STRIVES

- Slides approved from previous presentations. This presentation/recording to be posted on NESC Academy website upon final approval.

- Slides – 2, 6, 7, 23, 32 STRIVES approval (with minor stylistic changes, no new technical information) 20240015379
- Slides – 15-20 STRIVES approval (with minor stylistic changes, no new technical information) 20240000122
- Slides 3, 4 – STRIVES approval (with minor cosmetic/ changes, no new technical information added) 20230015269
- Slides 5, 22 – STRIVES approval (with minor stylistic changes, no new technical information)
- Slides 8, 10, 11, 27-31 STRIVES approval (with minor stylistic changes, no new technical information) 20230009566
- Slides – 1, 9, 14, 21, 26 – title slides
- Slides – 33-37 (references list)

(Autonomous) Intelligent Contingency Management Challenges and Opportunities

Presented by Irene M. Gregory

With contributions from

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NASA NESC Flight Mechanics Technical Discipline Team

February 19, 2025

NASA TTT Intelligent Contingency Management

Who are we?

- Subproject under NASA TTT Autonomous Systems
- Small Research Team (~3 Govt, ~2 Contractor totals)
- Larger "Virtual Team": Other NASA projects who work the same problems…
- Agile Development Team that works ALL aspects of contingency management…

- We are a small team and this is a huge research field!!
- We are active Collaborators with Academia and Industry!

What do we do?

- Aero-propulsive Modeling (novel configs)
- Adaptive, Robust, Unified control of transition vehicles
- Autonomy Benchmark Problems
- Control Allocation
- Flight Envelope Prediction (ML)
- Guidance and Trajectory planning: collision avoidance, VFR traffic pattern entry, etc.
- Intelligent Contingency Cognitive Architecture (AI, explainable AI, ML, deterministic, probabilistic…)
- Simulation development

Emerging Aviation Landscape

- **New Paradigm**: Anyone, Anywhere, Anytime (Advanced Air Mobility)
- Government/Industry/Academia are crafting new transportation system(s)
- Novel aerospace sectors: missions and vehicles (e.g., autonomous cargo delivery)
- Business case for **high levels of flight autonomy** (e.g., no onboard pilot, 1-to-many humans to autonomous vehicle)
- Proliferation of Electrified Vertical Takeoff and Landing (eVTOL) vehicle configurations
- Highly nonlinear, over-actuated, transition vehicles with very challenging aero-propulsive modeling

- New technologies: more likely to fail
- **Narrow performance margins** (e.g., battery life) with high safety levels required (e.g., urban flight)
- **Tight integration** between flight control and trajectory planning

Advanced Air Mobility - Safe, sustainable, affordable, and accessible aviation for transformational local and intraregional missions

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, 1st responders (e.g., rapid response to inaccessible disaster areas)
- **Benefits of Autonomy**:
  - System wide **performance** improvements, maximizes capability for fleet/vehicle operations over human operator
  - Enhance aviation **sustainability**
  - Maintains and enhances **safety** as density of heterogeneous fleet of vehicles and operations increases

Autonomy is REQUIRED to enable paradigm shift

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

Sources of Pressure/Threats and Contingency Management

- Sources of pressures/threats that can precipitate contingency management include:
  - Vehicle mechanical (e.g., system fault; fuel issue; MEL-ed equipment; etc.)
  - Airport/vertiport/airspace (e.g., challenging design features; NOTAMS; special ops area; etc.)
  - Air traffic control/management (e.g., challenging procedure; complex clearance; ATC-applied time-pressure; additional restrictions applied; etc.)
  - Automation (e.g., undesired mode or mode change; flight track or speed deviation; etc.)
  - Cabin (e.g., passenger issues, etc.)
  - Dispatch/paperwork (e.g., release errors; takeoff performance; EFB issues; etc.)
  - Environment (e.g., conflicting traffic; terrain; birds; etc.)
  - Weather (e.g., tailwind; wind gusts; turbulence; ice/snow; convective weather; etc.)
  - Ground servicing (e.g., clear zone not clear; pushback error; gate restrictions; etc.)
  - Maintenance servicing (e.g., impacts on flight crew duties, logbook issues, etc.)
  - Operations pressure (e.g., gate/customer service; operational changes; late arrival; etc.)

Source: American Airlines Department of Flight Safety (2021)

At the fundamental level all is predicated on vehicle dynamics, controllability and trajectory planning/replanning

Control

&

Trajectory replanning

(Autonomous) Intelligent Contingency Management

We have Nominal Autonomous Operations Nailed!!

Off-Nominal Autonomous Operations Major Research Challenge!!

Human (ICM):

- **Aviate**
- **Navigate**
- **Communicate**

Autonomous (ICM):

Aviate:

- **Robust & Adaptive Control**
- **Safety (Certificates) & Learning Control**
- **Failure ID** & Flt Envelope Estimation
- **Collision Avoidance & Pattern Entry**
- *Perception* & Environment…
- **ML training & off training guarantees**

Navigate:

- **Planners: Long, Short, Contingency (Spectrum)**
- *Perception* & Environment
- **Recognize Contingency /Failures and Replan..**
- **Multi-path and Optimizations…**

Communicate:

- *Algorithm to algorithm* (asynchronous, timescales)
- Aircraft system to system
- External aircraft (datalink, voice?)
- System of system communications
- Sift out Faulty Information…

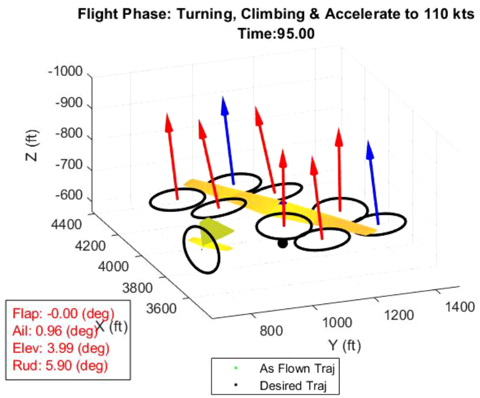
UAM ∈ AAM: Why is Autonomy for Transition Vehicles so Hard?

Vehicle challenges:

- Novel configurations **strain** capability for aero-propulsive modeling
- Electrical propulsion systems drive **lower** vehicle performance **margins**
- "**Transition**" vehicle operations: hover, transition and cruise
- Constant **low** altitude operations (most dangerous portion of flight)

Autonomy challenges:

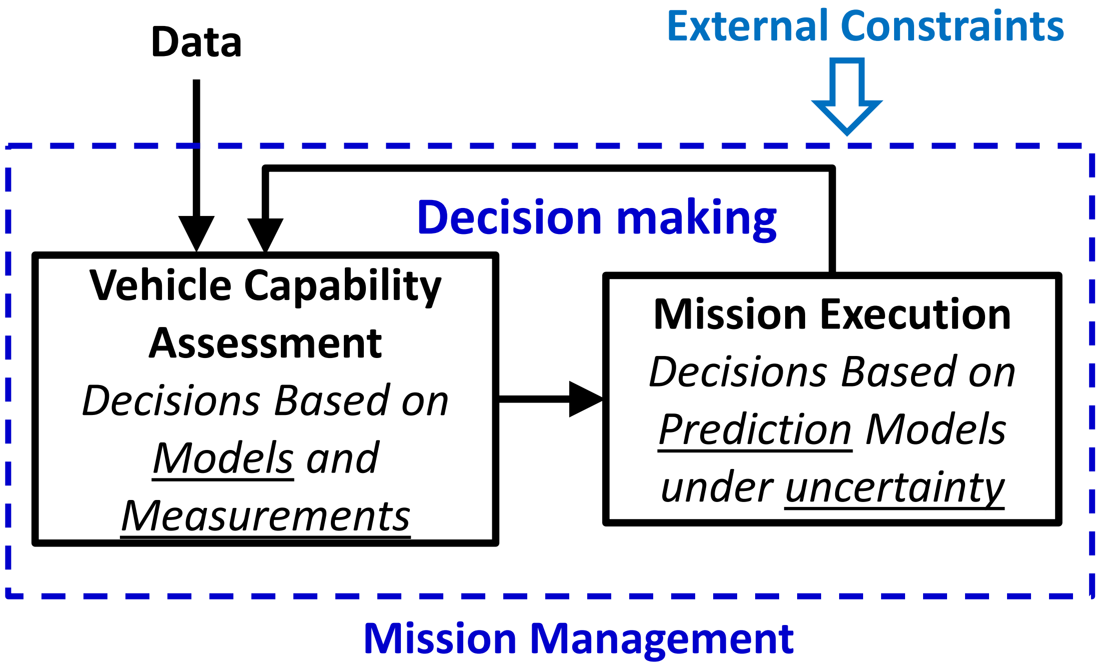
- **Dynamic**, unstructured, **3-D** environment compared to autonomous cars
- Autonomous **perception** (all-weather)
- **Severity** of **mishaps** necessitates requirement for high safety assurance
- Low profit margin missions **preclude** long and expensive vehicle development cycles



