Virtual Sully: Autopilot with Multi-Level Adaptation for Handling Large Uncertainties

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MOTIVATION

- In 2009, Airbus 320 lost both engines shortly after takeoff due to bird strike.
- Sully glided the plane to a ditching in the Hudson River off Midtown Manhattan. All 155 people aboard were rescued by nearby boats.
- Flight control outside of the operation window

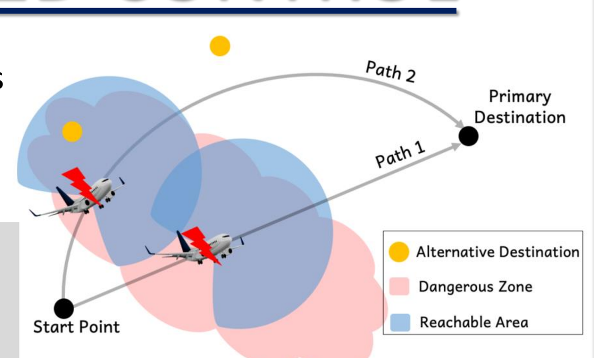

(Credit: Wikipedia)

What does it take to achieve the goal of fully autonomous autopilot (Virtual Sully) that can make the right decision in the presence of unexpected large uncertainties?

BACKUP PLAN CONSTRAINED CONTROL

- Traditional path planning problems for robotics and autonomous vehicles consider collision avoidance enough for safety. This consideration is not enough for emerging automated systems that perform complex tasks requiring safety criticality.

Given primary and alternative destinations, how to design a controller for the aircraft to arrive at the primary destination while maximizing the feasibility of safe landing at any destination in case of emergency?



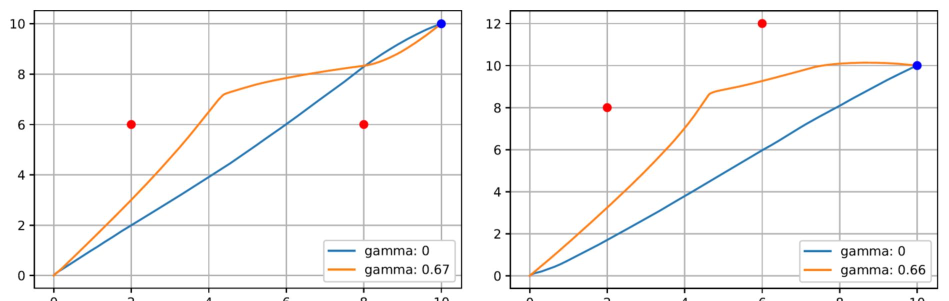
Illustrative example

- 3M (Multi-horizon Multi-objective Model predictive path integral control) maximizes feasibility of safe landing in case of emergency at any destination.

Multi-objective
- Address multi-destination control problems
- Closed-loop stable weight

Multi-horizon inputs
- Evaluate multiple different objectives by providing trajectories towards all the destinations

MPPI control
- Handle computational complexity by parallel computing

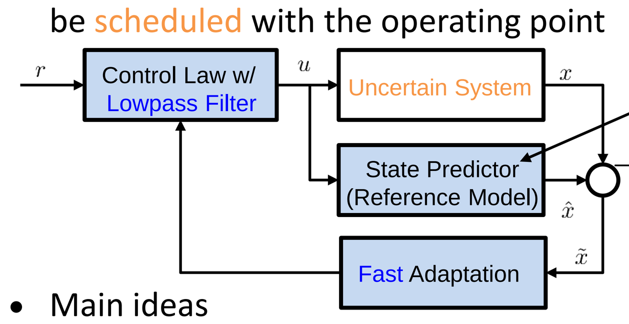


🔵 : Primary destination 🔴 : Alternative destination

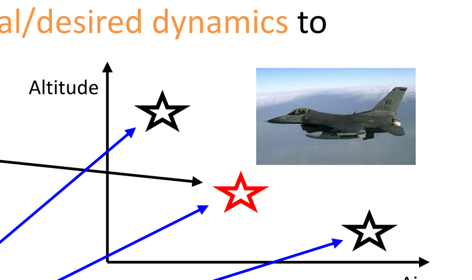
- The aircraft with 3M makes a detour to the primary destination in both cases, flying near alternative destinations.
- The detour trajectories are safer in the backup plan sense, providing a shorter path toward one of the alternative destinations when an emergency landing is in need.

