory Problem

Problem: Find optimal control (and states) to achieve a desired end state while minimizing cost

Discrete system nonlinear dynamics

$$\mathbf{x}_{t+1} = \mathbf{f}(\mathbf{x}_t, \mathbf{u}_t)$$

State Vector

$$\mathbf{x}_t \in \mathbb{R}^n$$

Control Vector

$$\mathbf{u}_t \in \mathbb{R}^m$$

Cost Function

$$\mathcal{J}(\mathbf{U}) = \sum_{t=1}^{T-1} \mathcal{L}(\mathbf{x}_t, \mathbf{u}_t) + \phi(\mathbf{x}_T)$$

Running Cost

$$\mathcal{L}(\mathbf{x}_t, \mathbf{u}_t)$$

Terminal Cost

$$\phi(\mathbf{x}_T)$$

State Trajectory

$$\mathbf{X} := \{\mathbf{x}_1, \ldots, \mathbf{x}_T\}$$

Control Trajectory

$$\mathbf{U} := \{\mathbf{u}_1, \ldots \mathbf{u}_{T-1}\}$$

Finite Time

$$T \in \mathbb{N}^+$$

Differential Dynamic Programming

DDP: Given nominal trajectory, use linear (or quadratic) approx. of system nonlinear dynamics and quadratic approx. of cost to yield updates to optimal controls that quadratically converge

Cost Function

$$\mathcal{J}_i(\mathbf{x}_i, \mathbf{U}_i) := \sum_{t=i}^{T-1} \mathcal{L}(\mathbf{x}_t, \mathbf{u}_t) + \phi(\mathbf{x}_T)$$

Truncated Control Sequence

$$\mathbf{U}_i := \{\mathbf{u}_i, \ldots, \mathbf{u}_{T-1}\}$$

Bellman's Principle of Optimality: find overall optimal control as sequence minimization for each truncated control sequence backwards in time (cost-to-go)

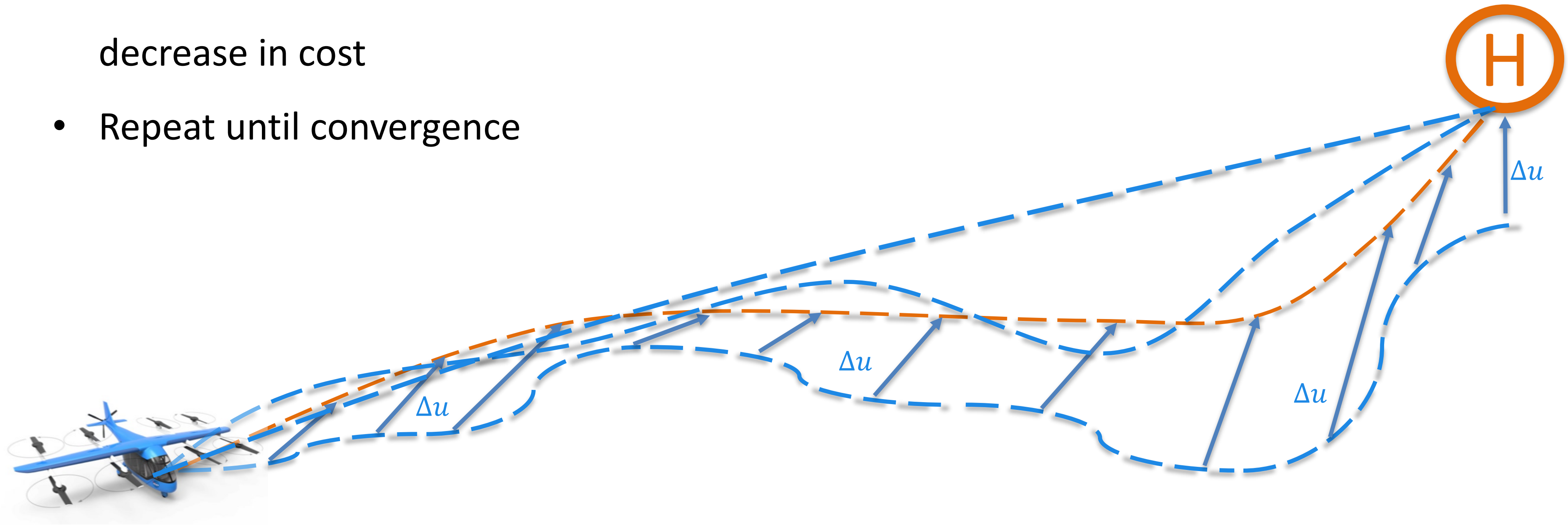
$$V(\mathbf{x}_i) = \min_{\mathbf{u}_i} \Big[\underbrace{\mathcal{L}(\mathbf{x}_i, \mathbf{u}_i) + V(\mathbf{x}_{i+1})}_{Q(\mathbf{x}_i, \mathbf{u}_i)} \Big]$$

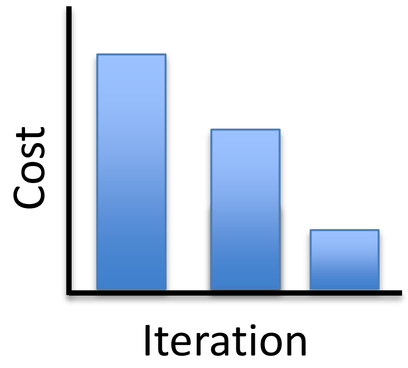
Differential Dynamic Programming

- Given: Initial state x_0, nominal control trajectory $\mathbf{u}_{0:T-1}$
- Repeat until convergence:
  - Forward pass:
    - Forward simulate dynamics from x_0 using $\mathbf{u}_{0:T-1}$ to get state trajectory $\mathbf{x}_{0:T}$
    - Compute derivatives of dynamics $f, f_x, f_u, f_{xx}, f_{xu}, f_{ux}, f_{uu}$ at each time t
    - Compute costs and derivatives $\ell, \ell_x, \ell_u, \ell_{xx}, \ell_{xu}, \ell_{ux}, \ell_{uu}$ at each time t
  - Backward pass:
    - Compute quadratic value function expansion $Q, Q_x, Q_u, Q_{xx}, Q_{xu}, Q_{ux}, Q_{uu}$ at each time t
    - Compute feedforward and feedback gains k and K at each time t
    - Update control $u_t \leftarrow u_t + \alpha k_t + K_t \delta x_t$
      - $\alpha \in [0, 1]$ is a learning rate that is tuned
      - Perform line search on α to heuristically find the best learning rate

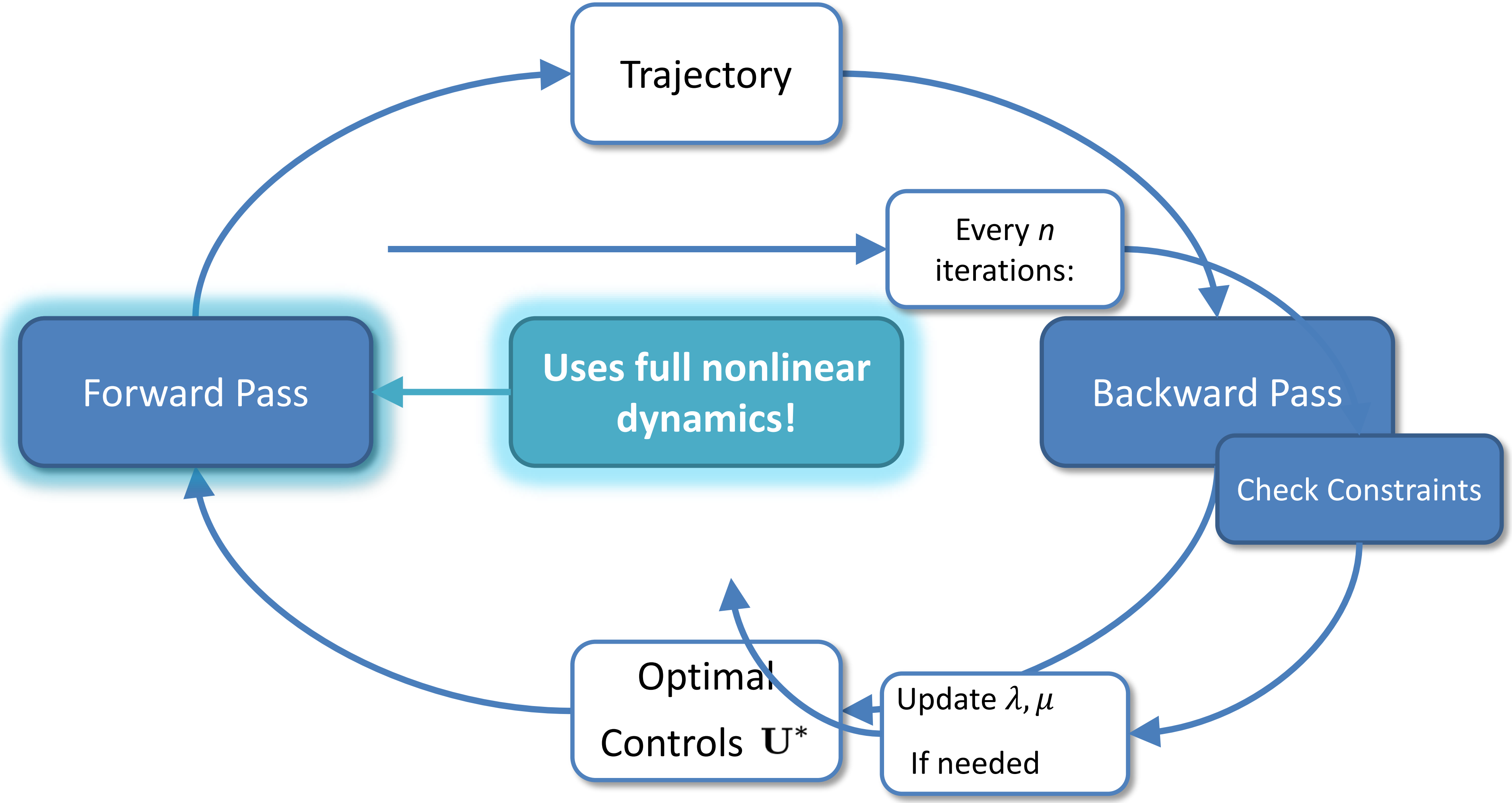
Differential Dynamic Programming

- Apply nonlinear dynamics to initial trajectory, $\boldsymbol{x_0}, \boldsymbol{u}$
- Find controls that minimize expected cost using approx. of cost and dynamics, $\Delta \boldsymbol{u}$
- Apply updated controls to determine if new trajectory leads to a decrease in cost
- Repeat until convergence