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**



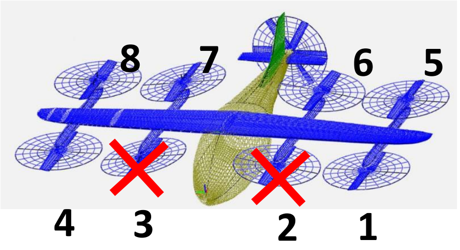
* I. M. Gregory *et al.*, "Intelligent contingency management for urban air mobility," in *AIAA SciTech Forum*, 2021.

AUTONOMOUS FLIGHT FOUNDATIONAL PILLAR: FAIL-OPERATIONAL STABILITY

FLIGHT CONTROL

Autonomous Flight Foundational Pillar – Fail-operational Stability

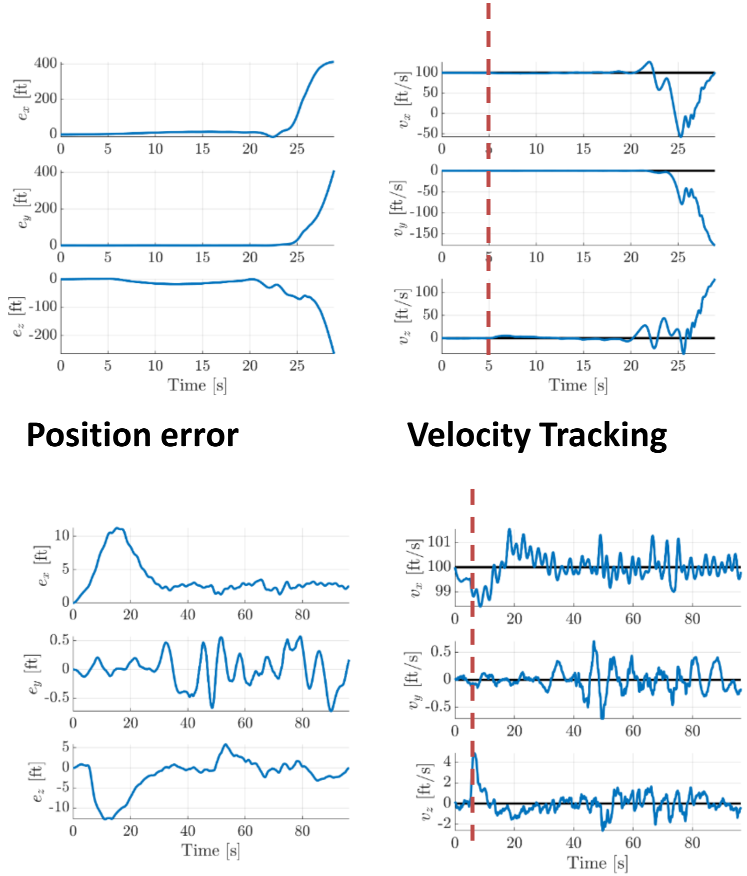
- **Fail-operational stability**
  - If physically capable, must maintain flight, graceful degradation to end mission
- During cruise – **rotors 2 & 3 fail -** vehicle loses half of the rotors that compensate for the longitudinal oscillatory modes, leading to **unstable** performance at this speed
- Without L1 adaptive control (AC), the aircraft is **unstable**
- With **L1 AC,** 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

L1 AC On
Stable



Position error

Velocity Tracking

Foundational Pillar – Robust + L1 Adaptive Control (Performance+Safety)

Variable Stability Learjet - USAF Test Pilot School

Pilot Onboard

VISTA F-16

X-62A VISTA
NDI Baseline
Successful USAF TPS Flight Test (September 2024)

$\mathcal{L}_1$ **MPwC Augmentation**

LOCKHEED MARTIN

Autonomous

Remotely Piloted

NASA Dynamically Scaled Transport 2010-2011

Source: NASA.gov

Robust flight control

Uncertainty compensation

Uniform performance bounds

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

Autonomous Flight – Robustness and Resilience → 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	Tactical	Full State Dynamic
Pre-determined velocity and acceleration profiles	Arbitrary derivative profiles	Vehicle specific dynamic behavior
Recommendation: What should the vehicle do?		**Capabilities: What can the vehicle do?**

- ❑ 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

Path planning, Trajectory Generation

Plans require degrees of dynamic complexity/timescales along a continuum

(Less) <-- Dynamic Complexity --> (More)

Recommendations:
What should the vehicle do?

- “By the book”
- Design considerations
- Low fidelity, general cases, low computational cost

Capabilities:
What is the vehicle capable of?

- Optimal control
- Reachability sets
- High fidelity, highly specific, high computational cost

Autonomy Algorithms:

Seamlessly generate and utilize trajectories based on minimum level of dynamic complexity and fidelity modeling necessary for the task while facilitating communication with other autonomy algorithms with dissimilar dynamic complexity needs

***AUTONOMOUS FLIGHT FOUNDATIONAL PILLAR*: DYNAMIC COMPLEXITY CONTINUUM FOR TRAJECTORY GENERATION**

COLLISION AVOIDANCE

***Requirement*: Real-Time Collision Avoidance of Stationary/Moving (Noncooperative) Obstacles with Separation Guarantees**

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

- Piecewise Bernstein Polynomial (BP) Curves:
  - *Advantages*: Fast and compact trajectory representation, smooth derivatives (position, velocity & acceleration)
  - *Disadvantages*: One piecewise segment cannot 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)

Real time limitation from DDP optimizing the entire trajectory

⇩

Change formulation for DDP as MPC , i.e., Receding Horizon COBRA-DDP formulation

⇩

Real-Time Collision Avoidance of Stationary/Moving (Noncooperative) Obstacles with Separation Guarantees

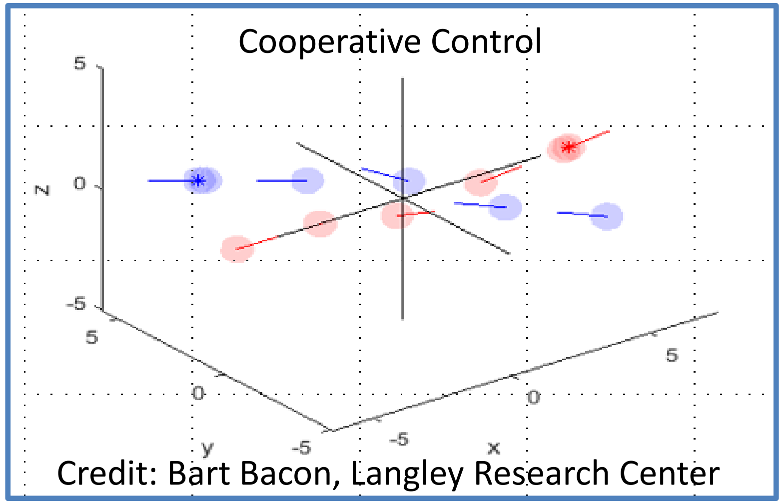
Optimal Reciprocal Collision Avoidance Algorithm (ORCA)

