Intelligent Contingency Management for Urban Air Mobility

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Third Aviation Revolution

• Urban Air Mobility
  – Part of **Anyone, Anywhere, Anytime**
    Advanced Air Mobility concept
  – Largely enabled by electrification and automation
  – **Autonomous flight** to fully realize the market potential
  – **Urban Air Mobility** is the most challenging subset
  – Operation in complex environment and densely populated areas

• Driving Factors
  – Cost
  – Reliability
  – Flexibility
  – Trustworthiness for safety-critical systems

• Dynamic data driven approaches play an integral part in enabling this emerging market
Challenges to Enable Urban Air Mobility

• Develop **assured autonomous functions** that enable safe and efficient operations in increasingly complex environments

• Driver is off-nominal conditions requiring robust **contingency management** and **graceful degradation** to unforeseen events

• Fundamental research challenges in adaptive mission management, robust autonomous decision making, explanatory intelligent systems, intelligent contingency management, and graceful performance degradation in the unique domain of **aviation safety-critical systems**

• External **degraded** information and communications

• High level of **assurance** and **safety**

• Systems designed to include understanding of human collaborators and **own capabilities and limitations**
Urban Air Mobility – Technical Challenges

Air traffic management system

Vehicle mission management system

• Resilient vehicle contingency management system, 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
• Real-time vehicle noise management
• Real-time mission planning & trajectory generation
UAM Mission Under Study

• Vehicle mission: target final phase of autonomous flight
  – Safely fly from pt. A to pt. B following a nominal trajectory

• Environmental and operational constraints:
  – Under all vehicle-allowable weather conditions,
  – In a high-density airspace and complex urban environment,

• React appropriately to off-nominal situations and contingencies without direct human control,

• Currently contingency management is a highly prescribed, rule-based approach.

• We are interested in exploring intelligent contingency management that can appropriately handle unanticipated situations.
Intelligent Contingency Management – Architecture

Vehicle Capability Assessment
*Decisions Based on Models and Measurements*

Mission Execution
*Decisions Based on Model Based Prediction under uncertainty*

Future State Prediction

External Constraints

Vehicle Current and Future State

Data

High level architecture
Intelligent Contingency Management – Major Component Blocks

External Constraints (Weather & Air Traffic Management)

Vehicle Model
• Model development (RAM-C)

Atmospheric Characterization
• Turbulence models for low altitude

Vehicle Capability Assessment
Decisions Based on Models and Measurements

Mission Execution
Decisions Based on Model Based on Prediction under uncertainty

Future State Prediction

Human Element
• Identification & Formalization of Safe Strategies

Vehicle Flight
• Trajectory planning
• Unified control – robust adaptive control with novel allocation

Data

Vehicle Current and Future State

Vehicle Safety
• Safe dynamic envelope
• Collision Avoidance

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MathWorks Matlab/Simulink® software

Simulation includes:
- Vehicle models
- Control systems
- Atmospheric disturbances
- Trajectory: internal and external sources

Existing vehicle types are:
- Lift+Cruise (RVLT reference) – contains multiple other variant subsystems
  - Control actuators (aerodynamic and propulsive)
  - Force & Moment computation method
  - EOM approach
  - Sensor
- LA-8
- Quad6 (RVLT reference) - 6 person capacity
- Generic Tilt Rotor – placeholder
Aerodynamic Modeling for ICM

• Objectives:
  – Develop full-envelope aerodynamic models for UAM-class aircraft that are suitable for nonlinear, flight dynamics and controls simulations.
  – Develop Rapid Aero Modeling or RAM, an automated testing and modeling process.
  – Research and develop best practices for eVTOL aircraft modeling and simulation development.

• Challenges:
  – In an Urban Air Mobility transportation system, aircraft may embrace many features from both aircraft and rotorcraft. These designs present greater complexity, aerodynamic nonlinearity, and a large number of interacting factors, compared to conventional aircraft.
  – Conventional experimental methods, in particular one-factor-at-a-time testing, fail to capture the complexity and numerous interactions, often resulting in costly studies in terms of time/resources and may still produce models with deficient information.

• Impact
  – High-fidelity aerodynamic model development for eVTOL vehicles enables accurate vehicle simulation essential for UAM intelligent contingency management research.
  – RAM improves test and modeling efficiency, in the face of greater complexity, nonlinearity, and large numbers of interacting factors associated with eVTOL vehicles.
ICM – Control Overview

UAM Aircraft Control Considerations
• VTOL capable
• Modes of flight:
  – Hover, Transition and Forward Flight
  – Reflect very different ways to operate the aircraft
• Transition between modes safely and efficiently

A Robust Uniform Control Approach
• Configuration independent
• Unifies the control design across all flight modes
• Uses well known control approaches
  – Robust Servo Mechanism Linear Quadratic Regulator (RSLQR) for stability and trajectory tracking
  – Gain scheduling
• Provides a uniform set of control commands across all flight regimes
• Augmented with L1 Adaptive Control and implemented with Affine Generalized Inverse control allocation
A **reliably-convergent algorithm for trajectory planning with incomplete or corrupt information** to provide an **alternative** to machine learning for autonomous response to contingencies

- Establish a path to be followed by the vehicle that
  - Satisfies dynamical and air traffic constraints
  - Accommodates uncertainty in knowledge of current and future vehicle performance, environmental conditions, and traffic flow.

