Information fusion for real-time national air transportation system prognostics under uncertainty

PI: Yongming Liu
Co-Is: Aditi Chattopadhyay, Nancy Cooke, Jingrui He, Mary Niemczyk, Pingbo Tang, Lei Ying
Arizona State University

Co-I: Sankaran Mahadevan
Vanderbilt University

Co-I: PK Menon
Optimal Synthesis Inc.

Co-I: Barron Bichon
Southwest Research Institute

University Leadership Initiative Technical Interchange, June 25, 2018
Outline

- Background and objectives
- Statement of work
  - Technical progress and achievements
  - Educational activities and achievements
- Project management
  - Project team
  - Research dissemination and broad impact
  - External advisory board
- Conclusions and future work
Background

- NASA Aeronautics Research Mission Directorate (ARMD) vision for aeronautical research that encompasses a broad range of technologies to meet future needs of the aviation community.
- Recent technology advances in sensors, networking, data mining, prognostics, and other analytic techniques enable proactive risk management for National Airspace System (NextGen).
- Technology convergence of multidisciplinary research to develop transformative concepts and to enable a safe and efficient aviation system.
- Systematic training of next generation engineers and workforce pipeline for future aerospace industries and research.
Objectives

- Real-time system-wide information fusion methodology for prognostics and safety assurance of the NAS
- Self-identified technical challenges (TC) and objectives
  - **TC 1:** Develop an extensible community-based NAS air traffic simulation system incorporating data-derived vehicle/subsystem level failure/fault models that can be used for system-wide safety assessment and integration with training simulations
  - **TC 2:** Determine information sources inventory associated with current ATM operations, model human ATM performance in simulator, and develop real-time sensors of human performance
  - **TC 3:** Determine faults and early damage indicators in the subsystems during ground and in-air fleetwide operations utilizing state-of-the-art multiscale, multimodal sensors, data mining, feature extraction and classification
  - **TC 4:** Uncertainty quantification, verification and validation, and risk assessment tools for 80% increase in computational speed and 60% increase in confidence in risk assessment compared with existing approaches
  - **TC 5:** Integrated diagnostics, prognostics, probabilistic modeling, and simulation tools for 50% increase in accuracy compared with existing approaches
Proposed methodology and tasks

- Highly multidisciplinary research themes are integrated together
- Seven major tasks:
  - Task 1. System-wide air traffic modeling and failure simulation
  - Task 2. Multi-modality safety monitoring, detection and data analysis
  - Task 3. Human system integration
  - Task 4. Uncertainty management and risk assessment
  - Task 5. Information fusion and prognostics
  - Task 6. Verification, validation, and safety assurance
  - Task 7. Integrated education, research, and demonstration

Schematic illustration of the proposed major research themes
Information fusion – Bayesian Entropy Network (BEN) framework

- Integrate multiple types of information among multiple domains within the airspace system
- Bayesian Entropy Network (BEN) – based information fusion for Data, Experiences and Knowledge (DEK)

\[ p(\theta) \propto \mu(\theta) \cdot \mu(x' | \theta) \cdot e^{\beta g(\theta)} \]

Entropy term for abstracted knowledge, physical constraints, and expert opinions

- Hybrid data-based and physics-based prognostics
- Assist the risk assessment and decision-making for safety assurance
Information fusion – classification for runaway incursion

- Adding entropy information:
  - Expert linguistic information representing historical experiences
  1. When the taxi clearance communication error is on the ATC side, the cause for runway incursion is more likely to be cross runway without clearance.
  2. LUAW communication error can only lead to and is the only reason for attempt take-off without clearance.
  ....
- Expressed as constraints on expected value of the posterior distribution
Information fusion – avoid mid-air collision

- Fuse machine learning models plus expert knowledge (fault trees)
  - Convert existing system fault trees to Bayesian networks, instead of building from scratch
  - Automate the conversion from fault tree to Bayesian network