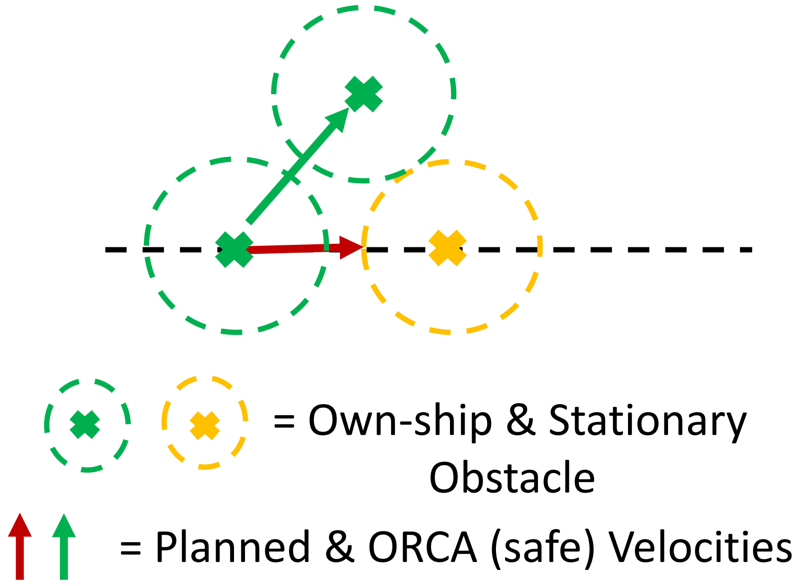
ORCA Algorithm (robotics community focused):

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

ORCA:

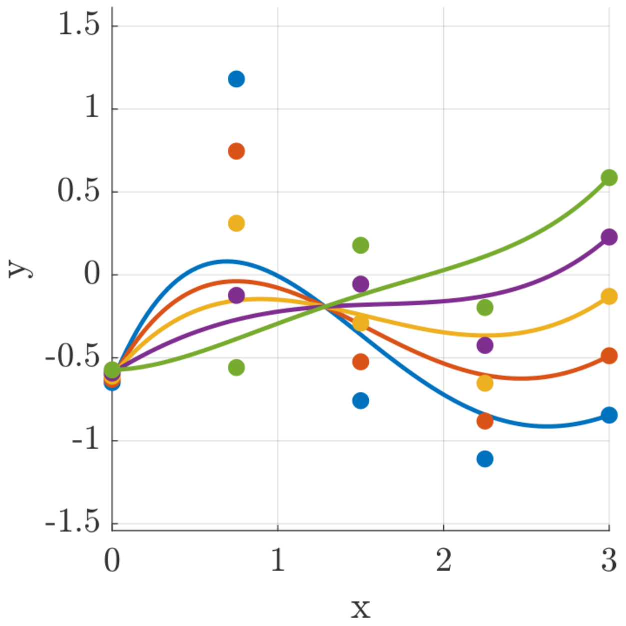
- *Input*: position and velocity knowledge (own-ship, obstacles/vehicles)
- *Output*: next own-ship velocity step (magnitude and direction)
- Point modeling (no vehicle dynamics) with safety sphere (keep-out radius)
- “Velocity object” representations*, provides mathematical guarantees of collision free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



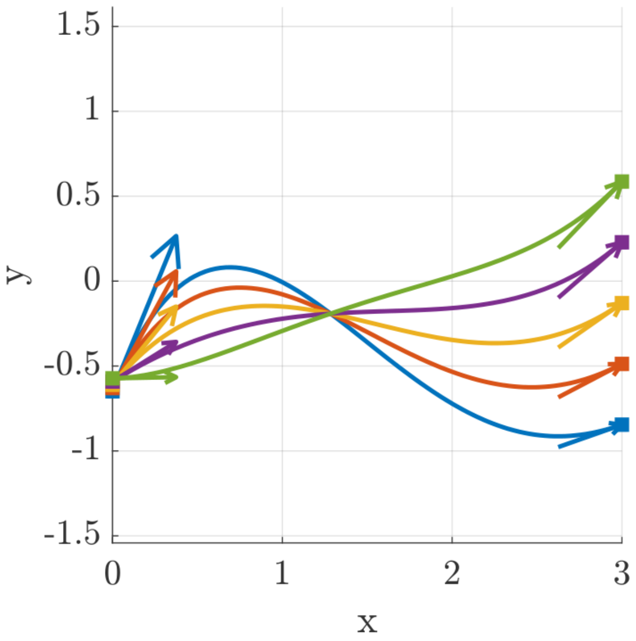


Bernstein Polynomials – Overview

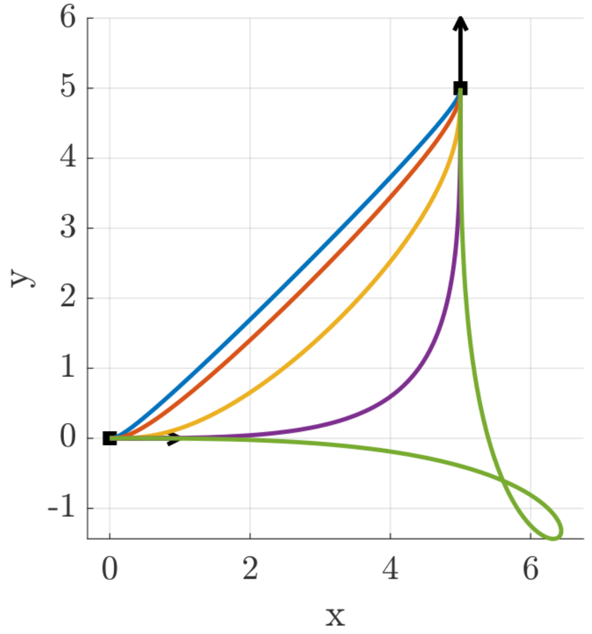
- Bernstein Polynomials have many mathematical properties that make them a good choice for trajectory planning
- Through a slight modification, they can be used to directly interface with other algorithms that have dynamic constraints on the endpoints, such as ORCA



Bernstein Polynomials are defined by parameters called control points



The derivative curve parameters can be computed in closed-form and used to meet dynamic constraints at end points

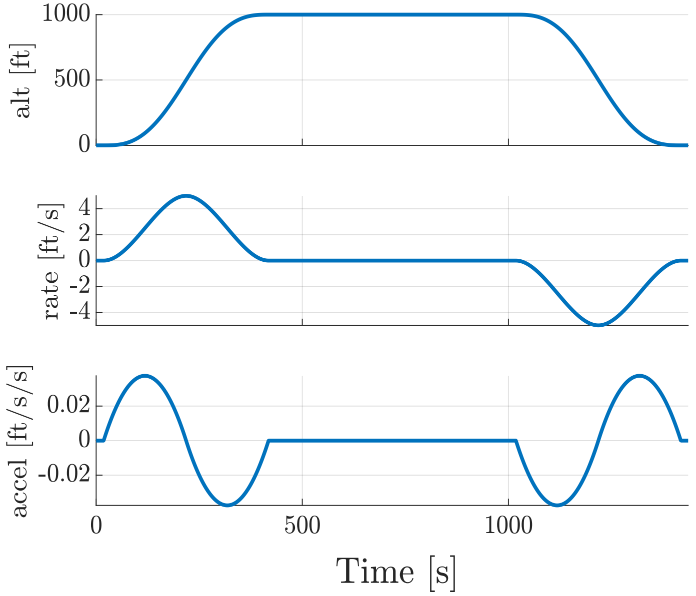


Fixing endpoints allows the curve to “tighten” or “extend” naturally for changing durations of the curve

