Dynamic Data Driven Methods for Self-Aware Aerospace Vehicles

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DDDAS Program Review
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A **self-aware aerospace vehicle** can dynamically adapt the way it performs missions by gathering information about itself and its surroundings and responding intelligently.

**Research Goal:** Create a **multifidelity framework for the DDDAS paradigm.**

**Objectives:**

- To systematically relate component-model fidelity to vehicle-level performance estimate and to enrich our collection of multifidelity models.
- To develop DDDAS methods that guide construction of an offline damage library given mission information, storage limits, data retrieval capability, and sensing capability.
- To develop DDDAS methods to exploit online sensor information for decision-making and for model adaptation, explicitly considering the opportunities associated with multiple modalities of sensor data.
- To develop design methods for DDDAS-enabled self-aware aircraft.

Leading to **dynamic health-aware mission re-planning** with quantifiable benefits in reliability, maneuverability and survivability.
A **self-aware aerospace vehicle** can dynamically adapt the way it performs missions by gathering information about itself and its surroundings and responding intelligently.

**Selected Key Milestones for Year 1:**

- Identification of representative aircraft components and the effect of damage cases on capability
- Development and demonstration of dynamic data-driven reduced model adaptation strategies
- Identification of alternate sensing methods for damage measurement
- Monte Carlo based approach for optimizing the contents of the offline library for a given sensing strategy and mission.
- Linkage created for between capability assessment and mission planner; used to determine accuracy and precision requirements of damage and models.
Project Overview

- A **self-aware** unmanned aircraft

![Diagram showing the flow of Estimate Capability, Re-plan Mission, Change Sensing Strategy, Offline Physics-Based Models, and Sensors.]

**Graphics:**
- Vishay Precision Group
- AeroVironment
- Microbotics

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**Table: Gage Pattern Data**

<table>
<thead>
<tr>
<th>GAGE SERIES</th>
<th>DESCRIPTION</th>
<th>RESISTANCE</th>
</tr>
</thead>
<tbody>
<tr>
<td>L2A-XX-062LR-120</td>
<td>Small 45° rectangular single-plane rosette.</td>
<td>±0.6%</td>
</tr>
<tr>
<td>C2A-XX-062LR-120</td>
<td>Small 45° rectangular single-plane rosette.</td>
<td>±0.6%</td>
</tr>
</tbody>
</table>

**Note 1:** Insert desired S-T -C number in spaces marked XX.
Today’s Focus

An approach for combining **offline** computation with **online** sensor data to provide a time-constrained, updated estimate of UAV **flight capability**.

**Offline Physics-Based Models**

**Change Sensing Strategy**

**Sensors**

**Estimate Capability**

**Re-plan Mission**

*Graphics: Vishay Precision Group, AeroVironment, Microbotics*
Approach – Offline/Online

1. Model Aircraft Behavior

2. Quantify Flight Capability

3. Infer Capability from Sensors
The ability of an aircraft to perform steady level turning maneuvers of a certain maximal curvature as it pertains to the limits on loads applied to the wing structure.

Directly related to the airspeed \( V \) and load factor \( n \) of the aircraft in flight:

\[
\sum F = \frac{mV^2}{R_{\text{turn}}} \Rightarrow R_{\text{turn}} = \frac{V^2}{g\sqrt{n^2 - 1}}
\]

\[
n = \frac{L}{W}
\]

\[
W = mg
\]

Graphic: AeroVironment
Global Aircraft Behavior with ASWING

**Global Kinematics**
- Airspeed
- Load Factor

**Wing Structure**
- Forces
- Moments
- Strains

- Cruise Speed: 140 KEAS
- Cruise Altitude: 25000 ft
- Range: 2500 nmi
- Payload Sizing: 500 lbs

- Conforms to FAR 23 guidelines

References:
- [http://web.mit.edu/drela/Public/web/aswing](http://web.mit.edu/drela/Public/web/aswing)
- AIAA SDM Paper, M. Drela, 1999
How to Represent Damage?

Stiffness modification in ASWING to capture effects of damage on aircraft behavior.

- “Smeared” effect
- We need another technique

Bending stiffness along wing about axis parallel to airfoil chord

\[ EI_{cc} \]

Location on span

(left wing tip) (right wing tip) (exaggerated)
Model Damage with VABS

Wing Structure
- Forces
- Moments
- Strains

Local Wing Structure
- Damage
- Sensors
- Failures

- Variational Asymptotic Beam cross-Sectional Analysis (VABS)
- Substitute for full 3-dimensional FEM
- Slender, thin-walled beams

Reference: Palacios and Cesnik, 2005

1D Beam Solver
- Stiffness properties
- Influence coefficients
- Reference line forces and moments

Reference: Palacios and Cesnik, 2005
Model Damage with VABS

We plan to collaborate with UCSD team and implement their higher fidelity damage models that are currently under development. We plan to use these models to create a new set of offline libraries in addition to the ones we have already generated using our ASWING+VABS approach.
Aircraft Model using ASWING and VABS

1. Model Aircraft Behavior

- Maneuver
- Damage

Coupled ASWING and VABS

Strain Sensor Readings

Maximum Failure Index

Baseline Aircraft

Damage
Finding Capability using Physics-Based Models

2. Quantify Flight Capability

Flight Capability is boundary between:

- **Red**: Unsafe $\Leftrightarrow$ $\max FI > 1$
- **Blue**: Safe $\Leftrightarrow$ $\max FI < 1$

Classification using $FI_{\max}$

- **VIAS** = 260 ft/s at 25 kft
- Damaged [location, width] on span: [+0.35, 0.075]
- Damaged region stiffness loss: 95%

