Terminal Airspace Anomaly Detection Using Temporal Logic Learning

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Background

• The National Airspace System (NAS) is vast and complex.
• The NAS evolves with additional sensing and data collection capabilities and newly deployed systems
  ⇒ Critical to effectively identify \textit{a priori unknown safety threats or emerging risks}

• The large-scale and complex natures of aircraft operations
  ⇒ Challenging to use classical dynamic analysis for detecting safety threats and risks.
  ⇒ Focus on analyzing aviation data to extract useful information
• Aviation data are typically \textit{unlabeled}
  ⇒ Apply \textit{unsupervised learning} approaches to support \textit{anomaly detection}

\textbf{Anomaly detection:} the problem of identifying events or observations that do not conform to \textit{expected behaviors} in a dataset
Objectives and Challenges

Unsupervised Learning Approach: to effectively identify \textit{a priori} unknown safety threats or emerging risks

- **Data**
  - Heterogeneous
    - Continuous and discrete states, text, voice recordings, etc.
  - Representing the \textit{various parts of the NAS operations}
    - En-route, terminal, surface, etc.

- **Algorithm**
  - Identify \textbf{statistically anomalous incidents}
    - Incidents: sequences from precursors to degraded states
  - Identify \textbf{operationally significant} incidents through \textbf{human feedback}
  - Learn from substantial \textbf{historical data} but also can be \textbf{updated in online} fashion (must be scalable)

- **Model**
  - Usable in \textbf{real time} to detect anomalies and precursors
  - Providing probability and time horizon information

By examining groups with similar properties, data analysis and anomaly detection can be made more effectively and efficiently

- Clustering
- Temporal Logic Learning Based Anomaly Detection

- Anomaly detection in sequential data
- Model with human-readable representations
- Off-line (historical data) / On-line learning
Proposed Framework

- **Clustering**: hierarchical, partitioning, density-based, and grid-based
- **Data**: spatial in nature, and with unstructured portion (abnormal flights)

⇒ **Density-Based Spatial Clustering of Applications with Noise (DBSCAN)**
  - Data is spatial in nature
  - No requirement to set the number of clusters *a priori*
  - Can handle noise

Anomaly Detection from Sequential Data

- Temporal logic learning based **Anomaly Detection (TempAD)**
  - Learned from data to classify data as normal and anomalous
  - Can express system properties such as **time bounds and bounds on physical parameters**
  - Results in formulas that are easy to be described in **natural language**

"An aircraft flying normally should reside in area $R_1$ up to 3 minutes before touchdown and then $R_2$ until touchdown."
Outline

Introduction

Anomaly Detection Algorithm Development

• Data Preprocessing via Clustering
• Temporal Logic Learning Based Anomaly Detection
• Feature Selection

Test and Analysis

Conclusions
Data Preprocessing via Clustering

- Example: Surveillance data of arrival flights at LGA airport (April 6-24, 2014)
Horizontal Patterns for 19 days
Identified Trajectory Patterns

- Horizontal trajectory patterns identified for the arrival flights at LGA for 19 days (April 6 – 24, 2016)
  - Each runway has 2 – 4 patterns (12 patterns in total)
Unsupervised TempAD

- **Learning**: Data → Model
- **Monitoring**: Unseen Data → Anomaly Score (through Learned Model)
A **temporal logic formula** $\phi = \varphi_\theta$ consists of its **structure** $\varphi$ and corresponding **parameters** $\theta$.

- Example formula describing normal behaviors of a system:
  $$\phi = (F_{[0,35]} x < 25) \land (G_{[0,20]} y > 20) \land (G_{[0,20]} y < 28)$$

Temporal Logic Learning

Temporal logic learning based Anomaly Detection (TempAD)

• We propose an algorithm that learns the structure and parameters of a temporal logic which classifies normal and abnormal behaviors of a system.