Fault tree meta model \(\rightarrow\) Fault tree instance model

Fault tree instance model \(\rightarrow\) Automated conversion

Fault tree instance model \(\rightarrow\) BN instance model

Automated conversion

Bayesian network metamodel \(\rightarrow\) BN instance model

Changes from the expert (addition of nodes)

BN instance model \(\rightarrow\) Updated BN instance model

Observation data, Automated calibration

Updated BN instance model \(\rightarrow\) Posterior distributions

FT to JSON plugin

Fault tree instance model \(\rightarrow\) JSON representation

JSON representation \(\rightarrow\) JSON to BN plugin

Updated BN model

Posteriors

User changes

Updated BN model \(\rightarrow\) BN analysis plugin

PyMC model in python

Model Calibration

Nannapaneni & Mahadevan, AIAA Aviation 2018

Aircraft self-separation example
Information fusion – prognostics and safety metrics

- Simulating accidents for landing on taxiway using NATS
- Update the trajectory using ADS-B information and BEN
  - Predict the landing point at the airport and confidence level
  - Prognostics for potential collision of any pair near terminal region
Community-based software for formulating and analyzing NAS safety prognostics problems under realistic NAS traffic environments.

- National Airspace Traffic Safety-Analysis (NATS) Server-Client Software released (Python, MATLAB, Java interfaces)
  - 55 Airports in the NAS with all the gates, taxiways, runways, approach, go-around, and departure procedures
  - Terrain Profile for the Contiguous United States
  - NOAA wind and convective weather
- Multiple application examples and software demos
- Interface with any user-defined real-time simulation
- Human Pilot/Controller error models
- 2018 PHM Conference paper summarizing the software status
Air traffic simulation – real-time cloud-based computing

- NATS
- NATS Server
- Flight Simulator(s)
- Pilot-in-the-loop Simulation(s)
- Controller-in-the-loop Simulation(s)
- FAA, NOAA Data Feed
- Flight Simulator(s)
- User n (Linux, Windows, Mac)
- Linux OS
- Internet
Air traffic simulation – information flow

- Nominal Surface, Terminal, En Route Controller Models
  - Controller & Communication Error Models
  - Aircraft Flight Plans
  - Nominal Pilot and Flight Deck Automation Models
  - Pilot, Communication, Navigation & Automation Error Models
  - Aircraft Dynamic Models

- NOAA Weather Data
- Accident & Incident Database
- FAA Traffic Data
- NAS, Airport, Terrain Database (FAA, USGS)
- NAS Safety Metrics

NAS Surveillance
Mode Transition & Rerouting Requests
Physics (State-space model)

Deep Residual RNN (DR-RNN)

Physics-based Learning (using 2-layer DR-RNN)

\[
\begin{align*}
q_{r+1}^{(k)} &= q_{r+1}^{(k)} - W \cdot \tanh(U_{r+1}^{(k)}), \text{ for } k = 1 \\
q_{t+1}^{(k)} &= q_{t+1}^{(k)} - \frac{\eta_k}{\sqrt{G_k + \epsilon}} r_{t+1}^{(k)}, \text{ for } k > 1
\end{align*}
\]

Air traffic simulation – hybrid learning for aircraft dynamics

<table>
<thead>
<tr>
<th></th>
<th>DR-RNN (step size = 0.1 s)</th>
<th>RK (step size = 0.002 s)</th>
<th>RK (step size = 0.005 s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Computation time (s)</td>
<td>7.4</td>
<td>605.4</td>
<td>241.1</td>
</tr>
<tr>
<td>Average prediction error</td>
<td>2.60e-4</td>
<td>3.78e-4</td>
<td>5.72e-4</td>
</tr>
</tbody>
</table>
Air traffic simulation – automatic weather avoidance

- Objectives:
  - Develop an automated trajectory prediction algorithm for arbitrary weather cell shapes at the pixel level
  - Include weather dynamics and forecasting uncertainties for planning
  - Combine simple geometric models and CNN-based learning to understand the decision making of pilot and controller