AL-DDP Depiction



Differential Dynamic Programming (DDP):

- Given nominal trajectory, use linear (or quadratic) approximation of system nonlinear dynamics and quadratic approximation of cost, yields updates that quadratically converge
- Standard DDP does not handle state or control constraints

Augmented Lagrangian DDP (AL-DDP):

- Adds state constraints to the original optimal control problem
- Convert single constrained problem into series of unconstrained problems using penalty functions
- Optimization for state constraints greatly **increases computational complexity**, requires an **inner and outer loop**

$$\min_{\mathbf{U}} \tilde{\mathcal{J}}(\mathbf{U}) = \min_{\mathbf{U}} \sum_{t=0}^{T-1} \tilde{\mathcal{L}}(\mathbf{x}_t, \mathbf{u}_t, \lambda_t, \mu_t) + \tilde{\phi}(\mathbf{x}_T, \lambda_T, \mu_T),$$

$$\text{subject to } \mathbf{x}_{t+1} = f(\mathbf{x}_t, \mathbf{u}_t), \ \forall t = 0, \ldots, T-1,$$

where

$$\tilde{\mathcal{L}}(\mathbf{x}_t, \mathbf{u}_t, \lambda_t, \mu_t) = \mathcal{L}(\mathbf{x}_t, \mathbf{u}_t) + \sum_{i=1}^{c} \mathcal{P}(g_{t,i}(\mathbf{x}), \lambda_{t,i}, \mu_t),$$

$$\tilde{\phi}(\mathbf{x}_T, \lambda_T, \mu_T) = \phi(\mathbf{x}_T) + \sum_{i=1}^{c} \mathcal{P}(g_{T,i}(\mathbf{x}), \lambda_{T,i}, \mu_T).$$

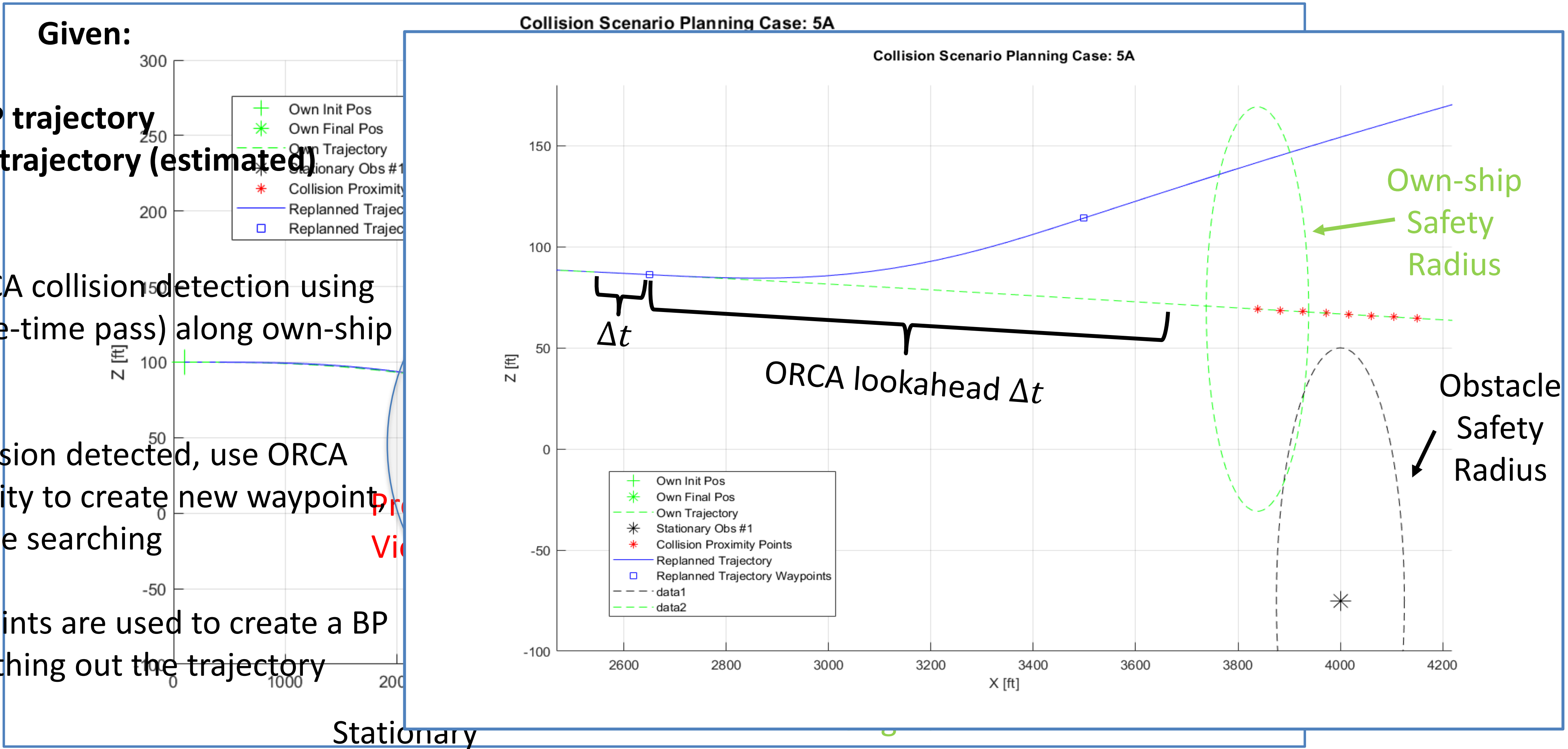
Integration: ORCA + Bernstein Polynomials

Goal: Modify own-ship BP trajectory to ensure smooth collision avoidance

Given:

- **Own-ship BP trajectory**
- **Obstacle BP trajectory (estimated)**

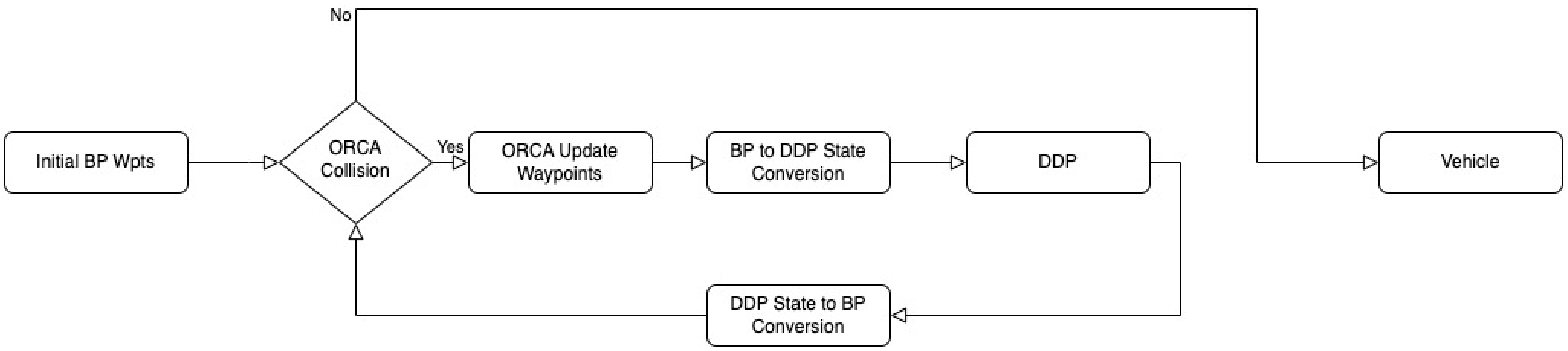
- Perform ORCA collision detection using Δt steps (one-time pass) along own-ship trajectory
- Pending collision detected, use ORCA output velocity to create new waypoint, then continue searching
- ORCA waypoints are used to create a BP curve, smoothing out the trajectory