Bernstein Polynomials – Dynamic Complexity

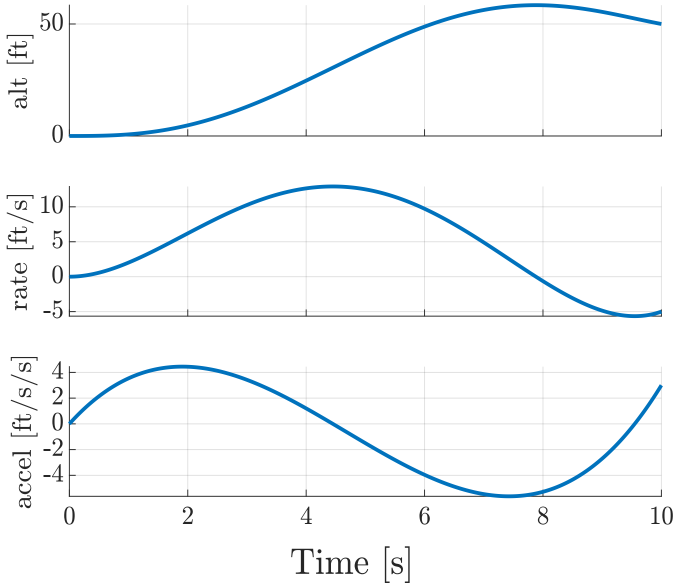
(Less) <-- Dynamic Complexity --> (More)

Strategic – BP



Constructed from waypoints, with constraints added enforce typical behavior, e.g., position/velocity holds

Tactical – ORCA/BP



Fundamental component, can be used to construct arbitrary plans and used to inform state trajectories

Full State Dynamics – DDP

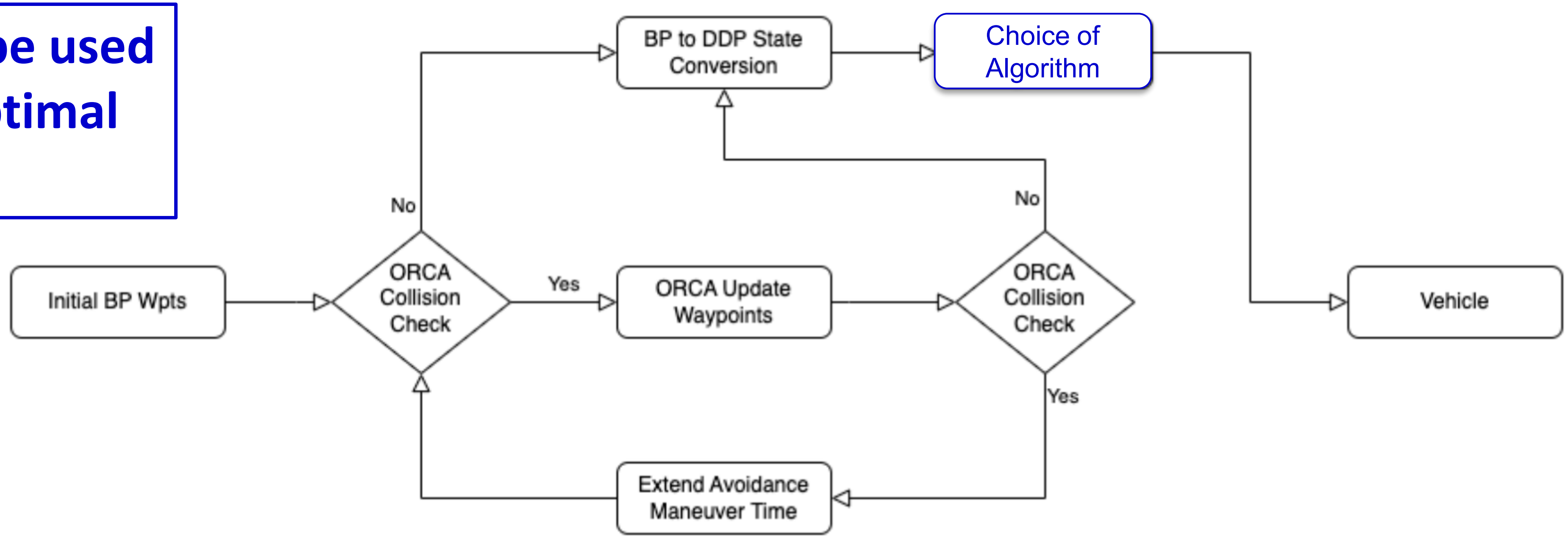
$$\dot{p} = \mathbf{v},$$
$$\dot{\eta} = S\omega,$$
$$\dot{\bar{\mathbf{v}}} = -\dot{\psi} e_3 \times \bar{\mathbf{v}} + g + m^{-1} \bar{F}\left(\bar{\mathbf{v}}, \omega, \bar{R}, u\right),$$
$$J\dot{\omega} = -\omega \times J\omega + \tau\left(\bar{\mathbf{v}}, \omega, \bar{R}, u\right),$$

Vehicle specific, waypoints define first equation fully. Additional waypoints may be needed to define orientation, etc.

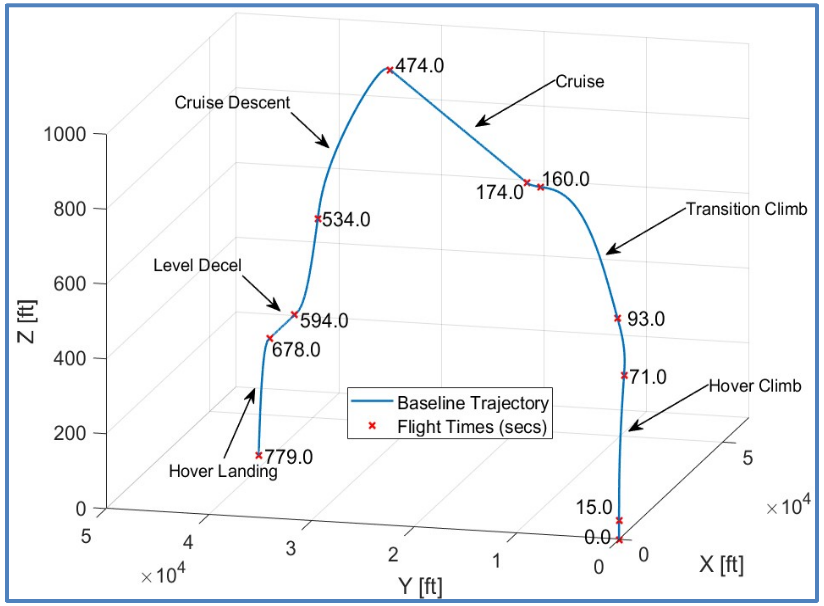
BP and Differential Dynamic Programming (DDP)

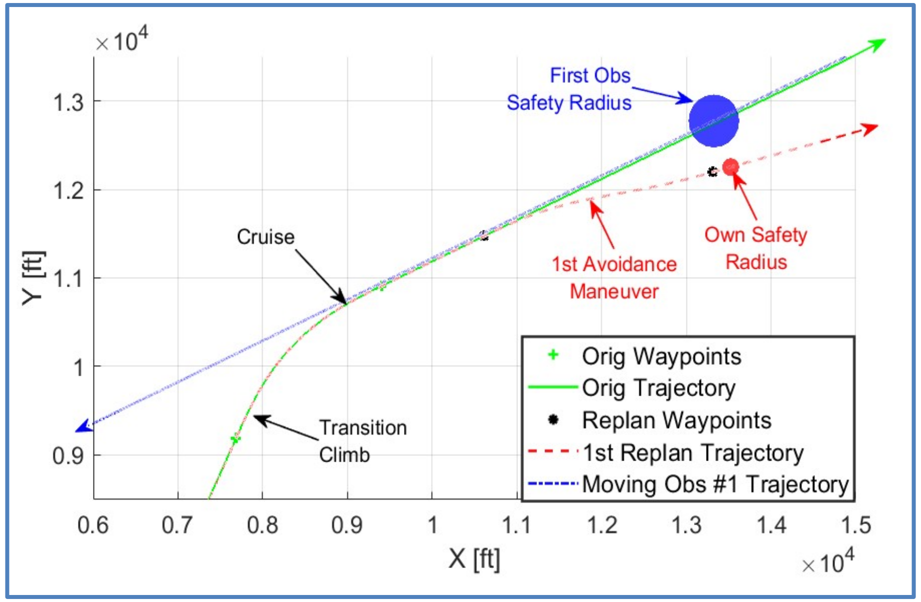
- Leverages ORCA *fast collision avoidance checks* and *preferential avoidance direction* selection
- BPs serve as compact trajectory representation between ORCA and DDP that can be quickly evaluated at any time along the curve
- DDP provides *short time horizon dynamically* feasible optimal trajectories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