Maximum load factor change due to damage

- **V** held constant, capability with respect to $n_{\max}$

Maximum load factor change due to damage

- **V** = 260 ft/s at 25 kft
- Damaged [location, width] on span: [+0.35, 0.075]
- Damaged region stiffness loss: 95%

Diagram showing flight capability classification with red and blue boundaries indicating unsafe and safe regions respectively for varying chord width and location.
We have a database with features:
- Damage conditions $X_D$
- Maneuver conditions $X_M$
- Strain sensor readings $X_S$
- Flight capability $R_{min}$ via classification using failure index $FI_{max}$

Size constrained by memory and/or lookup limitations

<table>
<thead>
<tr>
<th>$s$</th>
<th>$w_s$</th>
<th>$c$</th>
<th>$w_c$</th>
<th>$d$</th>
<th>$f$</th>
<th>$X_D$</th>
<th>$X_M$</th>
<th>$X_S$</th>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0.35</td>
<td>0.075</td>
<td>0.2</td>
<td>0</td>
<td>0.8</td>
<td>0.95</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>260</td>
<td>1</td>
<td>-1.13e+03</td>
<td>6.15</td>
<td>63.2</td>
<td>658</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

| 0.35| 0.075 | 0.28 | 0.089 | 0.8 | 0.95|       |       |       |
| 260 | 3.3  | -6.79e+03 | 366  | 378 | 674 |

| 0.35| 0.075 | 0.26 | 0.056 | 0.8 | 0.95|       |       |       |
| 260 | 3.3  | -5.99e+03 | 446  | 333 | 673 |

Table 2: Example records taken from the offline aircraft simulation library after flight envelope exploration.
Online Maximum Likelihood Estimation

Use library from offline phase

Notation:

Cases stored in library

\[ X_M \in \{ m_1, m_2, \ldots, m_K \} = \mathcal{M} \]
\[ X_D \in \{ d_1, d_2, \ldots, d_J \} = \mathcal{D} \]

Library lookup functions

\[ C : \mathcal{D} \to \mathbb{R} \]
\[ S : \mathcal{M} \times \mathcal{D} \to \mathbb{R}^{NS} \]
Online Maximum Likelihood Estimation

3. Infer Capability from Sensors

1. Likelihood of seeing sensor readings conditioned on the maneuver and damage

\[ p_{X_S|X_M,X_D}(\cdot|m_k, d_j) \sim \mathcal{N}(S(m_k, d_j), \sigma^2 I) \]

2. Maximize the likelihood over all possible damage cases in library

\[ \hat{R}_{min}(s, m_k) = C \left( \arg\max_{d_j \in \mathcal{D}} p_{X_S|X_M,X_D}(s|m_k, d_j) \right) \]
Online Demonstration

**Simulation Explanation**

- 100 Hz sensors
- MLE output for 100 sensor realizations
- Moving window, Gaussian KDE

**Current damage case: Pristine**

\[ t = 2.5 \text{ sec} \]

**Probability density**

- Minimum turn radius (ft)

<table>
<thead>
<tr>
<th>Damage</th>
<th>True $R_{min}$ (ft)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pristine</td>
<td>658</td>
</tr>
<tr>
<td>Mild</td>
<td>667</td>
</tr>
<tr>
<td>Severe</td>
<td>677</td>
</tr>
</tbody>
</table>

**“safe” turn radii**

**OBSTACLE**
Current damage case: Pristine

t = 0.0 sec

Probability density

Minimum turn radius (ft)
Optimizing Offline Information
What if damage experienced online is not in the offline library?

Need a measure of confidence in our online capability estimate

Our Approach

\[ \| S - \hat{S} \| \xrightarrow{\alpha} \| C - \hat{C} \| \]

“Closest” library record

“True” sensor reading

Capability of “Closest” library record

True capability
Offline record-by-record analysis

\[ D_n = \| C - \hat{C} \|, \quad D_S = \| S - \hat{S} \| \]
Online Uncertainty Quantification

\[ D_n = \| C - \hat{C} \|, \quad D_S = \| S - \hat{S} \| \]

1. Obtain sensor data
2. Maximum likelihood estimation
3. Compute \( D_S \)
4. Estimate \( D_n \) from regression
5. Set mean of capability to \( C \)
6. Set standard deviation to \( D_n \)

\[ C \sim \mathcal{N}(C, \sqrt{D_n}) \]
Prior Mission Plan Information

\[ I_{mp} := \text{Uncertain information pertaining to an upcoming mission} \]

For example:

Offline we can simulate the mission given the stochastic information pertaining to the upcoming mission.
**General Problem Statement**
Construct the offline library with a solution to

\[ \arg \min_{\mathcal{D}} \mathbb{E}[h(C^* | \mathcal{I}_{mp})] \]

s.t. \( |\mathcal{D}| \leq J \)

\( h := \) Information Entropy

**Demonstration Problem**
- Consider 30 possible records that can be used to construct a 5 record offline library
- 5 different online damage scenarios can occur, each with probability 0.2
- The pristine case is the only overlap between what is known offline and what can occur online
Exhaustive Search
Simulated Online Results

Optimal Libraries Conditioned on Offline Mission Information

Least informative offline library

Most informative offline library

Potential Damage incursion

10Hz sensing for 1 sec

Critical Decision Point
Conclusions & Future Work

• Developed and demonstrated an offline/online DDDAS paradigm for enabling self-aware UAVs
• There is a need to develop confidence metrics during online classification
• The offline library contents impact our ability to confidently make dynamic mission decisions

Future Work
• Efficient solution methodology for offline library optimization
• Online information gathering
  – Via Reduced-order and surrogate modeling
  – Via informative maneuvers
• Heterogeneous sensing capabilities
• Online sensor “placement”
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