Proposed Algorithm

Data → Discrete Search → Structure of a formula → Continuous Search → Parameters of a formula → Temporal Logic Formula
TempAD: Discrete Search

• Trajectories can be represented as **polynomials in a piecewise manner**
  • From the clustering results, get a centroid (single time-series)
  • Use a **piecewise regression** technique to find **polynomial predicates** that fit to the centroid, for example,
    
    \[ a_n x^n + a_{n-1} x^{n-1} + \cdots + a_1 x + b_n y^n + b_{n-1} y^{n-1} + \cdots + b_1 y = c \]

  • The order of polynomial and the breakpoints are determined
  • The coefficients are fed into the continuous search as an initial guess for the parameters of formula

• Compared to the simple predicates (e.g., \( x \leq c \)), the piecewise polynomial predicates allow **more expressive power**
TempAD: Continuous Search

Given observed signals \( \{y_i\}_{i=1}^{N} \) (not-labeled), solve the **One-Class Support Vector Machine (OCSVM)**-like optimization problem

\[
\min_{\theta, \varepsilon} d(\phi_\theta) + (\varepsilon) + \frac{1}{\nu N} \sum_{i=1}^{N} \mu_i
\]

- \( d(\phi_\theta) \): (heuristic) **tightness function** that penalizes the size of \( L(\phi_\theta) \)
  - \( L(\phi_\theta) \): language of formula (all possible trajectories satisfying \( \phi_\theta \))
  - prevents \( \phi_\theta \) from trivially describing all observed signals

- \( (\varepsilon) \): **gap** in signal space between normal and anomalous outputs
  - maximize the separation between normal and anomalous outputs

- \( \mu_i \): **hinge-loss function** which is positive if \( y_i \) does not satisfy \( \phi_\theta \) with minimum robustness (\( \varepsilon/2 \))

\[
\mu_i = \begin{cases} 
0 & \text{if } r(y_i, \phi_\theta) > \varepsilon/2 \\
\varepsilon/2 - r(y_i, \phi_\theta) & \text{otherwise}
\end{cases}
\]

- Minimize the number of signals that formula \( \phi_\theta \) classifies as anomalous

**Robust Degree (Signed Distance)**

- \( (+/-) \): signal \( y_i \) satisfies/violates formula \( \phi_\theta \)
- Large \( (+/-) \): large perturbation required for signal \( y_i \) to violate/satisfy signal \( \phi_\theta \)

To address numerical issues in nonlinear optimization (highly sensitive to an initial guess and noise), we implement **sequential convex optimization** which is less sensitive and has better convergence properties
Feature Selection

• Basic features: horizontal (longitude, latitude), vertical (altitude), and speed (groundspeed) dimensions.

• Energy management is important for aircraft operation in terminal airspace

⇒ Better metric for detection of energy excess or energy deficit anomalies

<table>
<thead>
<tr>
<th>Feature</th>
<th>Formula</th>
</tr>
</thead>
<tbody>
<tr>
<td>Specific Total Energy (STE)</td>
<td>( h + \frac{V^2}{2g} )</td>
</tr>
<tr>
<td>Specific Kinetic Energy (SKE)</td>
<td>( \frac{V^2}{2g} )</td>
</tr>
<tr>
<td>Specific Potential Energy (SPE)</td>
<td>( h )</td>
</tr>
<tr>
<td>Specific Total Energy Rate (STER)</td>
<td>( \dot{h} + \frac{\dot{V}V}{g} )</td>
</tr>
<tr>
<td>Specific Kinetic Energy Rate (SKER)</td>
<td>( \frac{\dot{V}V}{g} )</td>
</tr>
<tr>
<td>Specific Potential Energy Rate (SPER)</td>
<td>( \dot{h} )</td>
</tr>
</tbody>
</table>

Introduction

Anomaly Detection Algorithm Development
- Data Preprocessing via Clustering
- Temporal Logic Learning Based Anomaly Detection
- Feature Selection