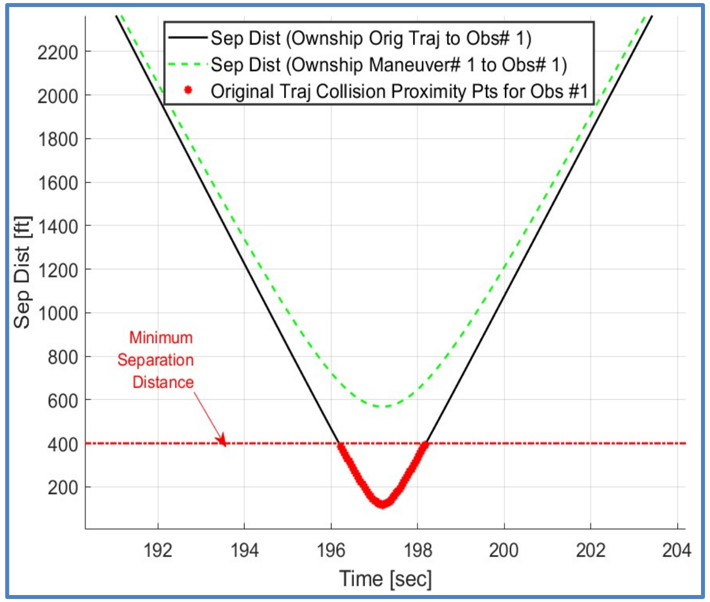
COBRA structure can be used with any iterative optimal control solver!

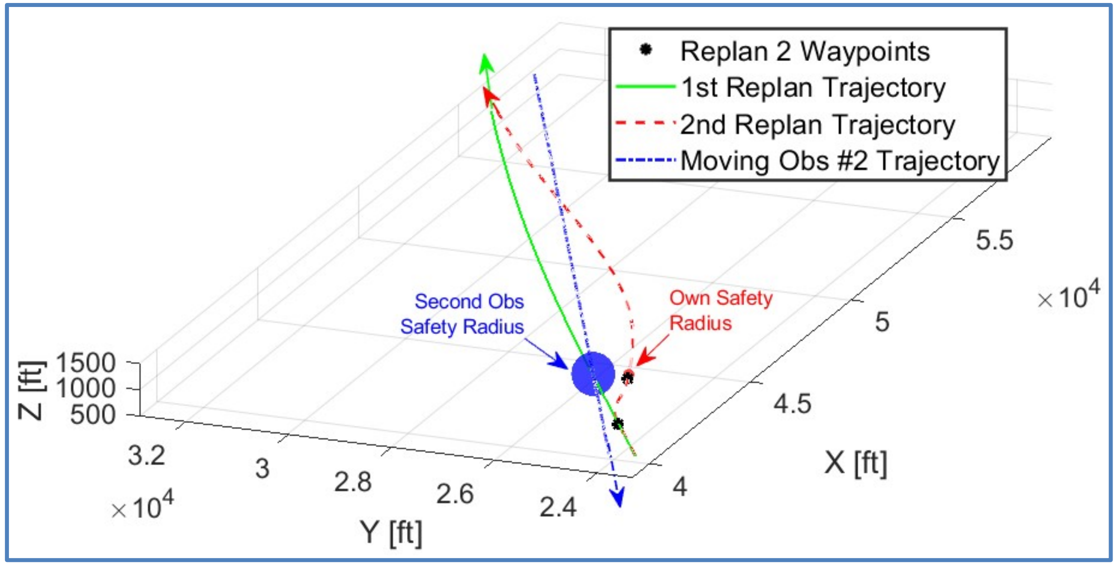


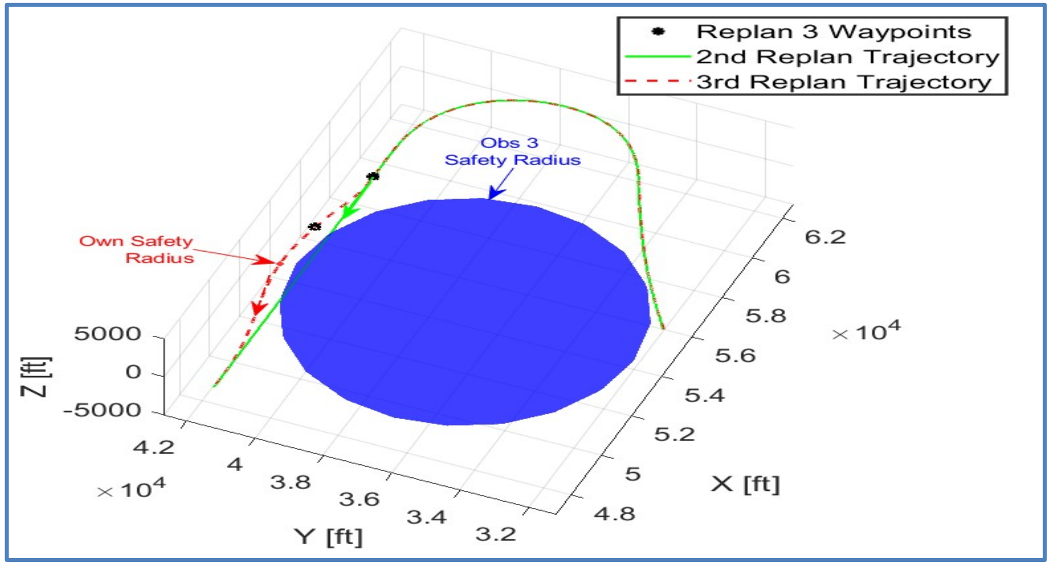
BP and Optimal Reciprocal Collision Avoidance (Continued)











AUTONOMOUS FLIGHT FOUNDATIONAL PILLAR: INFRASTRUCTURE – DEVELOPMENT, TESTING AND EVALUATION ENVIRONMENT

Algorithm performance only as good as the testing environment reflection of the real-world

Challenge problems with real-world assumptions within a collaborative open-source simulation

Capabilities Assessment: Simulation Environment

- Limited by knowledge and expertise of designers
  - Not possible to test edge cases not contained in simulation requirements
  - Full-fidelity real-world simulation environment is not attainable
  - Computational complexity of environment trades against simulation speed
- Must clearly understand and document levels of fidelity
  - Meaningful with respect to benchmark objectives
  - Metrics must not convey more fidelity than is possible to assess