Stationary Obstacle

Trajectory

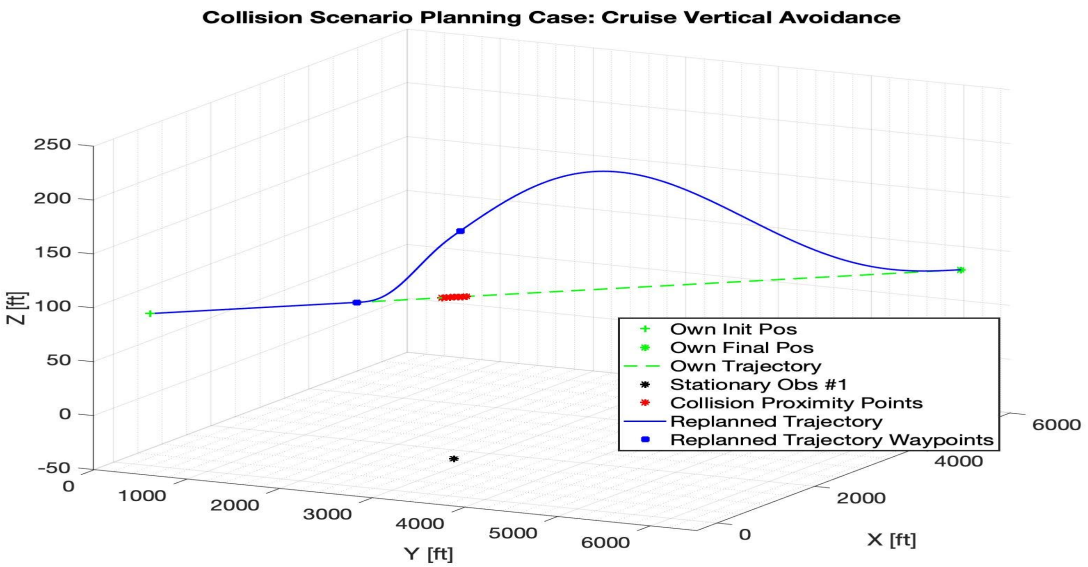
Algorithm Implementation

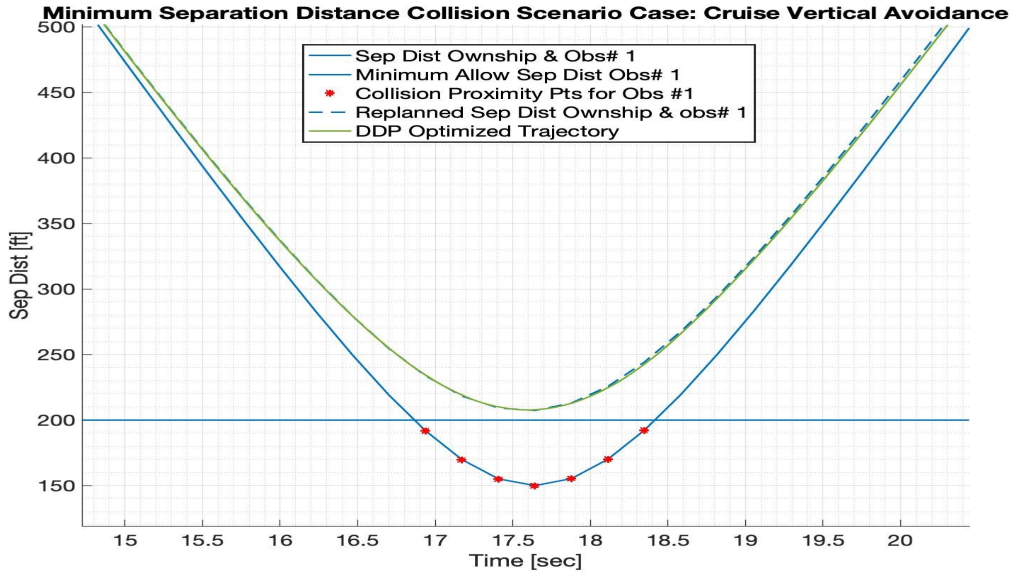


- Leverages ORCA fast collision avoidance checks and preferential avoidance direction selection
- BP’s serve as compact trajectory representation between ORCA and DDP that can be quickly evaluated at any time along the curve
- DDP provides dynamically feasible optimal trajectories given simplified ORCA information

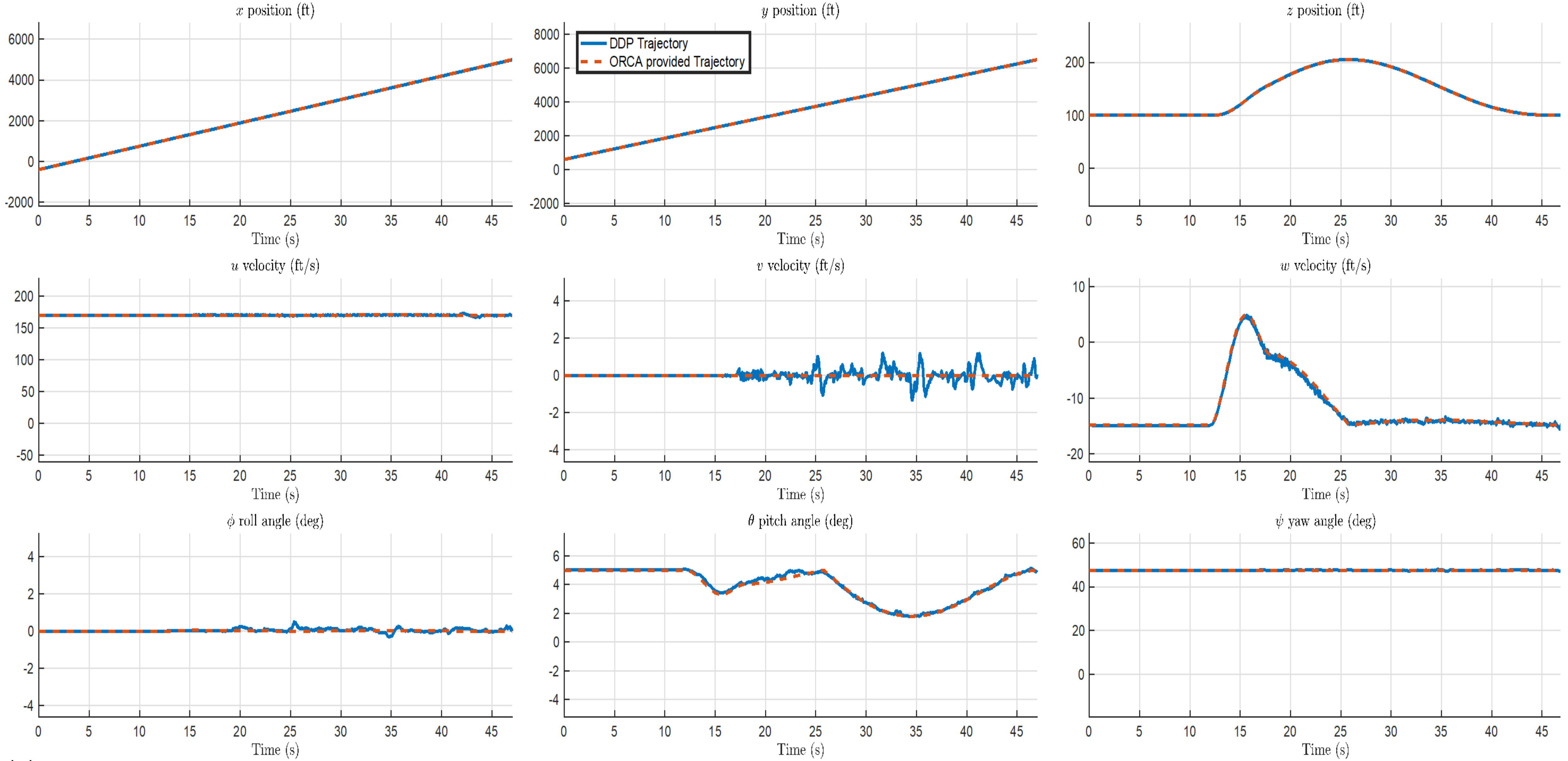
Experiments: Cruise to Altitude Change

- 170 ft/s cruise with 200 ft safety radius
- Static obstacle 150 ft below
- Recognizes safety breach
- ORCA recalculates, maintains safety radius
- ORCA waypoints converted into BP curves
- BP curves integrated with trim knowledge and passed to DDP
- DDP optimized new trajectory avoids obstacle