Test and Analysis

Conclusions
ASDE-X Data Preprocessing via Clustering

- Airport Surface Detection Equipment – Model X (ASDE-X) Data
  - Recorded variables: time, flight ID, longitude, latitude, altitude, and ground speed
  - Surveillance data about the flights around LGA airport

- Horizontal trajectory patterns identified by DBSCAN, for the arrival flights at LGA
  - Each runway has 2 – 4 patterns (12 patterns in total)

<table>
<thead>
<tr>
<th>Period</th>
<th>ASDE-X data</th>
</tr>
</thead>
<tbody>
<tr>
<td>Detection Range</td>
<td>~20 nm from LGA</td>
</tr>
<tr>
<td>Sampling Rate</td>
<td>1 sec</td>
</tr>
<tr>
<td>No. Arrival</td>
<td>9,748</td>
</tr>
</tbody>
</table>

Horizontal trajectory patterns at LGA
April 6 – 24, 2016
Test and Analysis with ASDE-X Data

- ASDE-X data: 19 days (April 6-24, 2016) with 9,748 arrival flights at LGA airport
- TempAD detects total of 445 anomalies
  \[0.0457 \text{ anomalies per arrival flight (1 anomaly per 21.9 arrival flights)}\]

<table>
<thead>
<tr>
<th>Day</th>
<th>No. anomalies identified along each dimension</th>
<th>No. Anomalies</th>
<th>No. Arr. Flights</th>
</tr>
</thead>
<tbody>
<tr>
<td>6</td>
<td>H 6 V 9 S 3 STE 2 SPER 10</td>
<td>30</td>
<td>562</td>
</tr>
<tr>
<td>7</td>
<td>H 6 V 9 S 3 STE 7 SPER 7</td>
<td>32</td>
<td>504</td>
</tr>
<tr>
<td>8</td>
<td>H 2 V 7 S 3 STE 9 SPER 9</td>
<td>24</td>
<td>588</td>
</tr>
<tr>
<td>9</td>
<td>H 3 V 6 S 4 STE 11 SPER 11</td>
<td>28</td>
<td>393</td>
</tr>
<tr>
<td>10</td>
<td>H 9 V 4 S 1 STE 6 SPER 6</td>
<td>22</td>
<td>426</td>
</tr>
<tr>
<td>11</td>
<td>H 2 V 5 S 2 STE 4 SPER 4</td>
<td>18</td>
<td>475</td>
</tr>
<tr>
<td>12</td>
<td>H 8 V 5 S 3 STE 7 SPER 7</td>
<td>30</td>
<td>541</td>
</tr>
<tr>
<td>13</td>
<td>H 6 V 6 S 2 STE 10 SPER 10</td>
<td>29</td>
<td>562</td>
</tr>
<tr>
<td>14</td>
<td>H 3 V 7 S 4 STE 6 SPER 4</td>
<td>24</td>
<td>576</td>
</tr>
<tr>
<td>15</td>
<td>H 9 V 8 S 0 STE 6 SPER 2</td>
<td>25</td>
<td>581</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Day</th>
<th>No. anomalies identified along each dimension</th>
<th>No. Anomalies</th>
<th>No. Arr. Flights</th>
</tr>
</thead>
<tbody>
<tr>
<td>16</td>
<td>H 8 V 6 S 2 STE 7 SPER 8</td>
<td>31</td>
<td>373</td>
</tr>
<tr>
<td>17</td>
<td>H 6 V 2 S 1 STE 0 SPER 6</td>
<td>15</td>
<td>578</td>
</tr>
<tr>
<td>18</td>
<td>H 2 V 2 S 1 STE 10 SPER 10</td>
<td>16</td>
<td>525</td>
</tr>
<tr>
<td>19</td>
<td>H 3 V 4 S 7 STE 4 SPER 5</td>
<td>23</td>
<td>525</td>
</tr>
<tr>
<td>20</td>
<td>H 6 V 3 S 3 STE 3 SPER 7</td>
<td>22</td>
<td>565</td>
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<tr>
<td>21</td>
<td>H 8 V 4 S 1 STE 3 SPER 3</td>
<td>19</td>
<td>579</td>
</tr>
<tr>
<td>22</td>
<td>H 5 V 3 S 2 STE 2 SPER 2</td>
<td>14</td>
<td>592</td>
</tr>
<tr>
<td>23</td>
<td>H 3 V 6 S 1 STE 5 SPER 7</td>
<td>22</td>
<td>375</td>
</tr>
<tr>
<td>24</td>
<td>H 6 V 5 S 2 STE 3 SPER 5</td>
<td>21</td>
<td>428</td>
</tr>
<tr>
<td>Total</td>
<td>101 101 45 75 123 445 9,748</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