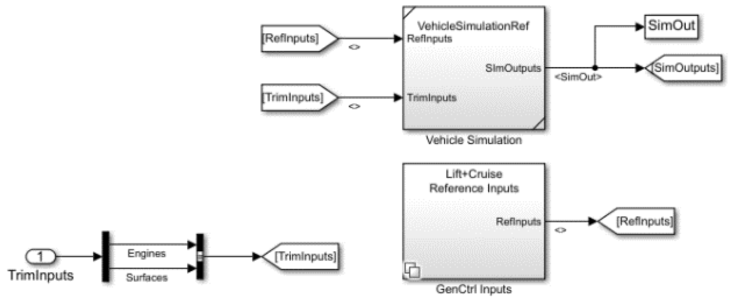
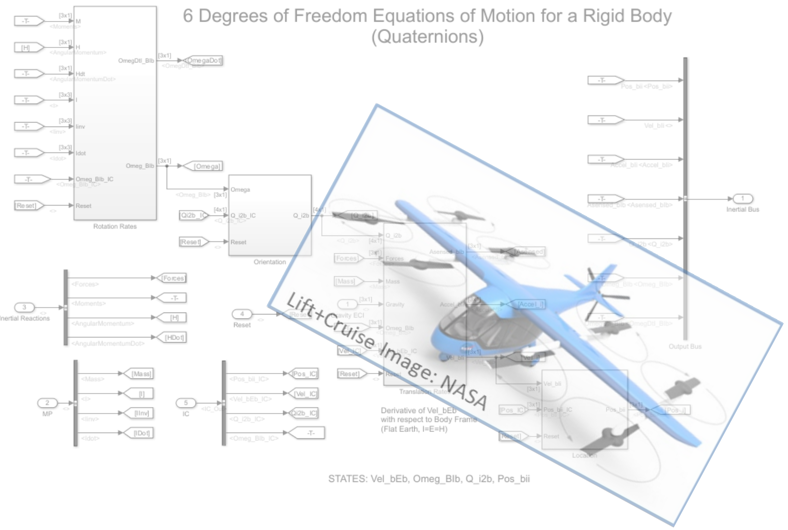


Image credits: NASA

Generalized Urban Air Mobility (GUAM)

What is it?

- Open source, 6-DOF, non-linear, rigid body simulation framework for Urban Air Mobility (UAM) vehicles
- Modular simulation architecture facilities easy implementation of vehicle model, controller, sensor (perception), autonomy algorithms



Why is NASA releasing it?

- Foster collaboration to address wide array of research challenges for UAM autonomy
- Provide common simulation architecture for collaboration and performance comparison within the autonomy UAM research community
- Address barriers of proprietary information, limited research staffs, and limited access to medium/high fidelity UAM models

What is in the initial release?

- Single NASA Lift+Cruise vehicle configuration
- Two aero-propulsive models: strip theory and polynomial models
- Baseline unified (across hover/transition/cruise) iLQR controller
- Aero/propulsor effector and failure models
- Matlab-autocode capable
- Compact, continuous trajectories using piece-wise Berstein polynomials

Challenge Problems:

- Provide code & data that formulates large research challenges for the autonomous UAM community
- Examples: collision avoidance, effector failure (control and flight envelope estimation), traffic pattern entry, trajectory replanning, etc.

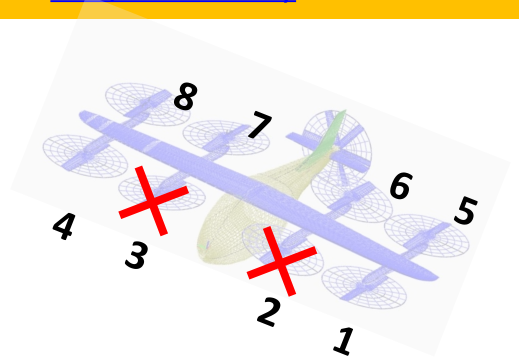
GUAM Community:

GIT repo:
https://www.github.com/nasa/generic-urban-air-mobility-GUAM
Challenge Problems:
https://nari.arc.nasa.gov/ttt-ram/community

What is in the next release?

- Flight visualization and large visualization data sets
- Artificial Intelligence/Machine Learning friendly
- Cognitive (decision making) architecture
- Python and Robot Operating System (ROS) capable

Perception
Aero-propulsive Modeling
Transition vehicle control
Cooperative & uncooperative collision avoidance
Flight envelope estimation
Control allocation
Dynamically feasible trajectory
Trajectory optimization
Cognitive architecture
Human machine interface
Safety guarantees



Community Challenge Problems

Who is the focus?

- Diverse UAM autonomy research teams: university, industry, government, aircraft designers, regulators, GN&C, perception/sensors, ML & AI researchers

What is a Community Challenge Problem?

- Challenging issues that the UAM research community must tackle to enable safe, efficient and certifiable autonomous UAM operations (e.g., trajectory tracking, collision avoidance, effector failures, pattern entry, etc.)

Where will research be conducted/presented?

- AIAA SciTech, within universities, formal/informal collaboration among research groups, online forums, within NASA

When?

- Starting now! GUAM V1.0 released (see github) V2.0 (ML and visualization version) targeting summer 2025. GOAL is for enduring research efforts…

How?

- Simulation release, challenge problem release, metrics definitions, AIAA SciTech 2025, 2026 invited sessions, ULIs, actively seeking collaboration opportunities…

Why?

- Problems are too “big” for any one research group to tackle! Limited staffs, limited funding, proprietary data issues, lack of access to relevant (transition vehicles), barriers to collaboration

Community Challenge Scripts and Data Files:

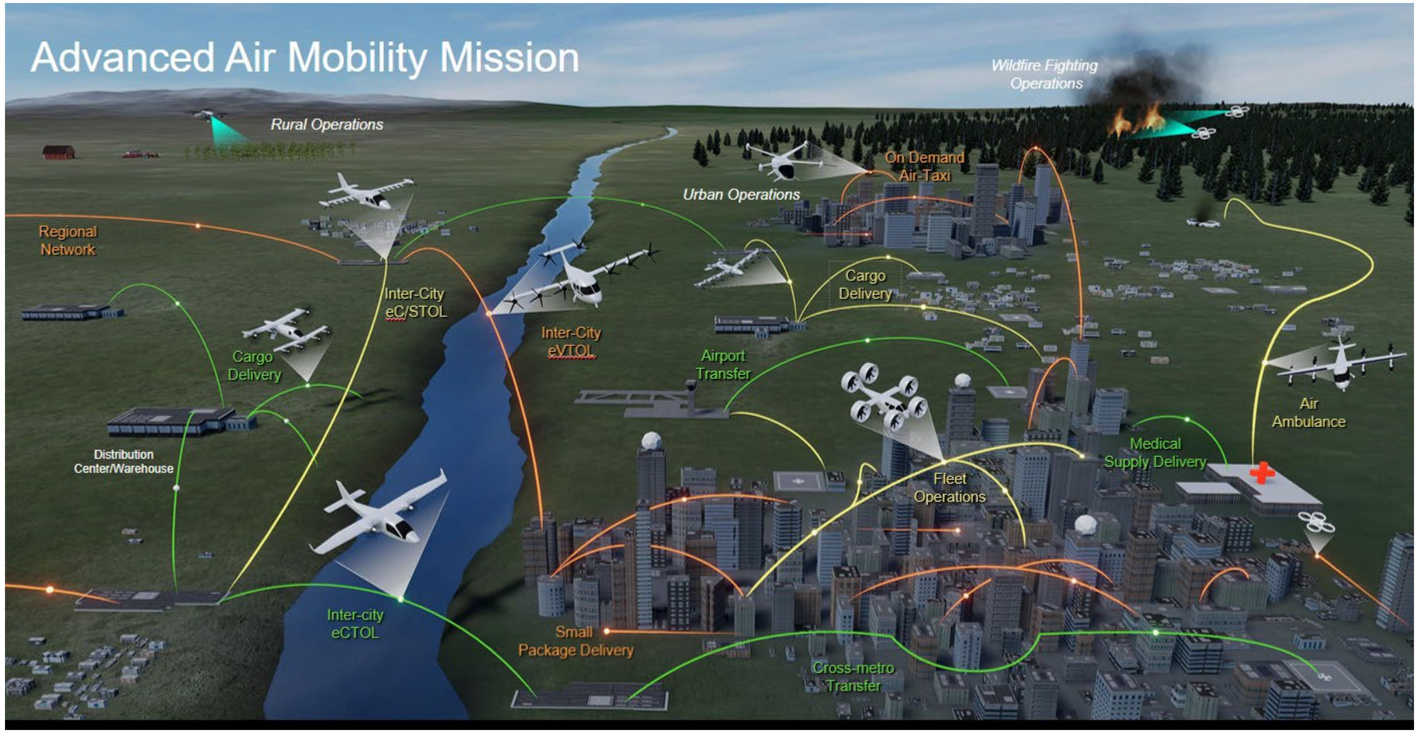
- **Developing four data sets to facilitate a variety of challenge problems:**
  1. ***Own-ship trajectories***: randomly created piecewise Bernstein polynomials, modifying straight line segments to be generically dynamically feasible (not aircraft specific). *Full flights*: take-off to cruise and landing
  2. ***Stationary obstacles***: randomly generated spherical obstacles of various sizes designed to *correlate with own-ship* trajectories
  3. ***Moving intruder trajectory segments***: randomly created piecewise Bernstein polynomials. Designed to correlate with own-ship trajectories to generate a *variety of collision/near collision scenarios*
  4. ***Effector failure scenarios***: randomly created *single/multiple effector* failure scenarios designed to correlate with own-ship trajectories
- **Matlab scripts used to generate the data files:**
  – Insight into the creation of challenge problem data sets
  – Enables users to customize for their own research
- **Metrics**
  – Important for comparison and evaluation of performance
  – Forthcoming..