ROBUST ADAPTIVE CONTROL WITH SCHEDULE

- Many systems with large operating envelopes require the nominal/desired dynamics to be scheduled with the operating point



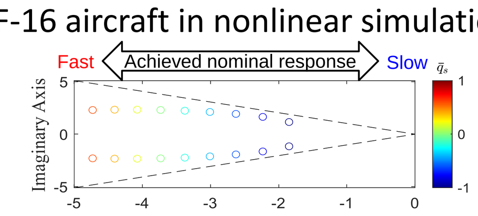
Usually characterized by an LTI system
$\dot{x}_{ref} = A_m x_{ref} + B_m u$



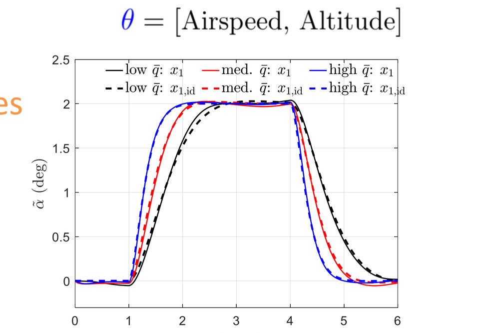
$\dot{x}_{ref} = A_m(\theta)x_{ref} + B_m(\theta)r$

$\theta = [\text{Airspeed, Altitude}]$

- Main ideas
  - Use LPV models to characterize the variation of desired dynamics
  - Leverage robust control method to handle unmatched uncertainties
  - Validated on an F-16 aircraft in nonlinear simulations



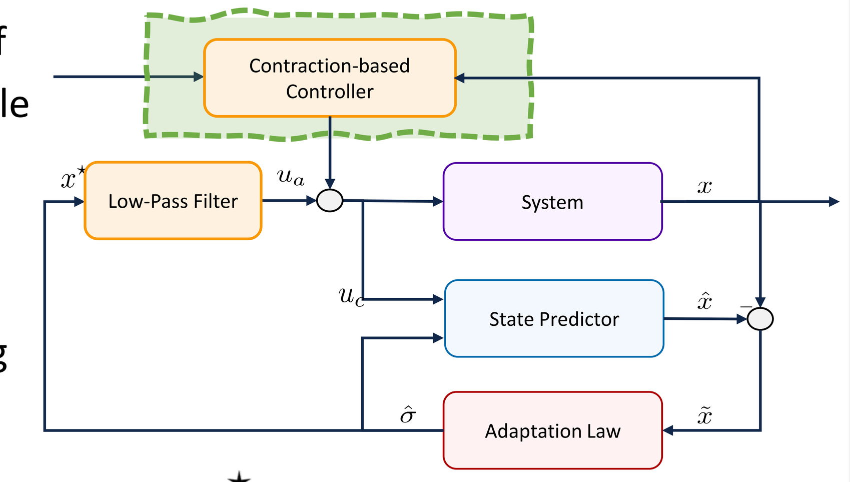
Poles of the nominal closed-loop system VS (scaled) dynamic pressure

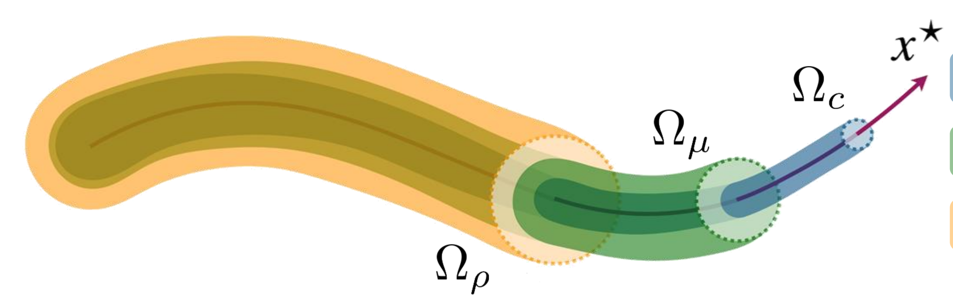


Trajectories of angle of attack (AoA) under different operating points
(Dashed lines: desired, Solid lines: actual)