- Multiple anomalies (violations of the learnt TempAD model) over different dimensions can occur within a single anomalous flight
Anomalies along Trajectory Patterns

- Number of anomalies along the trajectory patterns during 19 days:

<table>
<thead>
<tr>
<th>Runway</th>
<th>Pattern</th>
<th>H</th>
<th>V</th>
<th>S</th>
<th>STE</th>
<th>SPER</th>
<th>No. Anomalies</th>
<th>No. Arr. Flights</th>
<th>Anomalies per Arr. Flights</th>
</tr>
</thead>
<tbody>
<tr>
<td>R4</td>
<td>R4-NE-E</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>2</td>
<td>5</td>
<td>0.400</td>
</tr>
<tr>
<td></td>
<td>R4-NE-W</td>
<td>9</td>
<td>4</td>
<td>4</td>
<td>8</td>
<td>15</td>
<td>40</td>
<td>281</td>
<td>0.142</td>
</tr>
<tr>
<td></td>
<td>R4-SW</td>
<td>7</td>
<td>14</td>
<td>7</td>
<td>2</td>
<td>13</td>
<td>43</td>
<td>1119</td>
<td>0.038</td>
</tr>
<tr>
<td>R22</td>
<td>R22-NE</td>
<td>24</td>
<td>29</td>
<td>13</td>
<td>15</td>
<td>18</td>
<td>99</td>
<td>1104</td>
<td>0.090</td>
</tr>
<tr>
<td></td>
<td>R22-SW-E</td>
<td>11</td>
<td>15</td>
<td>5</td>
<td>11</td>
<td>24</td>
<td>66</td>
<td>1026</td>
<td>0.064</td>
</tr>
<tr>
<td></td>
<td>R22-SW-W</td>
<td>25</td>
<td>22</td>
<td>7</td>
<td>20</td>
<td>22</td>
<td>96</td>
<td>3535</td>
<td>0.027</td>
</tr>
<tr>
<td>R31</td>
<td>R31-NE-W</td>
<td>6</td>
<td>7</td>
<td>8</td>
<td>6</td>
<td>13</td>
<td>40</td>
<td>382</td>
<td>0.105</td>
</tr>
<tr>
<td></td>
<td>R31-NE-E</td>
<td>2</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>4</td>
<td>46</td>
<td>0.087</td>
</tr>
<tr>
<td></td>
<td>R31-SW</td>
<td>12</td>
<td>9</td>
<td>5</td>
<td>6</td>
<td>12</td>
<td>44</td>
<td>1733</td>
<td>0.025</td>
</tr>
<tr>
<td></td>
<td>R31-SW-2</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>155</td>
<td>0.000</td>
</tr>
<tr>
<td>R13</td>
<td>R13-NE</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>4</td>
<td>4</td>
<td>60</td>
<td>0.067</td>
</tr>
<tr>
<td></td>
<td>R13-SW</td>
<td>5</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>7</td>
<td>302</td>
<td>0.023</td>
</tr>
<tr>
<td></td>
<td><strong>Total</strong></td>
<td><strong>101</strong></td>
<td><strong>101</strong></td>
<td><strong>45</strong></td>
<td><strong>75</strong></td>
<td><strong>123</strong></td>
<td><strong>445</strong></td>
<td><strong>9,748</strong></td>
<td><strong>0.046</strong></td>
</tr>
</tbody>
</table>