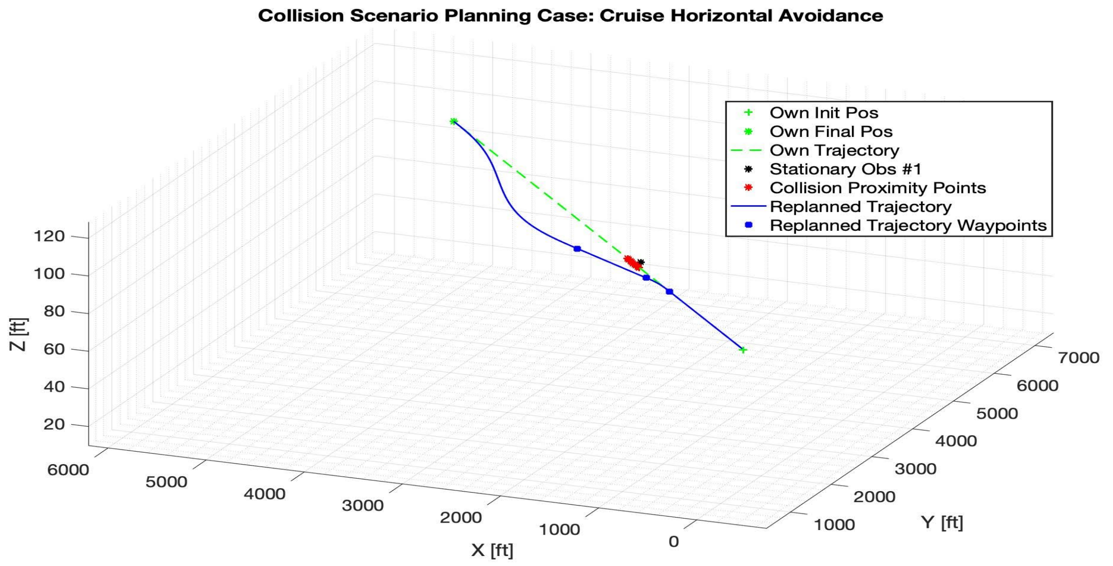


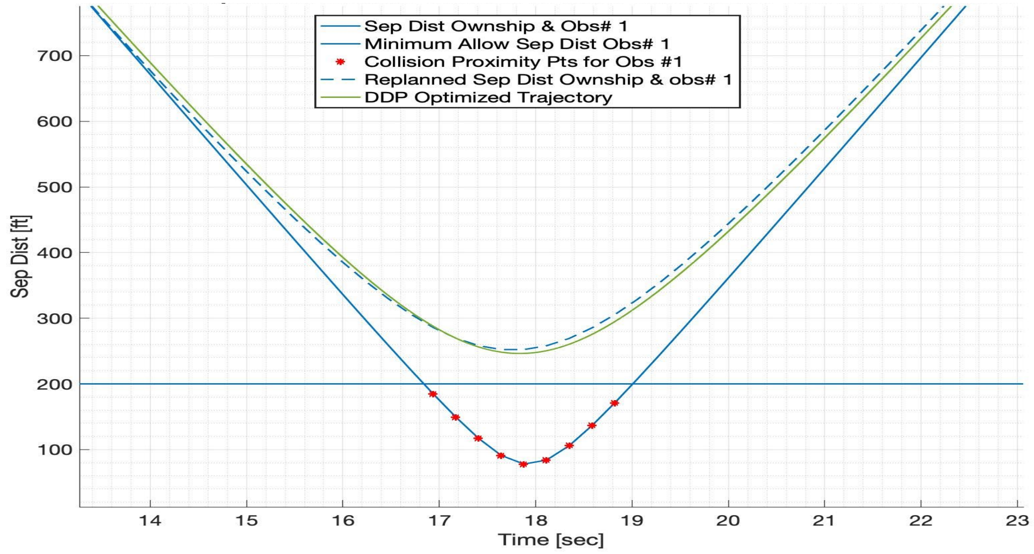
Cruise to Altitude Change



Cruise to Horizontal Maneuver

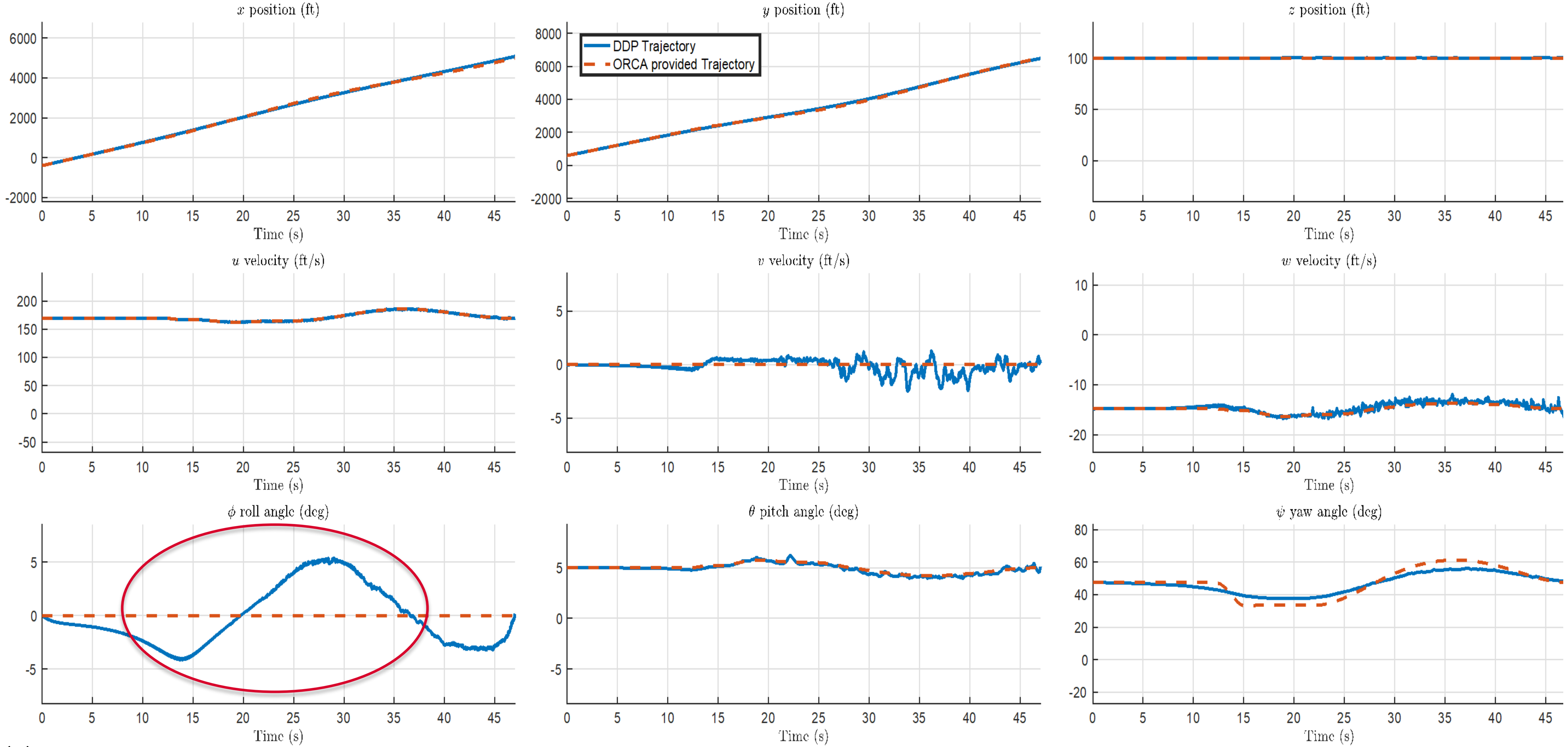
- 170 ft/s cruise with 200 ft safety radius
- Static obstacle 75 ft to the right
- Recognition of safety radius breach
- ORCA recalculates, maintains safety radius
- ORCA waypoints converted into BP curves
- BP curves integrated with trim knowledge and passed to DDP
- DDP optimized new trajectory avoids obstacle





Cruise to Horizontal Maneuver

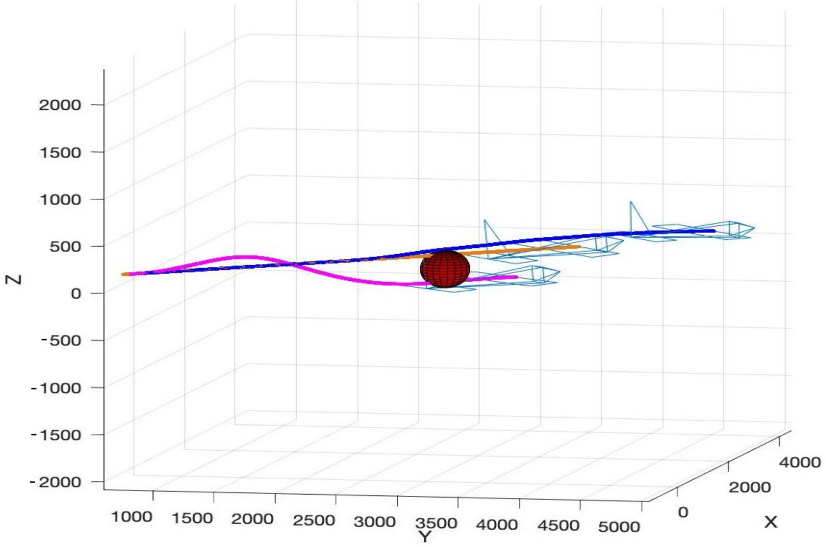
DDP was provided wing-level cruise trim values for suggested trajectory



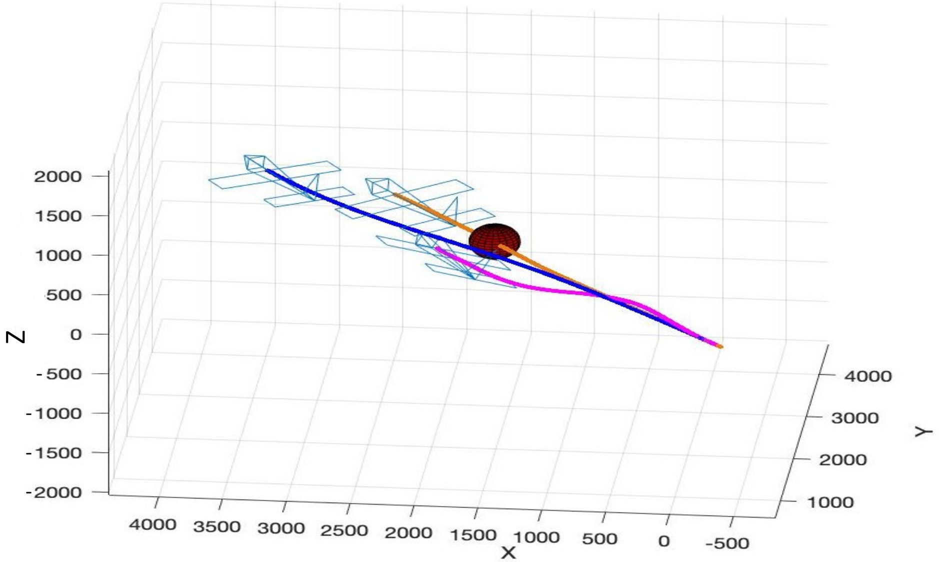
AL-DDP Warmstarting with COBRA-DDP

AL-DDP Warmstart Experiments

- Provided cruise initial trajectory:
  - AL-DDP **Fails** (orange trajectories)
- Provided no warmstart initial trajectory:
  - AL-DDP **always** avoids under obstacle (magenta trajectories)
- Provided COBRA-DDP trajectory:
  - **Successful** replanning and avoids collision (blue trajectories)
- COBRA-DDP's trajectory provides a feasible warmstart trajectory to help minimize computation of AL-DDP
- COBRA-DDP enables selection of desired velocity, allowing for the set up of potential flight rules or expected avoidance patterns (e.g. left to left)



Cruise Altitude Change Experiment



Cruise Horizontal Turn Experiment

Conclusions and Ongoing Work:

Conclusion:

- BP curves serve as an effective transfer of trajectory information between ORCA and DDP
- COBRA-DDP plans dynamically feasible collision avoiding trajectories and can select preferential avoidance direction
- COBRA-DDP can enhance the optimization of other state-constrained optimizers such as AL-DDP