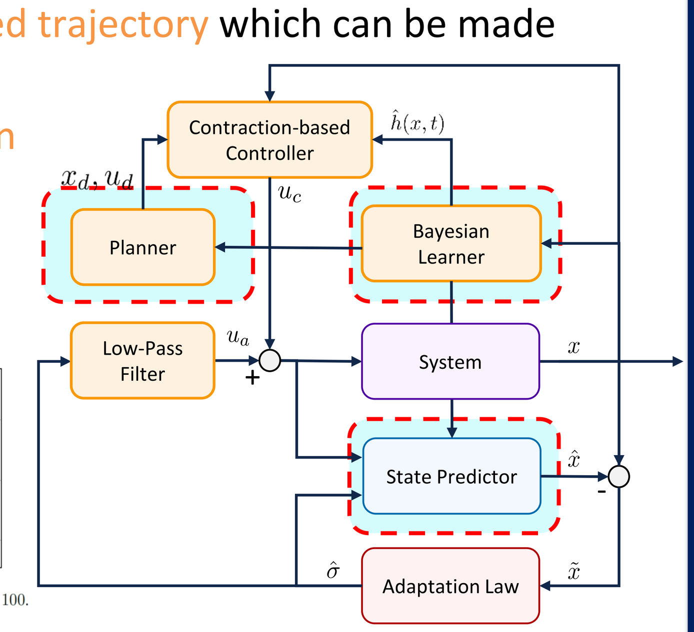
SAFE CONTROL

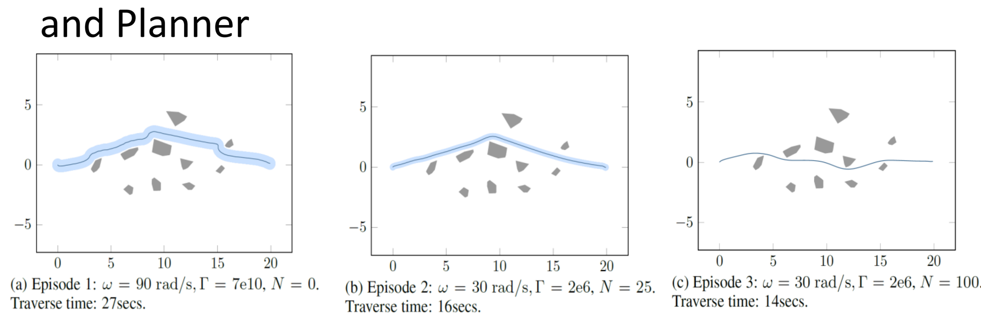
- Contraction theory enables consideration of nonlinear reference systems and is applicable to a large class of nonlinear systems.
- $\mathcal{L}_1$-adaptive control compensates for uncertainties with guaranteed robustness.
- Combined architecture allows for publishing certificates of performance and robustness.





- Enables robots with nonlinear dynamics to safely operate under the presence of model uncertainties and external disturbances
- $\mathcal{RL}_1$-Control ensures safety tubes around the desired trajectory which can be made arbitrarily small in the trade-off with robustness
- $\mathcal{RL}_1$-$\mathcal{GP}$ safely incorporates the learned information regardless of the state of learning, the tube shrinks without sacrificing robustness
- Learned estimates incorporated into State-predictor and Planner





Learning kicks in ➡ tube shrinks ➡ better planning and control

FAST REPLANNING

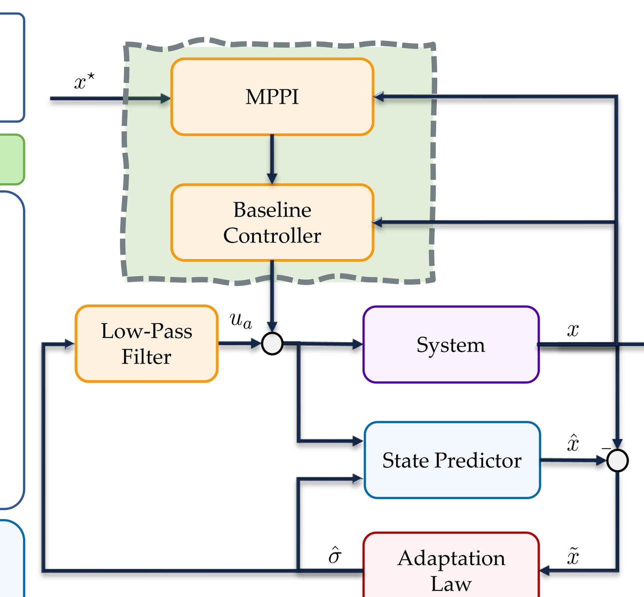
- Fast and robust re-planning is needed for mission success in complex, dynamic and uncertain environments.
- Model predictive path integral (MPPI) control provides a framework for solving nonlinear MPC with complex constraints in near real-time.
- Robustness against dynamic uncertainties and disturbances is achieved through an $\mathcal{L}_1$ augmentation.