- Pattern R22-NE has a relatively high anomaly rate
- Pattern R22-SW-W has a relatively low anomaly rate

⇒ This can be attributed to the characteristics of trajectory patterns e.g., permissible descent rate, alignment between runway and approach, etc.
Anomaly Types in ASDE-X Data

- Anomalies in a single dimension

### Horizontal (latitude and longitude)

- Late convergence to approach

\[ G_{[8,0]}(-1.1135x + y - 123.0444 < 0) \]
\[ \land G_{[10,8]}(-0.411x + y - 71.0476 < 0) \]
\[ \land G_{[10,0]}(-1.3041x + y - 137.1171 > 0) \]

- Repeated horizontal deviations

\[ G_{[10,0]}(-1.2466x + y - 132.8728 < 0) \]
\[ \land G_{[10,0]}(-1.1867x + y - 128.443 > 0) \]
Anomaly Types in ASDE-X Data

• Anomalies in a single dimension

**Vertical (altitude)**
- Above/below glideslope
  
  \[ G_{15,0}(-353.2667x + y - 401 < 0) \]
  \[ \land G_{20,8}(-107x + y - 2226.3 > 0) \]
  \[ \land G_{8,0}(-292x + y + 24 > 0) \]

**Speed**
- Excessive speed
  
  \[ G_{6,0}(-3.8333x + y - 158 < 0) \]
  \[ \land G_{10,6}(-32.5x + y + 14 < 0) \]
  \[ \land G_{10,0}(-1.8x + y - 82 > 0) \]
Anomaly Types in ASDE-X Data

- Anomalies in a single dimension

**STE (specific total energy)**
- Energy deficit approach, but normal in altitude and groundspeed
  
  \[ G_{[8,0]}(41.875x + y - 320 < 0) \]
  
  \[ \wedge G_{[8,0]}(-104.4286x + y - 120 > 0) \]

**SPER (altitude rate)**
- Anomalous altitude rate, but normal in altitude
  
  \[ G_{[8,0]}(y - 14.8 < 0) \]
  
  \[ \wedge G_{[8,0]}(0.7x + y + 9.4 > 0) \]
Anomaly Types in ASDE-X Data

• Anomalies in multiple dimensions: Go-around

Go-around results in a violation of TempAD models for all the features
Anomaly Types in ASDE-X Data

- Anomalies in multiple dimensions: Repeated go-around with change in runway

- First attempt on RWY31
- Second attempt on RWY31
- Finally landing on RWY22

⇒ Violations of TempAD models for all the features twice
TempAD: Monitoring

• Illustrative example: Go-around flight
Further Extension: Precursor Detection

**Precursor Detection**

- **Labeled** time-series data: \((s_{i,c}, p_i)\)
- **Supervised Learning**
  - Reactive TempAD
  - Model separating normal/abnormal behaviors: **CAUSE formula** \((\varphi_c)\)

**Anomaly Detection**

- **Unlabeled** time-series data: \(s_{i,e}\)
- **Unsupervised Learning**
  - TempAD
  - Model describing normal behaviors: **EFFECT formula** \((\varphi_e)\)
  - Labels (normal \(p_i = 1\)/abnormal \(p_i = 0\))

Assumption: normal/abnormal behaviors occur in the last \(\tilde{t}\) seconds.

\[ T - \tilde{t} \]
Further Extension: Precursor Detection
Further Extension: Overnight Update

Comparison between a **batch update** (using whole data) and a **mini-batch update** (using only a newly obtained daily data)

- **Batch update**: the model becomes too conservative
- **Mini-batch update**: gives good results for anomaly detection throughout the month
Conclusions

• An **unsupervised anomaly detection** algorithm is proposed using **temporal logic learning**.

• The learned model in the form of temporal logic formula is **easy to be interpreted in natural language** and can be used in **real-time monitoring** for safety.

• Further works will be performed for **precursor detection** and **overnight update**.

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