Layering of data sets creates increasingly complex challenge problems

AUTONOMOUS FLIGHT :
NEXT LAYER OF CAPABILITY ASSESSMENT AND DECISION MAKING

INCORPORATING LEARNING

Complex Dynamics and Environments



Adapted from
N. Hovakimyan

Challenges

- Unpredictable environments
- Obstacle-rich and dynamic
- Nonlinear uncertain dynamics

Solutions

- Fast (re-)planning
- Safe planning
- Safe learning
- Guaranteed robustness

Challenges and the Tools

Complex Dynamics | Uncertain Models | Uncertain Environments

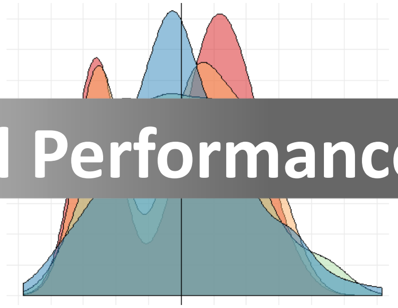
Control theoretic tools

- Structured models
- Parametric uncertainties
- Deterministic representations

Data-driven ML tools

- General models
- Unstructured uncertainties
- Stochastic representations

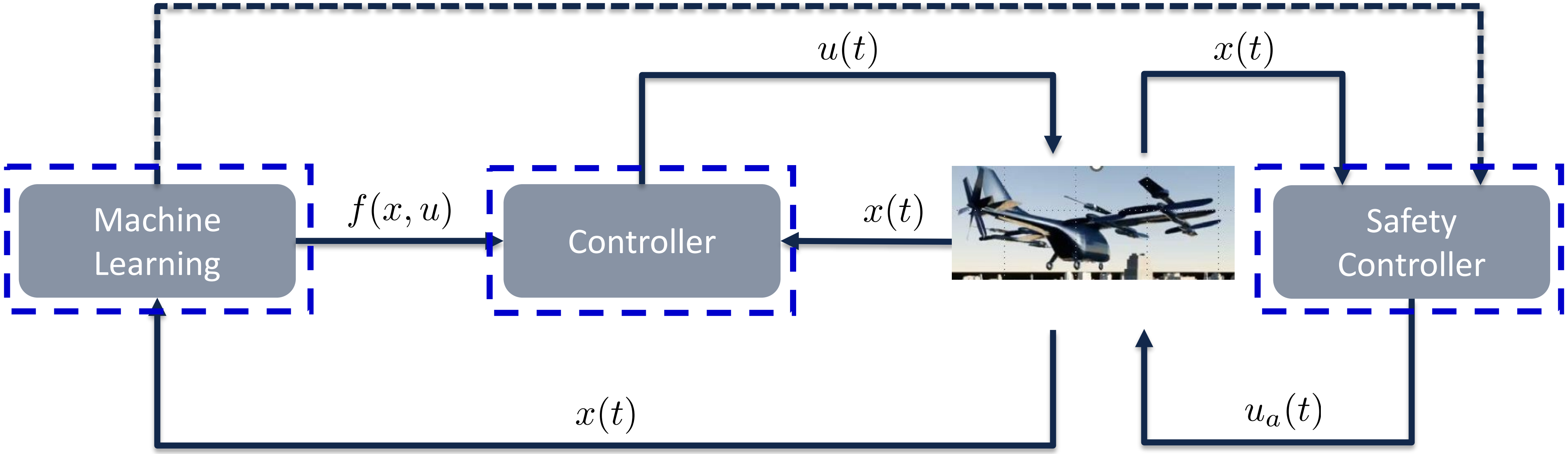
Safety & Robustness ⟷ **Empirical Performance**