<table>
<thead>
<tr>
<th>Network Configuration</th>
</tr>
</thead>
<tbody>
<tr>
<td>Layer number</td>
</tr>
<tr>
<td>1</td>
</tr>
<tr>
<td>2</td>
</tr>
<tr>
<td>3</td>
</tr>
<tr>
<td>4</td>
</tr>
<tr>
<td>5</td>
</tr>
<tr>
<td>6</td>
</tr>
<tr>
<td>7</td>
</tr>
<tr>
<td>8</td>
</tr>
<tr>
<td>9</td>
</tr>
<tr>
<td>10</td>
</tr>
<tr>
<td>11</td>
</tr>
<tr>
<td>12</td>
</tr>
</tbody>
</table>

Raw weather image  
Fast Marching Map  
Probabilistic decision 1  
Probabilistic decision 2
How do human factors (e.g., SA, cognitive load) of ATCs interact with factors in the NAS to affect ATC performance (operational errors) and a safe and effective NAS?

- Need access to real-time data that provides information on problematic human states that may lead to operational error.

- Real Time Communication Data as a Surrogate (voice and data communications)

- Operational Errors
  - Scorecard

- Safe & Effective NAS

- How do human factors (e.g., SA, cognitive load) of ATCs interact with factors in the NAS to affect ATC performance (operational errors) and a safe and effective NAS?

- Need access to real-time data that provides information on problematic human states that may lead to operational error.
Communications data can serve as a sensor for the human part of the NAS

Changes in the ATC-pilot state may correspond to changes in communication patterns which can signal potential operational errors/risk

We are addressing this hypothesis through:

- Literature Review
- Existing ATC voice comms
- SWIM data
- Simulation (in which we can push the boundaries of ATC performance)
Human system integration – design of ATC experiment

- 12 Experienced (retired) and inexperienced (students) ATCs
- Up to 4 pseudo pilots (students) each controlling 4-8 planes
- Simulated approach scenarios
- Baseline normal conditions and increasing traffic density
  - Traffic density – 4-32 planes per sector
  - Complicating events
    - Separation issues
    - Loss of engine
    - Pilot miscommunication
    - Measures
- ATC Operational Error – breach of separation limits
- Measures
  - Voice Communication (patterns over time – detect change)
    - Volume – how much communication over time
    - Flow – who talks to whom patterns
    - Voice – pitch, volume changes over time
  - Facial Expression – cameras and affective software labeling
  - Eye blink rate (Pingbo Tang)
  - Keystrokes/Data comm
Voice Recognition for Air Traffic Simulators (VORATS)
- Simulator independent
- Automatic recording and translating, self-triggering
- IoT with distributed computation
- Easily expandable (N x Pi)
- Automatic recognize the people (with Pi ID)
- Data with time stamp for integration

Fulton Undergraduate Research Initiative (FURI) project (pending)

Integrated research and student education

Total $99
Problem Definition: Using 2246 accident Reports from NTSB (Part 121) to accomplish two tasks:
1. Task 1: Classify the states in which the accident happened
2. Task 2: Classify the actual causes which led to the accident

Experiment Process:
4 machine learning algorithms: Linear SVM, Non-linear SVM, Multinomial Naïve Bayes (MNB), Gradient Boosting Decision Tree (GBDT).

Conclusion: Linear SVM and GBDT are the optimal models for our tasks, in terms of the tradeoff among accuracy, efficiency, and explanation capabilities.
Task 1: The indicators whose bars are marked red are taxi, taxiway, pushback, gate, ramp and land, which are intuitively relevant to our classification task.

Task 2 (aircraft issue as an example): Similarly, the keywords with red bars are relevant words to this issue. Examples include gear, nut, trunnion, land, tire, march, carcass, touchdown and overhaul, which are intuitively relevant key indicators to identify Aircraft issues for accident reports.

Conclusion: Our machine learning models match our intuition by using highly relevant features instead of using the metadata from the reports in the database.
A Novel Model for Learning Representations from Imbalanced Data
- A novel random walk model named Vertex-Diminished Random Walk
- It encourages the random particle to walk within the same class, leading to more accurate node-context pairs
- Semi-supervised method for learning representations from both label information and graph structure

Existing method: Poor separability between classes

ImVerde: Good separability between classes

Furthermore, we compared the new embedding features with the original TF-IDF features. As shown below, the concatenation of embedding and TF-IDF features improves the classification performance with linear SVM. And a smaller parameter $C$ is preferred for the embedding features compared to TF-IDF features alone.