Further Details on Future Work

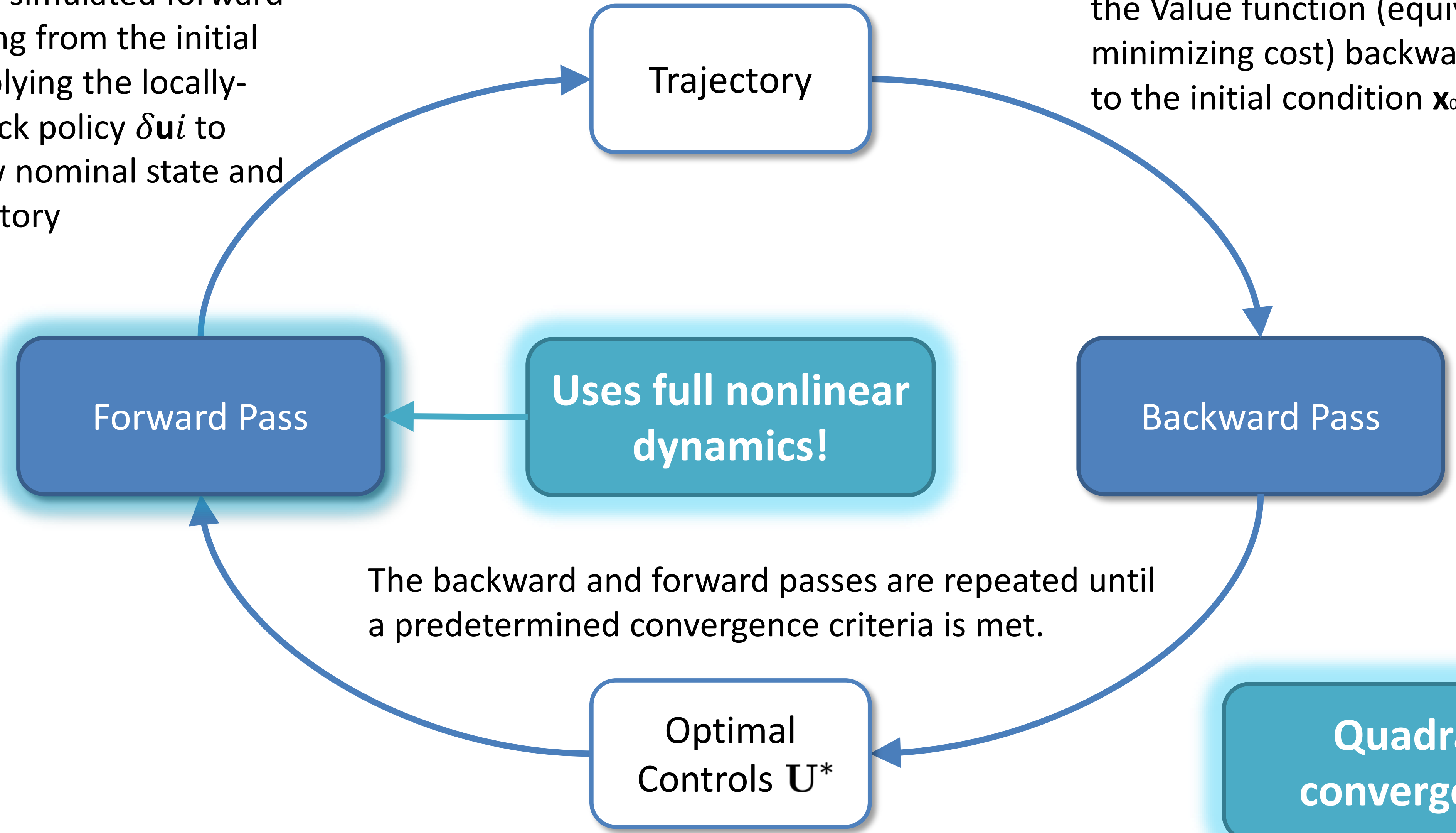
Ongoing Work:

- MPC implementation of COBRA-DDP
- Demonstration of collision avoidance with multiple moving/stationary, cooperative/uncooperative obstacles
- Further ORCA augmentation to consider complex vehicle maneuvers
- What advantages are available to vehicles that communicate to each other using BP curves?

Differential Dynamic Programming (DDP)

Dynamics are simulated forward in time starting from the initial state and applying the locally-linear feedback policy $\delta \mathbf{u} i$ to receive a new nominal state and control trajectory

Solving for quadratic approximation of the Value function (equiv. to minimizing cost) backwards in time up to the initial condition $\mathbf{x}_0$ at time $t = 0$



The backward and forward passes are repeated until a predetermined convergence criteria is met.

Quadratic convergence!

Parameterized Differential Dynamic Programming (PDDP)

PDDP is a trajectory optimization algorithm that builds upon DDP

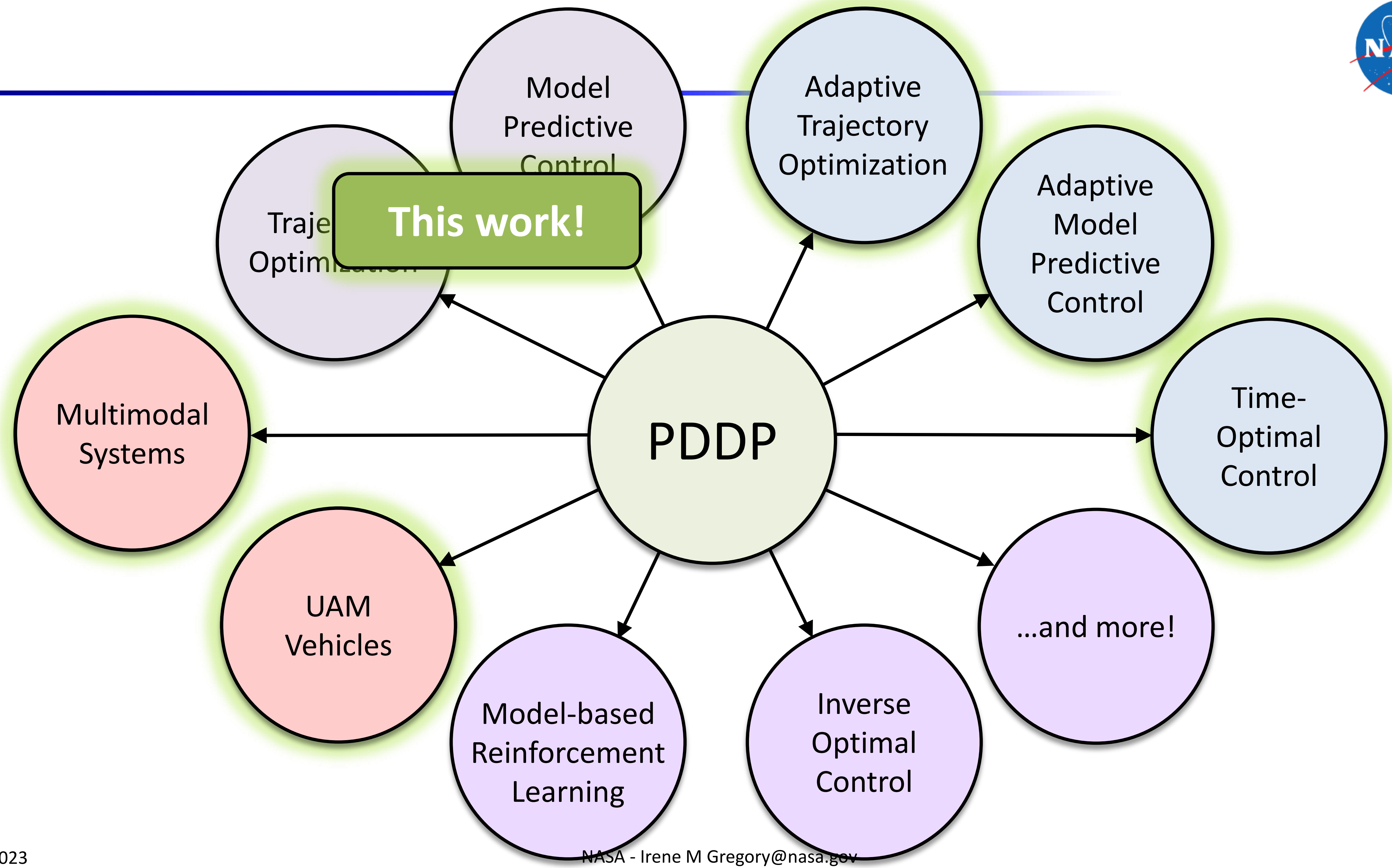
- Enables the **co-optimization** of a **trajectory** and time invariant **parameters** in the same process.
- Parameters can be extremely diverse and goal specific
- Experiments tested PDDP's ability to successfully **estimate vehicle dynamic parameters** while implementing **optimal trajectories**, resulting in Adaptive Model Predictive Control

Switching Time Optimization

- Calculation of **optimal transition time** between flight regimes (Difficult for highly nonlinear vehicles like L+C)
- **Decreases tuning** work for engineers when planning for common maneuvers that transition between flight regimes (Vertical takeoff into fixed-wing cruise)
- Allows for the input and optimization of multiple target states for long-term planning and replanning

Fault Detection

- Online estimation of vehicle **dynamic** parameters
- **Online estimation** of **degradation** level for effectors + rotors
- **Replan trajectory** based on new estimation of vehicle parameters
- Deviations in estimation from norms can alert system ID of vehicle to run further diagnostics of vehicle health



Model Predictive Control
Adaptive Trajectory Optimization
Trajectory Optimization
This work!
Adaptive Model Predictive Control
Multimodal Systems
PDDP
Time-Optimal Control
UAM Vehicles
...and more!
Model-based Reinforcement Learning
Inverse Optimal Control

Brief Overview of DDP and PDDP

Differential Dynamic Programming:

- Given nominal trajectory, use linear (or quadratic) approx. of system nonlinear dynamics and quadratic approx. of cost to yield updates to optimal controls that quadratically converge

Parametric Differential Dynamic Programming:

- Discrete system with nonlinear dynamics
- θ represents time-invariant system parameter(s)
- Goal is now to minimize the cost function with respect to both the controls, u and the parameters, θ
    - Estimation of unknown parameters and states of a dynamical system through Moving Horizon Estimation (MHE)
    - Initial parameters are set for a dynamical system, θ and for this example do not match the real system
    - The vehicle applies a portion of the trajectory given these initial parameters using a typical MPC cost
    - The resulting trajectory taken is fed into the estimation cost, which tries to find the correct parameters given the difference between the planned trajectory and what occurred on the real system
    - The new parameters are used to update the model of system. A combined cost can be derived over both task simultaneously using PDDP

Acknowledgements & References

Acknowledgements:

- NASA Aeronautics Research Mission Directorate (ARMD), Transformative Tools and Technologies (TTT) project, under the Revolutionary Air Mobility / Autonomous Systems / Intelligent Contingency Management (ICM)

References:

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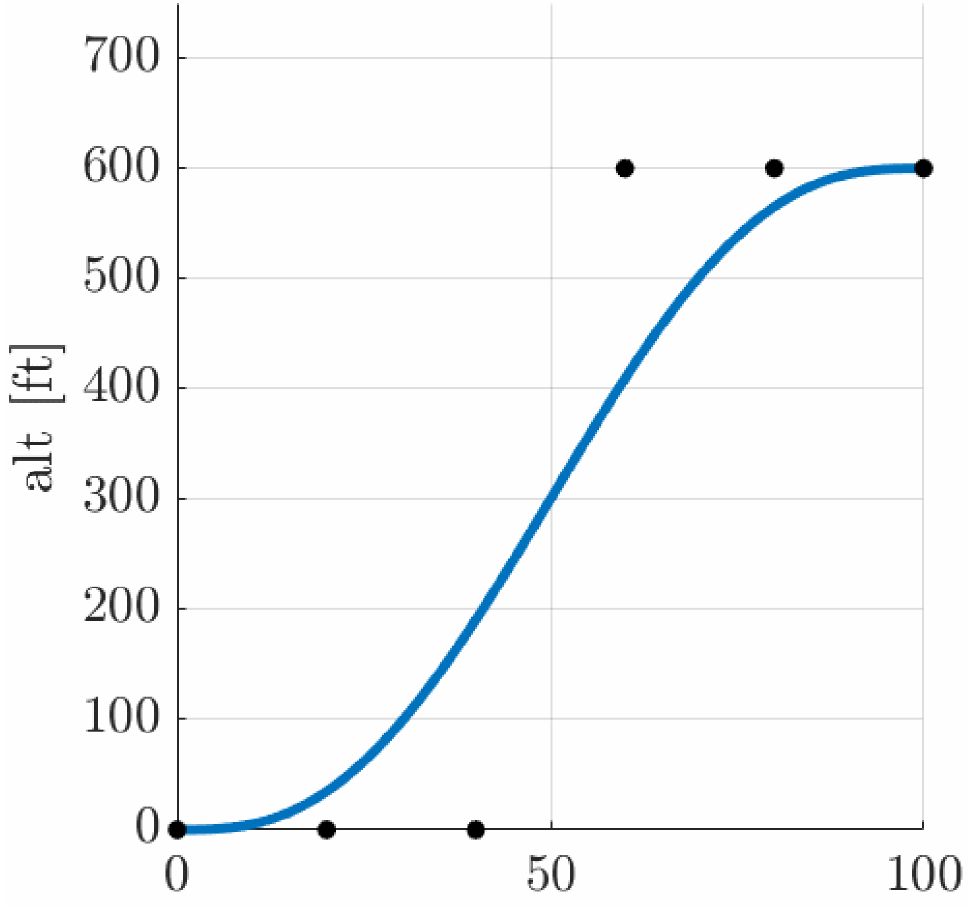
- Jacobson, D. H., and Mayne, D. Q., Differential Dynamic Programming, American Elsevier Pub. Co., 1970.
- Birgin, E. G., Castillo, R. A., and Martinez, J. M., “Numerical comparison of augmented Lagrangian algorithms for nonconvex problems,” Computational Optimization and Applications, Vol. 31, No. 1, 2005, pp. 31–55.
- van den Berg, J., Guy, S. J., Lin, M., and Manocha, D., “Reciprocal n-body Collision Avoidance,” In Proc. of the IEEE International Conference on Robotics and Automation, 2010.
- Silva, C., Johnson, W. R., Solis, E., Patterson, M. D., and Antcliff, K. R., “VTOL urban air mobility concept vehicles for technology development,” Aviation Technology, Integration, and Operations Conference, 2018.

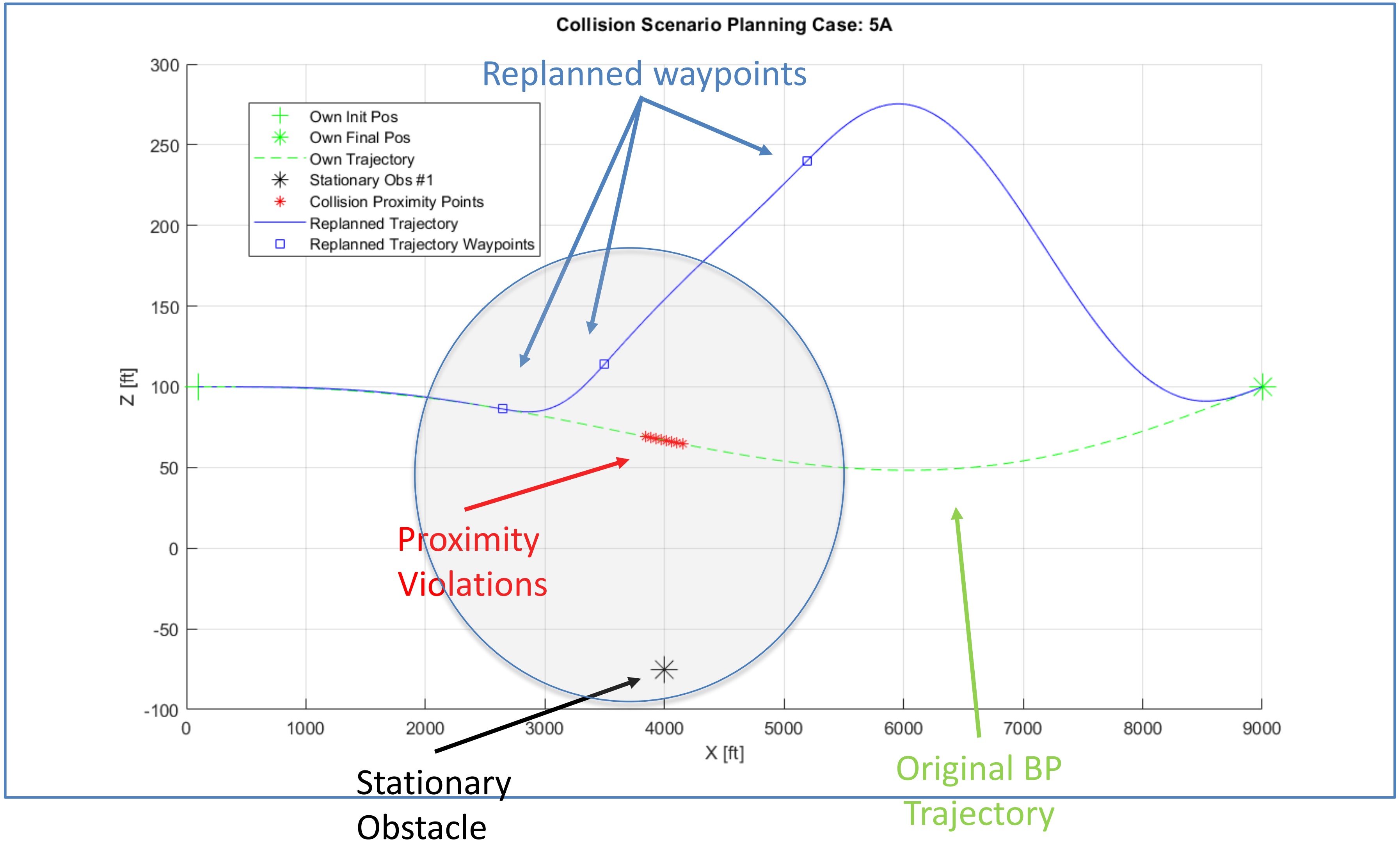
Bernstein Polynomials

- Original Emphasis was mathematical
- Explain the artistic benefits to familiarize audience with the idea
- Can we use sliding example or video of it?
- Reference to website for hands on view?