Bridging the divide

Adapted from
N. Hovakimyan

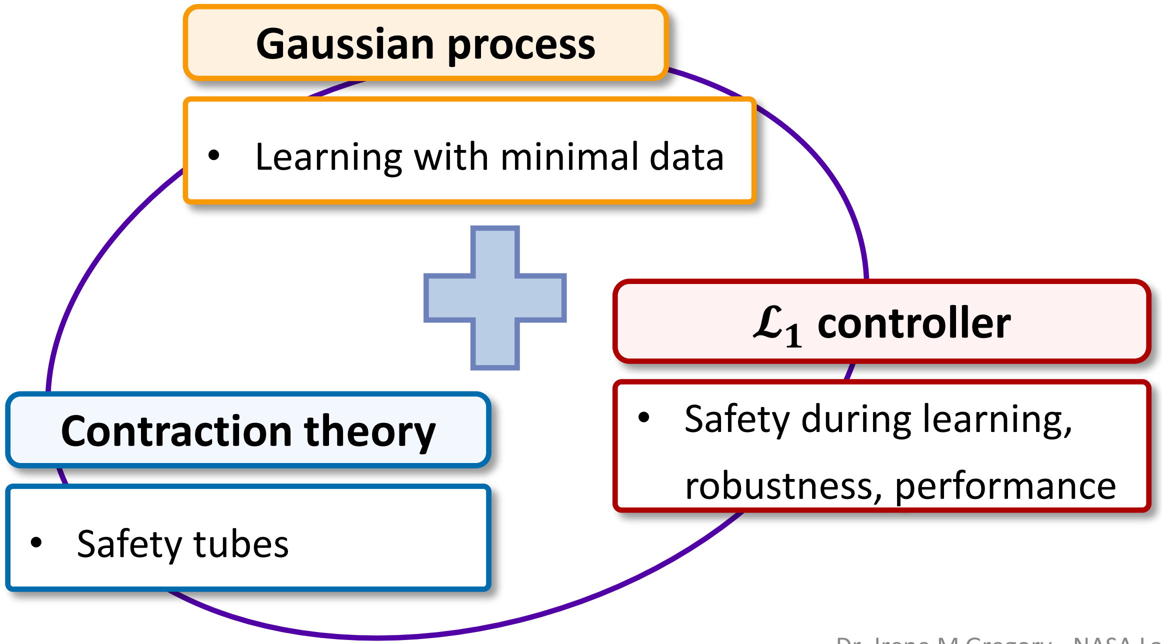
Safe Learning & Control: Framework



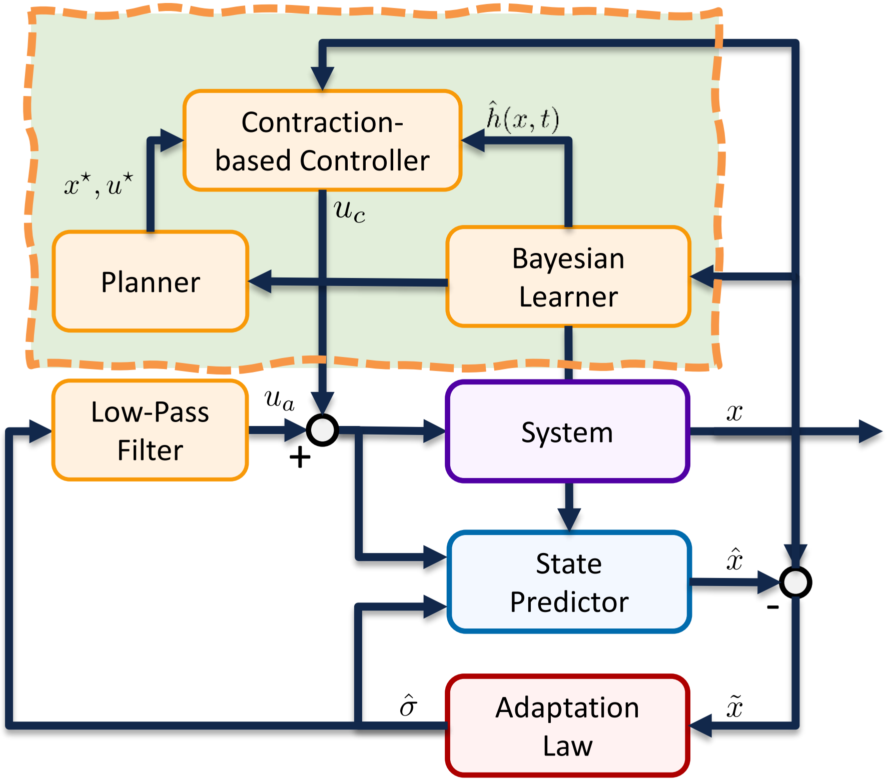
- Nominal Control Design – Foundation for desired properties
- Robust Adaptive Augmentation – Build-up for safety
- Learned Models – Performance and robustness

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

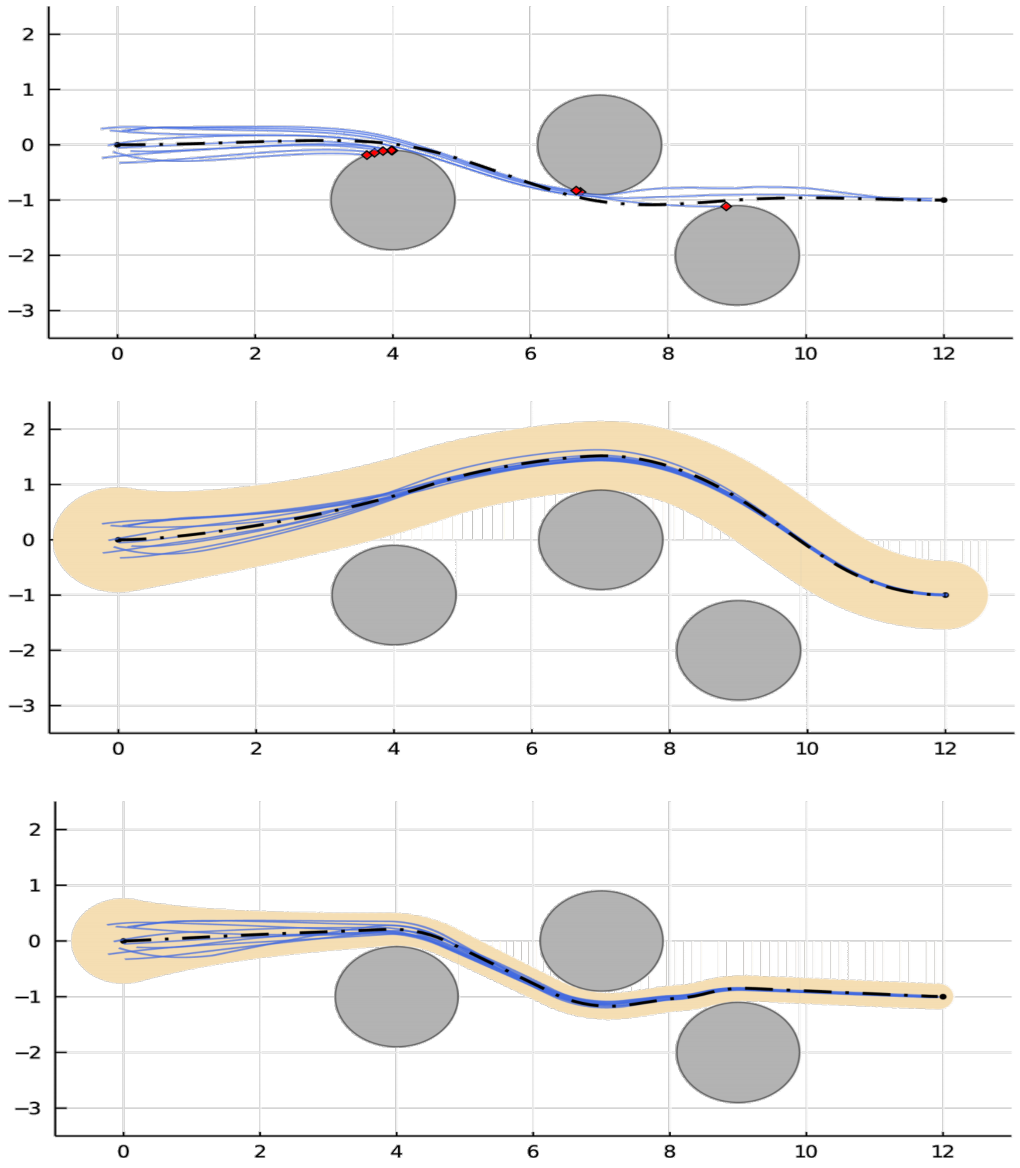


$C\mathcal{L}_1$-$\mathcal{GP}$ Architecture



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

$\mathcal{CL}_1$-$\mathcal{GP}$: Contraction $\mathcal{L}_1$ with Bayesian Learning



CCM only feedback → No safety guarantees

Out of 10 random initial conditions, 8 end in collision

Contraction $\mathcal{L}_1$ → Safety guaranteed

No learning → Safe but conservative

$\mathcal{CL}_1$-$\mathcal{GP}$ → Safety & Performance

As the uncertainty is learned → Performance improvement without sacrificing robustness

Adapted from N. Hovakimyan

Gahlawat, et al. Contraction $\mathcal{L}_1$-Adaptive Control using Gaussian Processes. *Annual Conference on Learning for Dynamics and Control (L4DC)*, 2021.

GUAM v2.0 New Capabilities

- High fidelity visualization: Unreal Engine v4 & v5
- Ease of sensor implementation (e.g., camera lidar): Microsoft Airsim and CodexLabsLLC Colosseum
- ROS2 HUMBLE integration: no Matlab toolbox required
- Cognitive architecture/framework and py-guam libraries (connection with Python ecosystems, including PyTorch, etc.)
- Example Collision Avoidance: Optimal Reciprocal Collision Avoidance (ORCA) integrated with Bernstein Polynomials

- GUAM v1.0 Legacy Capabilities:
  - Extensive six degree-of-freedom, nonlinear, rigid-body aircraft simulation framework
  - Urban Air Mobility (UAM) concept transition vehicle (NASA Lift+Cruise)
  - Two aero-propulsive models (strip theory and polynomial)
  - Baseline: iLQR unified controller
  - Aerodynamic and rotor failure models
  - Community Autonomy Challenge Problem data sets (own-ship full flight trajectories, stationary and moving obstacles, effect failures)

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 systems approach, integrated individual algorithms/methods
  - Openly sharing knowledge and unifying community around remaining challenges
  - Taking **higher technical risk** and focus beyond immediate time horizon

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