Preliminary Results on NTSB Data Set

<table>
<thead>
<tr>
<th>Methods</th>
<th>Recall@k</th>
</tr>
</thead>
<tbody>
<tr>
<td>DEEPWALK</td>
<td>0.500</td>
</tr>
<tr>
<td>Node2vec</td>
<td>0.467</td>
</tr>
<tr>
<td>GraRep</td>
<td>0.516</td>
</tr>
<tr>
<td>Planetoid</td>
<td>0.472</td>
</tr>
<tr>
<td>ImVerde-x</td>
<td>0.522</td>
</tr>
<tr>
<td>ImVerde-e</td>
<td>0.500</td>
</tr>
<tr>
<td>ImVerde-a</td>
<td>0.538</td>
</tr>
</tbody>
</table>
Data analytics – hybrid model assembling

**Data Sources**
1. Aviation Safety Reporting System (ASRS)
2. System-wide Information Management (SWIM) data
3. National Transportation Safety Board (NTSB) accident analysis reports

**Four-step Framework**
1. Risk-based event outcome categorization
2. Hybrid model construction
3. Probabilistic fusion rule development
4. Map the risk-level prediction to event-level outcomes

\[
p(Y_a = i) = \sum_{j=1}^{S} p(Y = i|Y = j)p(Y_a = j) \cdot \frac{p(j)}{p(Y_j)}
\]

**Prediction Accuracy**
- Precision: 81%
- Recall: 81%
- F1 Score: 81%

Zhang & Mahadevan, AIAA Aviation 2018
Monitoring and sensing – big picture of airside monitoring

- Dimensional reduction – Autoencoder
- Feature extraction for handling critical system parameters
- Anomaly detection in real airline dataset & simulated flight dataset

Uncertainties due to Environmental conditions

Uncertainties due to Airside Systems Information

Uncertainties due to pilot action and operation

Uncertainties due to Groundside Systems Information

**Task Contribution**
- Probability characteristics & uncertainty quantification for aircrafts with subsystem faults
- Changes to aircraft dynamics due to existence of faults
  - Air traffic system response to aircraft faults

Information Fusion and Prognostics
Monitoring and sensing - anomaly detection

- Current model tested with a reduced dataset in cruise phase for online monitoring using simulated fault cases
Monitoring and sensing – indication of pilot behavior

- 458 flight data investigated
- Distribution of global safety probability constructed in logscale (threshold set to be -200)
- Anomalies in aircraft detected in 3/458 flights

- Identical aircraft dynamics in three detected anomaly cases
- Drop in path longitudinal acceleration; increases in angle of attack & patch angle
- Pilot reduces power lever angle

Anomaly in sensing signal

Aircraft response

Distribution of global safety probability

- Flight path acceleration
- Angle of attack
- Power lever angle
- Pitch angle
Monitoring and sensing – human behavior monitoring

HMM-based Human Behavior Monitoring
- Facial Landmark Detection
- EAR Extraction
- HMM Model

Detected Anomalies
- Fatigue
- Distraction
- Poor Situation Awareness

Bayesian Network
1. Risk Knowledge
   - Anomalous behaviors
   - Human errors
   - Accident types
2. Correlation between elements

Learn knowledge from the accident report
- ASRS Accident Reports
- ATC anomalous behaviors
- ATC errors
- ATC-related accidents

Output
- Risk Prediction
  1. Probabilities of human errors
  2. Probabilities of accidents

*EAR - Eye Aspect Ratio
Monitoring and sensing – computer vision technique

Person level analysis
EAR - Eye Aspect Ratio

Team level analysis
Indoor trajectories of groups of people

Outdoor Site level analysis
Groups of people across job site for collaboration analysis
Uncertainty management – uncertainty in diagnostics and prognostics