- **Technical Approach:**
  - Model:
    - Mission requirements and constraints expressed in terms of probabilistic moments.
    - Vehicle models are dispersed by random parameter values.
  - Computation
    - Vehicle command trajectory computed via constrained optimization of a collection of trajectories starting from the current state, and dispersed by random values of parameters
    - With the exception of the randomly varying parameters, the system representation is deterministic, employing Monte Carlo sampling to build up higher-level moments. Each sample trajectory is explicitly tied to a trajectory that satisfies mission requirements for the current mission moment estimate.
    - Resulting trajectory is explicitly in feedback form.
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Mission Execution
Decisions Based on Model Based on Prediction under uncertainty

Human Element
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Vehicle Capability Assessment
Decisions Based on

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• Safe dynamic envelope
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Vehicle Flight
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Collision Avoidance via Deep Reinforcement Learning

- Approach motivated by learning algorithms used for autonomous navigation through crowds extended to 3D urban air environment
- Challenges are similar
  - Each agent is aware of only a subset of other agent states
  - Need to anticipate interaction patterns
  - Be computationally tractable for real time implementation
- Supervisory training from a known solution provides initial baseline policy
- DRL uses an epsilon-greedy version of baseline policy to explore other options and improve it.
  - Offline learning offloads online computation for real time implementation.

Result of baseline policy
Resilient Performance and Safety

- Resilient performance strategies enabled development of Soar rules to facilitate novel human-machine role allocation in a safe fashion
- Soar agent’s learned behavior was not just to avoid an undesired state, but to adapt its functioning to facilitate desired states enabling resilient performance
  - Resolution of impasses via learning
- Seven requirements were formally verified in UPPAAL
  - Impasse resolution requirement had verification time of 20.85 sec, and maximally observed worst case time of 23.97 seconds over 1000 runs
- Future work on evaluation of the effects of resilient strategies on multi-agent teaming performance (specifically human-machine teams)
- Check out the full paper!
Summary

• Urban Air Mobility for the masses is a major component of user-driven, immediate and flexible air travel
• Autonomous flight for full market potential
• One of the primary challenges is responding to off-nominal events, both common and unforeseen
• Intelligent contingency management (ICM) is one of the enabling technologies
• Basic premise of vehicle ICM:
  – Vehicle aware of its internal state and external environment at all times
  – Ascertain its capability
  – Makes decisions about mission completion or modification
• Propose overall architecture incorporating deterministic and learning algorithm to
  – Assess vehicle capabilities
  – Project these into the future
  – Make decision on mission management level
• Layered approach to allow mature technologies to be incorporated into early phases of UAM
QUESTIONs?

Related Publications at SciTech 2021

Session: IS-31, Enabling Autonomous Advanced Air Mobility II
- **Intelligent Contingency Management for Urban Air Mobility**
  Authors: Irene M Gregory, Michael J Acheson, Barton J Bacon, Thomas C Britton, Newton H Campbell, Jacob Cook, Jon Holbrook, Daniel D Moerder, Patrick C Murphy, Natasha A Neogi, Benjamin M Simmons, John D. McMinn, and Pieter Bunning

- **Rapid Aero Modeling for Urban Air Mobility Aircraft in Computational Experiments**
  Authors: Patrick Murphy, Benjamin Simmons, Pieter Bunning

- **Dynamic Vehicle Assessment for Intelligent Contingency Management of Urban Air Mobility Vehicles**
  Authors: Newton Campbell, Michael Acheson, Irene Gregory

- **Examination of Unified Control Incorporating Generalized Control Allocation**
  Authors: Michael Acheson, Jacob Cook, Irene Gregory

Session: IS-33: Enabling Autonomous Advanced Air Mobility III
- **Creating Formal Characterizations of Routine Contingency Management in Commercial Aviation**
  Authors: Natasha Neogi, Jon Holbrook

Session: IS-24, Autonomy VI - Spacecraft, Robotics and Flight Planning
- **Loss of Control Detection for Commercial Transport Aircraft Using Conditional Variational Autoencoders**
  Authors: Newton Campbell; Jared Grauer; Irene Gregory

Session: ACD-15/TF-09: Design/Analysis of Urban and Regional Air Mobility Vehicles
- **A Strip Theory Approach to Dynamic Modeling of eVTOL Aircraft**
  Author: Jacob Cook

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