$$\dot{x}_{t+1} = \underbrace{f(x_t, u_t + \epsilon)}_{\text{Nominal system}} + \underbrace{h(x_t, u_t)}_{\text{Unknown nonlinearity, disturbance}}$$

MPPI
- Optimal control computation forward in time for nominal system
- Update the control sequence iteratively by sampling (thousands of) trajectories

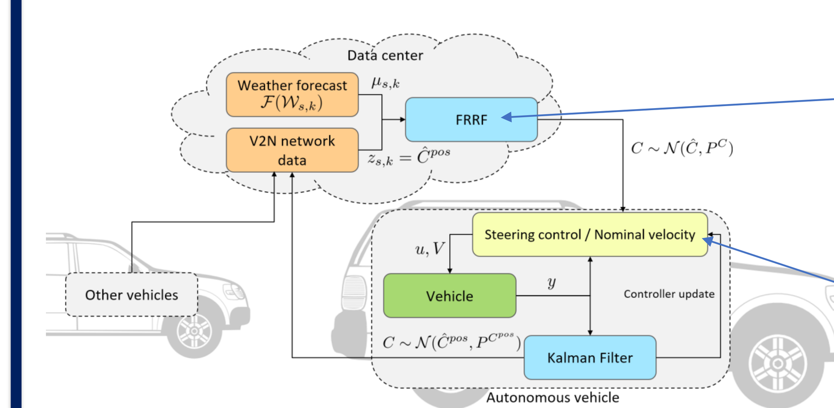
$\mathcal{L}_1$ adaptive control
- Robustifies against the discrepancy
- Guaranteed robustness and transient and steady-state bounds for performance

- Can leverage parallel sampling for modern GPUs
- Can handle complex (possibly non-differentiable) dynamics and cost functions



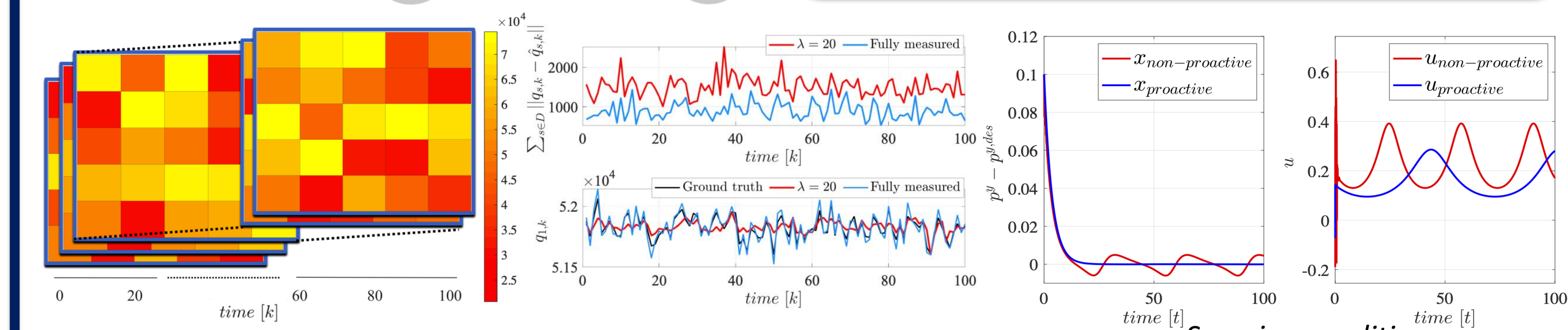
NETWORKED PROACTIVE ADAPTATION

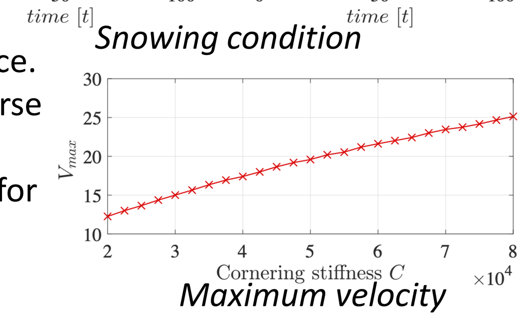
This is motivated by the need for proactive adaptive control in response to complex and unforeseen environments.