Data
- Simulated data: NATS
- Field data: SWIM (FAA)

Modeling flight trajectory
Bayesian network → state-space model
System states: aircraft position, velocity, heading
System input: wind velocity

Anomaly detection
Track multiple flights using state estimation
Measured data: position, velocity, heading
Anomaly:
1. discrepancy between measured and predicted aircraft position
2. separation distance below threshold

Fault diagnosis
- Identify cause of anomalous behavior (e.g., wind gust, engine malfunction, pilot error)
- Quantify uncertainty in diagnosis

Probabilistic prognosis
- Update state-space model using identified faults
- Quantify uncertainty in prognosis

Safety assessment
Determine safety metric and risk using probabilistic fault prognosis

Zhang, Kong, Subramanian, Mahadevan, PHM 2018

Near-terminal safety assessment examples
Uncertainty management – an illustration example

ATL Air Traffic in BlueSky

In-conflict aircraft (orange) undergo conflict detection and resolution (CD&R) based on their state-space diagrams to avoid LoS.

State-Space Diagrams (SSDs)

The state-space diagram is the intersection of forbidden and reachable velocities and defines the set of Forbidden and Allowable Reachable Velocities (FRVs and ARVs) [1]

\[ \text{FPF} = 1 - \frac{\text{Area(FRV)}}{\text{Area(FRV)} + \text{Area(ARV)}} \]

Flight Plan Flexibility (FPF)

- An FPF close to 0 indicates that most velocities among the aircraft's reachable velocities that will result in a LoS.
- An FPF of 1 means that the aircraft may assume any reachable velocity and not incur any LoS.
- An FPF of 0 means that a LoS is inevitable if no CD&R action is taken by any other aircraft in the system.


SWIM Flight Plans to BlueSky Scenario

- Create aircraft by ID, type, position, and speed
- Assign origin, destination, and runway (for ATL)
- Per SWIM modify HDG, ALT, SPD

\[
\begin{array}{ccc}
0:02:09.04>CRE & DAL2396 & B732 & 33.019 \\
0:02:09.04>DAL2396 & ORIG & KRSW & \\
0:02:09.04>DAL2396 & DEST & KATL & RW27L \\
0:02:09.03>CRE & DAL369 & A320 & 33.207 \\
0:02:09.03>DAL369 & ORIG & KATL & RW27R \\
0:02:09.03>DAL369 & DEST & MMM3 & \\
0:02:16.14>ENT3758 & HDG & 177.665 & \\
0:02:16.14>ENT3758 & ALT & 32000.0 & \\
0:02:16.14>ENT3758 & SPD & 395.0 & \\
\end{array}
\]
Uncertainty management – uncertainty quantification of single ADS-B

- **Reasons for positional uncertainty**
  - Navigation satellite and onboard receiver derive the aircraft’s position
  - Normal and abnormal (fault) error induce the positional uncertainty

- **Two levels of positional uncertainty broadcasted in ADS-B data**

  **Level 1: Accuracy**
  - Position error at 95% confidence level only considering normal error
  - In ADS-B data, this term is represented by NACp (Navigation Accuracy Category for position) from 0 to 11.
  - The EPU (Estimated Position Uncertainty) is position error range denoted by NACp

  **Level 2: Integrity**
  - Position error at 99.99999% confidence level considering navigation service failure cases
  - In ADS-B, this term is represented by NIC (Navigation Integrity Category) from 0 to 11
  - The Rc. (containment radius) is position error range denoted by NIC.