Integration: ORCA + Bernstein Polynomials

Goal: Modify own-ship BP trajectory to ensure smooth collision avoidance



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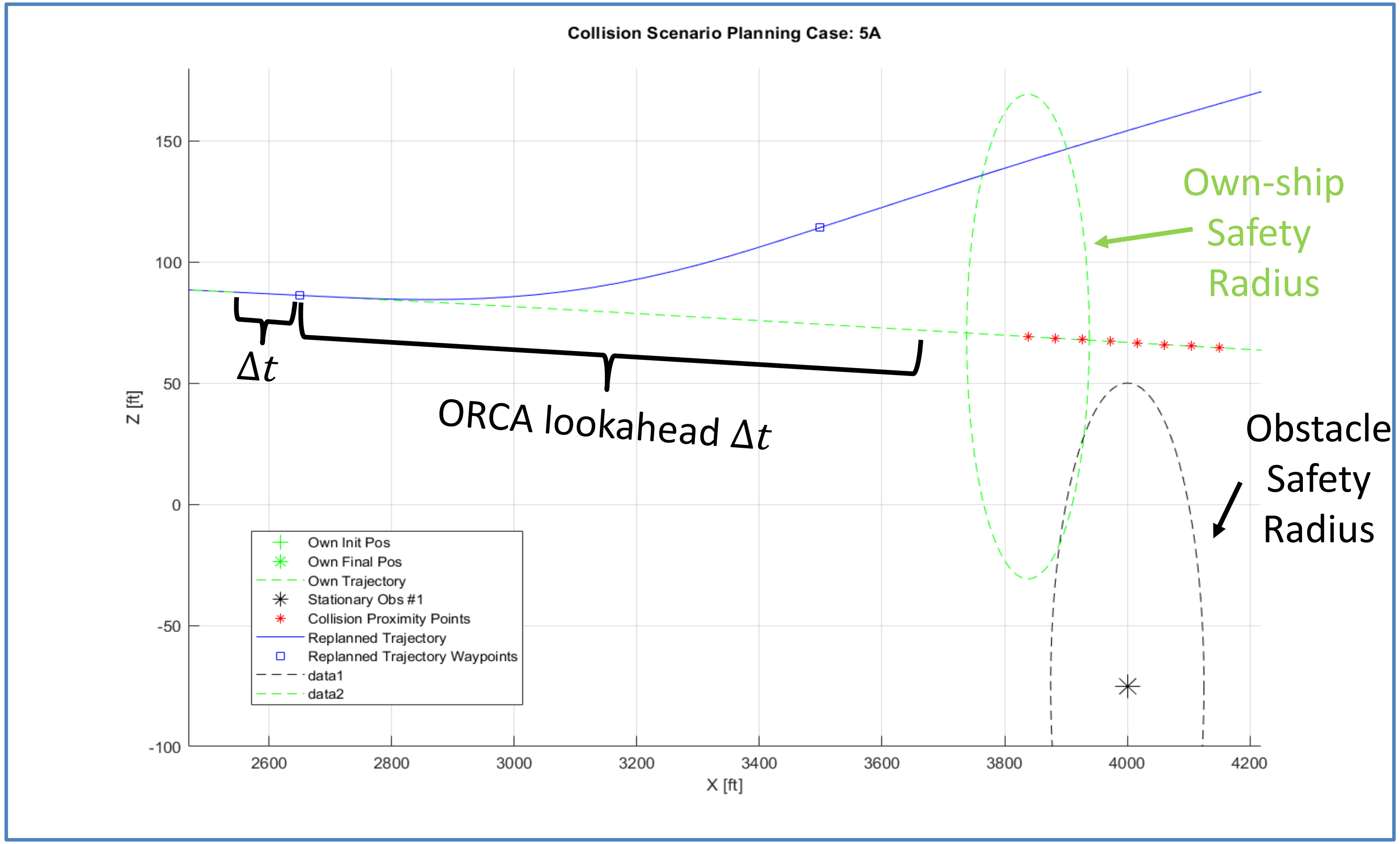
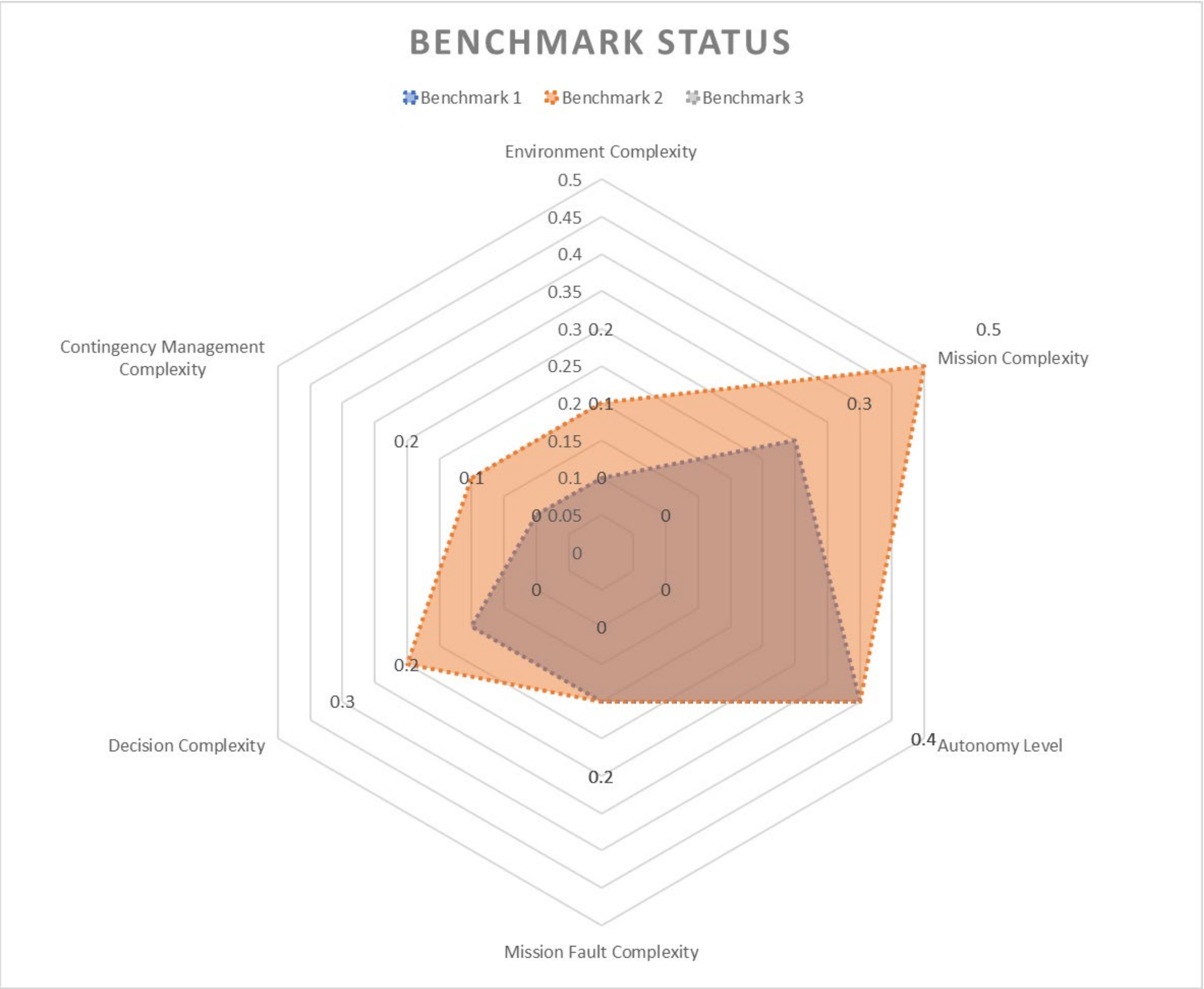


Benchmark III

- Complexity of environment
  - Structured/unstructured, static/dynamic, known/unknown
- Complexity of Mission
  - Simple/complex flight plan, normal/off-nominal operations, recoverable/unrecoverable failure (in current mission sense)
- Complexity (level) of Autonomy
  - No automation to full autonomy; 1-5 similar to SAE
- Complexity of decision
  - Immediate system to mission level
- Mission fault complexity
  - External/internal, correctable/uncorrectable
- Complexity of contingency management
  - Evaluates the potential hazards and consequences of the vehicle in case of a failure or emergency
  - Contingency risk assessment - level of risk posed by a specific contingency action



Benchmark Scoring

- Complexity of Environment
  - ✓ Structured Known Static
  - ✓ Structured Known Dynamic
  - ✓ Structured Unknown Static
  - ✓ Structured Unknown Dynamic
  - ✓ Unstructured Known Static
  - ✓ Unstructured Known Dynamic
  - ✓ Unstructured Unknown Static
  - ✓ Unstructured Unknown Dynamic

- Complexity of Mission
  - ✓ Simple Flight Plan, Normal Operations, Unrecoverable Failures
  - ✓ Simple Flight Plan, Normal Operations, Recoverable Failures
  - ✓ Simple Flight Plan, Abnormal Operations, Unrecoverable Failures
  - ✓ Simple Flight Plan, Abnormal Operations, Recoverable Failures
  - ✓ Complex Flight Plan, Normal Operations, Unrecoverable Failures
  - ✓ Complex Flight Plan, Normal Operations, Recoverable Failures
  - ✓ Complex Flight Plan, Abnormal Operations, Unrecoverable Failures
  - ✓ Complex Flight Plan, Abnormal Operations, Recoverable Failures

Benchmark Scoring

- Complexity of Autonomy
  - ✓ Manual Control
  - ✓ Flight Stability
  - ✓ Envelope Protection
  - ✓ Navigation and Collision Avoidance
  - ✓ Conditional Automation (Level 3)
  - ✓ Conditional Automation (Level 3) with AI
  - ✓ High Automation (Level 4)
  - ✓ Full Automation (Level 5)

- Complexity of Decision
  - ✓ Recovery-Level
  - ✓ Fault-Level
  - ✓ Health-Level
  - ✓ Control-Level
  - ✓ Maneuver-Level
  - ✓ Plan-Level
  - ✓ Task Level
  - ✓ Mission-level

Benchmark Scoring

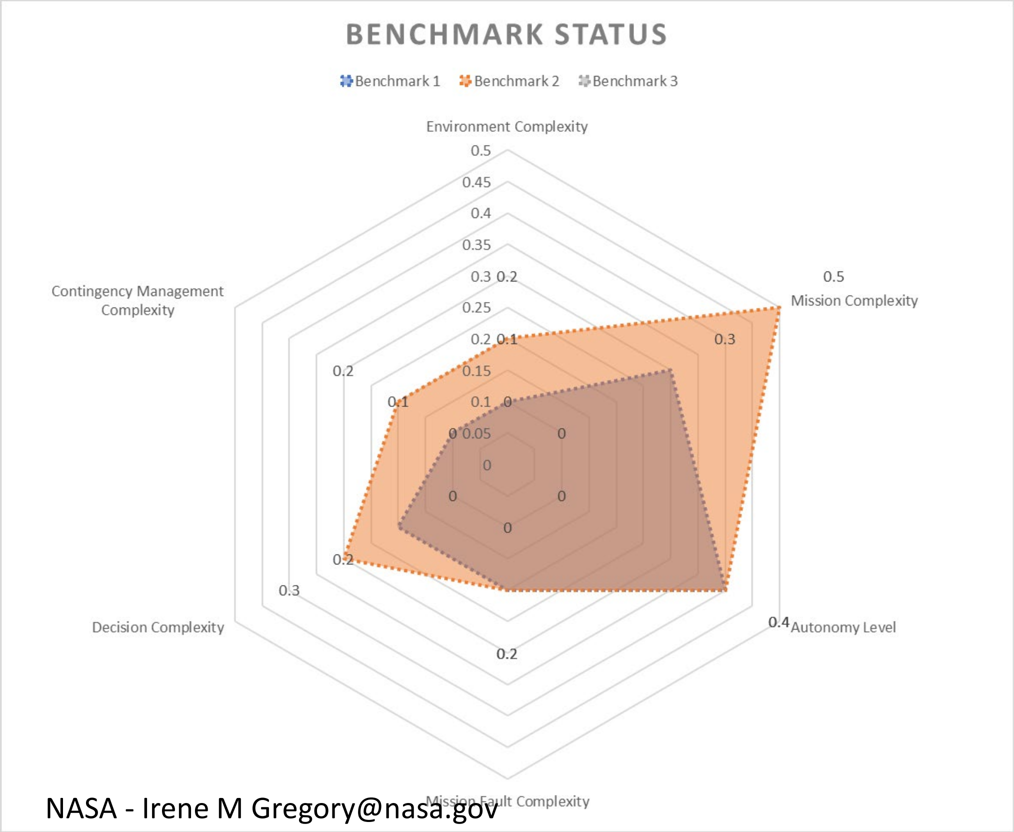
- Complexity of Mission Fault
  1. Expected External Correctable
  2. Unexpected External Correctable
  3. Expected External Uncorrectable
  4. Unexpected External Uncorrectable
  5. Expected Internal Correctable
  6. Unexpected Internal Correctable
  7. Expected Internal Uncorrectable
  8. Unexpectable Internal Uncorrectable