Fixed Rank Resilient Filtering (FRRF)
- Efficient recursive estimation for large area
- Robust to modeling error

Proactive $\mathcal{L}_1$ Adaptive Controller and Velocity Design
- Robust design for all predicted uncertainty range
- Rapid disturbance compensation
- Guaranteed transient and steady-state performance
- Safe velocity range

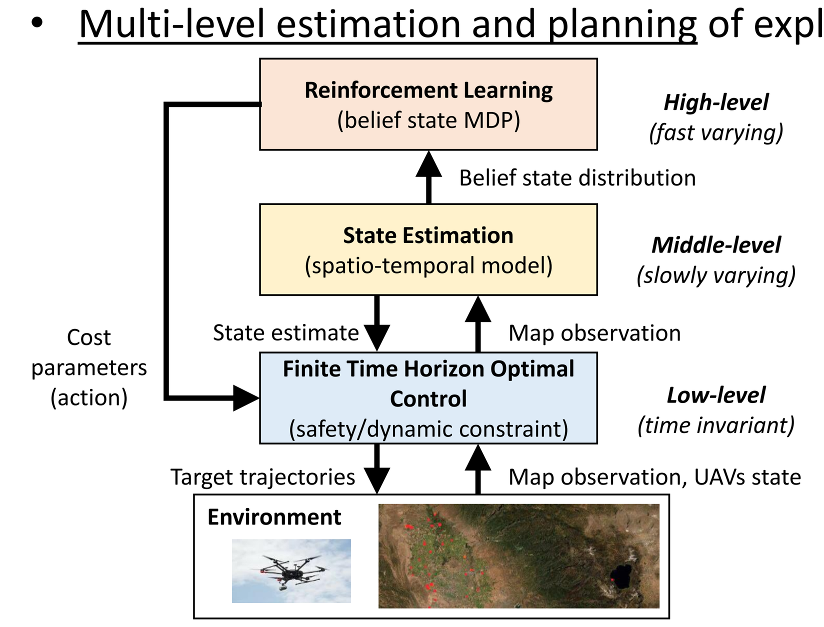




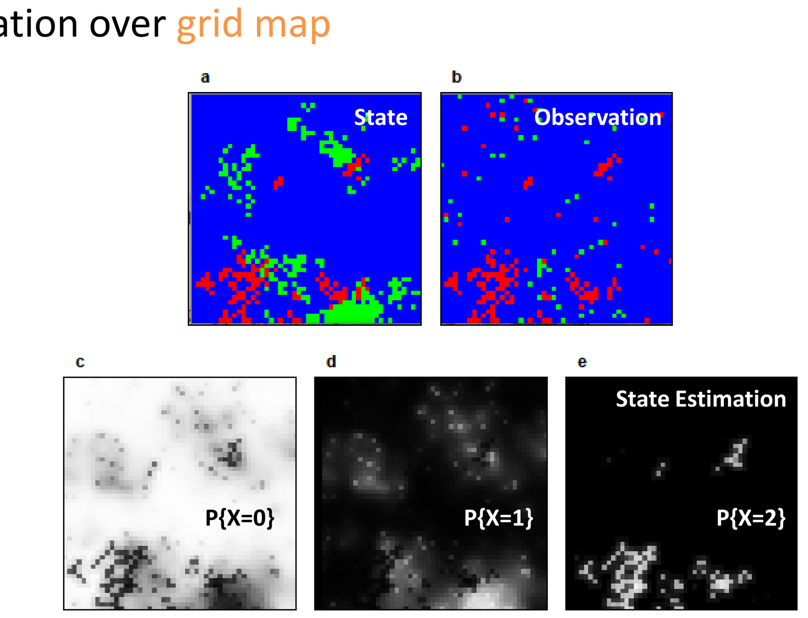
- FRRF generates prior estimation heatmap characterized by mean and variance.
- Estimation performance has been compared with full measurement and sparse measurements in the presence of modeling uncertainty.
- Proactive control maintains desired transient and steady state performance for all environmental conditions.
- The velocity design program provides maximum safe velocity.

NETWORKED PROACTIVE ADAPTATION

- Spatiotemporal model of dynamically changing environment
- Multi-level estimation and planning of exploration over grid map



- Multi-level Framework -



- Estimating Hidden State (GREEN) -
https://youtu.be/ajCEbuEkpbY

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