Position estimation:
\[
\hat{x} = (H^T H)^{-1} H^T z = x + (H^T H)^{-1} H^T v
\]

where \( H = \begin{pmatrix} h_1 \\ h_2 \\ \vdots \\ h_n \end{pmatrix}, v \sim N(0, \sigma) \)
Uncertainty management – uncertainty quantification of a pair of aircraft

- The two aircrafts may view different satellite-set at a specific time

For example:

- Position error correlation
  - The aircraft pair position error correlation is sharply reduced at real separation of 4nm when the sky-plots become different (time:03:33:00)

- Monte Carlo simulation (real separation: 5nm)
Propagating ADS-B Uncertainty through BlueSky Simulations:

- BlueSky was connected with NESSUS® to propagate uncertainty with FPF as QoI
- 1000-point LHS was based on probability distributions of ADS-B signals for three Navigational Accuracy Categories for position (NACp) [2]

<table>
<thead>
<tr>
<th>NACp Value</th>
<th>Standard Deviation (NM)</th>
<th>Standard Deviation (degrees)</th>
</tr>
</thead>
<tbody>
<tr>
<td>4</td>
<td>1.0</td>
<td>0.0016</td>
</tr>
<tr>
<td>5</td>
<td>0.5</td>
<td>0.008</td>
</tr>
<tr>
<td>7</td>
<td>0.1</td>
<td>0.016</td>
</tr>
</tbody>
</table>

Arrival and Takeoff Scenario

Runway Scenario
Terrestrial objects such as mountains and buildings can cause multipath interference, different scenarios require different channel models.

Terrestrial objects such as mountains and buildings can cause multipath interference, different scenarios require different channel models.

The relationship between SNR and BER under different K factor

Figure 5: BER in a fading environment
Uncertainty management – uncertainty reduction via channel optimization

- Optimal scheduling of data transmissions to minimize the overall tracking error
- Significant reduction of uncertainty in the round-robin communication pattern
- Large impact of communication with terrain information for safety evaluation on the ground and near the airport
Educational activities and achievements

- 30+ students (PhD + MS + undergraduate students) from 7 majors (air traffic management, aerospace engineering, psychology, mechanical engineering, computer science, electrical engineering, and civil engineering)
- First MS graduate hired in ATM field
- First undergraduate design competition submitted for Airport Cooperative Research Program - SMART LINE UP AND WAIT SYSTEM FOR AIRPORT
- Fulton Undergraduate Research Initiative proposal – A $99 VORATS system (VOice Recognition for Air Traffic Simulators)
- Intergradation with ASU ATM program and PHX controller training program
Diverse, multidisciplinary team that includes faculty in ASU’s Ira A. Fulton Schools of Engineering and collaborators from Vanderbilt University, Southwest Research Institute and Optimal Synthesis Inc.

Big data analysts, applied statisticians, image processors, psychologists, computer scientists, and aerospace engineers

Expertise from information theory, applied statistics, data mining and analytics, risk management, airspace software systems, monitoring and imaging, and network science

Smooth transition from academia basic research to applications of aerospace industry
Research dissemination and community impact

- Development of simulation tools (NATS) to be used for future NextGen research
- Wide dissemination of research outcomes to aviation community
  - Prognostics Analysis and Reliability Assessment (PARA) - ATM
- Organize special sessions in conference to enhance the program impact
- External Advisory Board (EAB) that consists of various experts from industry, government agencies, and academia
External Advisory Board (EAB) – members from various different disciplines and industries

EAB roles: 1) provide feedback and comments on the proposed research and research progress; 2) participate (in person or via telecom) in annual project meeting; 3) participate in regular progress teleconferences; 4) provide feedback and suggestions on future research directions to address important gaps in the community.
Conclusions and future work

- Fusing knowledge among multiple domains within the airspace system.
- Creating a multidisciplinary team of big data analysts, applied statistician, image processors, psychologists, computer scientists, and engineers.
- Improving air travel safety through complex human-cyber-physical system simulations using ultra-fast algorithms for real-time analysis.
- Developing extreme-scale, in-air and on-ground data sources to increase system reliability and risk management.
- Integrating multi-level education with K12 Education Outreach Program, Fulton Undergraduate Research Initiative, graduate student advising, and pilot training.
- Close collaboration with aviation industry enables future technology transfer.
Thanks!
Questions?

Acknowledgments

The research reported in this presentation was supported by funds from NASA University Leadership Initiative program (Contract No. NNX17AJ86A, Project Officer: Dr. Kai Goebel, Program coordinator: Koushik Datta, Principal Investigator: Dr. Yongming Liu). The support is gratefully acknowledged.