- Complexity of Contingency Management
  1. Low Risk, Rural Area
  2. Low Risk, Suburban Area
  3. Medium Risk, Urban Area, Moderate Population
  4. Medium Risk, Urban Area, High Population
  5. High Risk, Urban Area, High Population
  6. High Risk, Any Area, Any Population, Degraded Conditions
  7. Very High Risk, Any Area, Any Population, Any Airspace, Poor Conditions
  8. Extremely High Risk, Any Area, Any Population, Any Airspace, Severe Conditions

Benchmark Status

Score	Complexity of Environment Categories	Complexity of Mission Categories	Complexity of Autonomy Categories	Complexity of Decision	Complexity of Mission Fault Categories	Complexity of Contingency Planning Categories
0.1	Structured Known Static	Simple Flight Plan, Normal Operations, Unrecoverable Failures	Manual Control	Recovery-Level	Expected External Correctable	Low Risk, Rural Area
0.1	Structured Known Dynamic	Simple Flight Plan, Normal Operations, Recoverable Failures	Flight Stability	Fault-Level	Unexpected External Correctable	Low Risk, Suburban Area
0.1	Structured Unknown Static	Simple Flight Plan, Abnormal Operations, Unrecoverable Failures	Envelope Protection	Health-Level	Expected External Uncorrectable	Medium Risk, Urban Area, Moderate Population
0.1	Structured Unknown Dynamic	Simple Flight Plan, Abnormal Operations, Recoverable Failures	Navigation and Collision Avoidance	Control-Level	Unexpected External Uncorrectable	Medium Risk, Urban Area, High Population
0.1	Unstructured Known Static	Complex Flight Plan, Normal Operations, Unrecoverable Failures	Conditional Automation (Level 3)	Maneuver-Level	Expected Internal Correctable	High Risk, Urban Area, High Population
0.1	Unstructured Known Dynamic	Complex Flight Plan, Normal Operations, Recoverable Failures	Conditional Automation (Level 3) with AI	Plan-Level	Unexpected Internal Correctable	High Risk, Any Area, Any Population, Degraded Conditions
0.1	Unstructured Unknown Static	Complex Flight Plan, Abnormal Operations, Unrecoverable Failures	High Automation (Level 4)	Task Level	Expected Internal Uncorrectable	Very High Risk, Any Area, Any Population, Any Airspace, Poor Conditions
0.1	Unstructured Unknown Dynamic	Complex Flight Plan, Abnormal Operations, Recoverable Failures	Full Automation (Level 5)	Mission-level	Unexpectable Internal Uncorrectable	Extremely High Risk, Any Area, Any Population, Any Airspace, Severe Conditions

Scores are additive
e.g. For Complexity of Autonomy,
if the Benchmark has Manual Control
and Flight Stability, it receives a score
of 0.2



Enhanced Operational Capabilities – Flight Control and Path Planning

- Where has it been applied? How has it been tested?

Variable Stability Learjet - NTPS

Pilot Onboard

Remotely Piloted

NASA Subscale Transport

Multirotor Drones

Lifting Body Incident (1967) and the 2018 Flight Test

Puig-Navarro et al. “An $\mathcal{L}_1$ Adaptive Stability Augmentation System Designed to MIL-HDBK-1797 Level 1 Specifications.” *In Proceedings of* AIAA Guidance, Navigation and Control Conference, San Diego, CA, 2019.

L1 on Calspan's VSS Learjet – USAF Test Pilot School

- **Vehicle: Calspan's VSS Learjet 25D Inflight Simulator**
  - *Onboard Variable Stability System (VSS) can alter the apparent dynamics of the Learjet through feedback control*
  - *Safety trips protect the vehicle (and passengers) from dangerous flight conditions*
  - *Right seat is an evaluation pilot, left seat is a safety pilot*
  - *Rear seat(s) for engineers conducting the test and managing the VSS.*

- **Two flight test campaigns with $\mathcal{L}_1$ adaptive control**
  - *20 sorties by USAF TPS students (+2 landing checkout sorties by Calspan pilots) Feb-Mar 2015 and Mar 2018*
  - *L1 recovered consistent and safe handling qualities in the presence of (severe) failure dynamics*
  - *L1 was useful for low-gain tasks*
  - *Touch-and-Go Landings – including off-nominal VSS configs*
- **FCL Configuration:**
  - *Stability Augmentation System (SAS)*
  - *Standalone or Augmentation a full baseline SAS*
  - *SISO L1 for the longitudinal dynamics, and MIMO L1 for the lat-dir dynamics*

Designed to maintain 'nominal' handling qualities, and to prevent adverse aircraft-pilot interactions in the presence of aircraft failures

Robust Flight Control: Learjet at Edwards AFB

- *Recovered flying qualities* of different Variable Stability System configurations
- *Restored handling qualities* to *a safe and consistent level* despite the off-nominal dynamics
- The controller was shown to be *easily adjusted to improve handling qualities*.

Calspan

Ackerman, et al. "Evaluation of an $\mathcal{L}_1$ Flight Control Law on Calspan's Variable-Stability Learjet." AIAA Journal of Guidance, Control and Dynamics, vol. 40, No. 4, pp. 1051-1060, 2017.

New Implementations for Multi-rotor Vehicles

Source: NASA.gov


Source: Unmanned aerial online

Safety

Robust flight control

Uncertainty compensation

Uniform performance bounds

Performance: Adaptation rate Γ

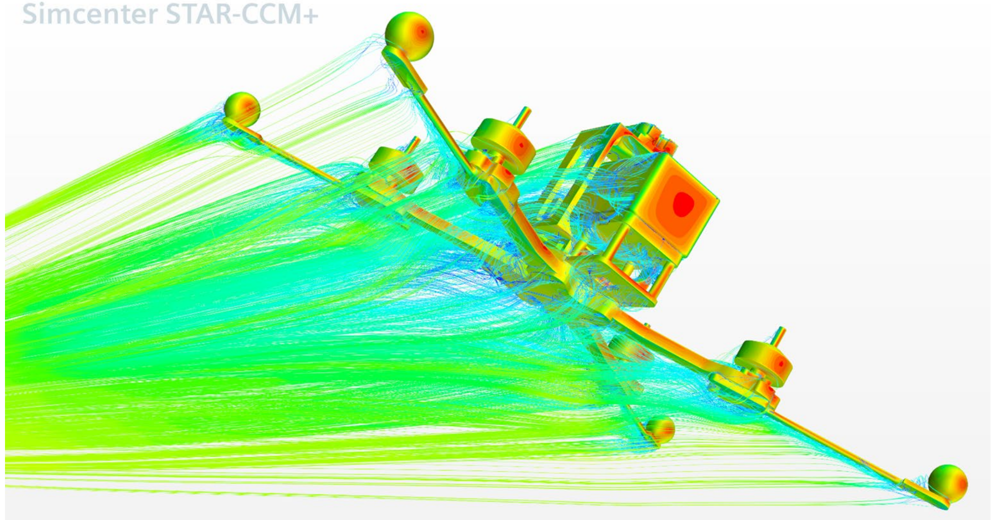
$$\boxed{\|x_r(t) - x(t)\| \leq \rho_a(\Gamma^{-1})}$$

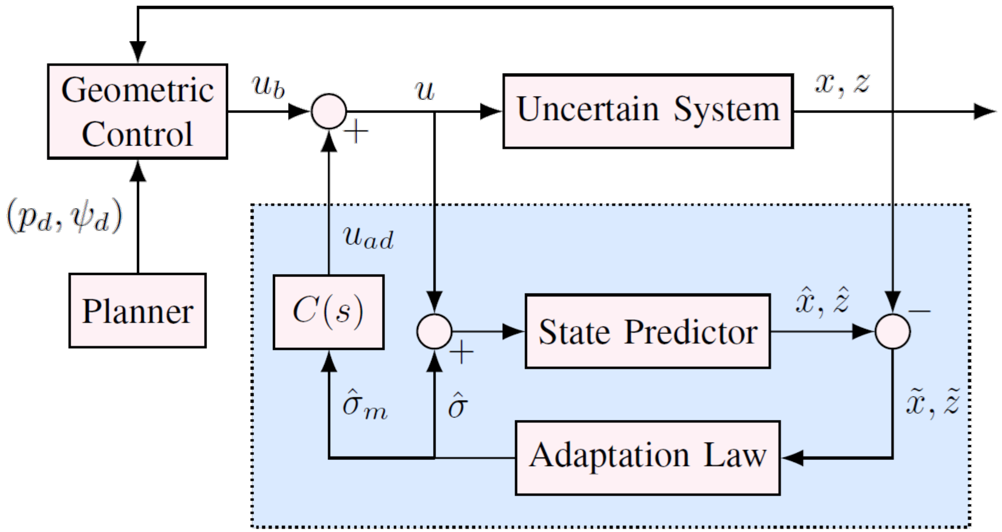
Decoupling

$$\boxed{\|x^\star(t) - x_r(t)\| \leq \sqrt{ke^{-2\lambda t}\|x^\star(0) - x(0)\| + \rho_r(\omega^{-1})}}$$

Robustness: Filter bandwidth ω

Quadrotor Control with $\mathcal{L}_1$ Adaptive Augmentation





Z. Wu, S. Cheng, K. A. Ackerman, A. Gahlawat, A. Lakshmanan, P. Zhao and N. Hovakimyan, "L_1 Adaptive Augmentation for Geometric Tracking Control of Quadrotors", ICRA 2022.

Challenges:

- **Underactuated** dynamics
- **Coupled** translational and rotational motions
- **Uncertainties** and **disturbances**
  - Aerodynamic drags
  - Varying payload/moment of inertia/center of gravity
  - Wind and gust

Our solution:

- The uncertainties are lumped into **unknown forces** σ_F and **moments** σ_M applied to the drone.
- $\mathcal{L}_1$ adaptive control **compensates for** the unknown forces and moments.
- Low-level control: all computations are onboard (400 Hz)
- All the demos next use the **same set of control parameters**.