APPLICATION OF REINFORCEMENT LEARNING TO DETECT AND MITIGATE AIRSPACE LOSS OF SEPARATION EVENTS

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Abstract

The volume of both manned and unmanned air traffic in the National Airspace (NAS) is projected to increase substantially over the coming decades with the consequence of increasing Air Traffic Control (ATC) workload, airspace congestion and the risk of mid-air collisions. Current ATC traffic management practices are human intensive. Separation is managed by ATC through open-loop vectoring and monitored on-board through collision avoidance systems such as the Traffic Collision Avoidance System (TCAS). In this paper, we discuss a machine learning based system that uses real-time system-wide traffic surveillance data to identify anomalous traffic behaviors that can lead to loss of separation (LOS) events. Specifically, this work presents an application of reinforcement learning to detect and mitigate impending airspace loss of separation events. We discuss the model representation and learning techniques, demonstrate the alert and recommended model actions, review our findings, and highlight future steps. With the mandatory Automatic Dependent Surveillance-Broadcast (ADS-B) usage being enforced in the NAS by 2020, it is expected that a significant amount of real-time traffic surveillance data will be available to leverage and build upon the developed technique.

Introduction

The need for systems that assess and give advanced warning for possible airspace safety incidents will expand alongside the growth of manned and unmanned air traffic congestion in the NAS. While the current rate of airspace safety incidents is low, existing systems that identify and mitigate such events need to advance technologically to retain or reduce this rate in the future [1]. The FAA, as part of NextGen, is currently updating existing systems and developing new systems to meet the demands of future air traffic. Along with new and updated systems comes growth in available real-time data sources. The availability of data provides an opportunity to utilize machine learning methods to build anomaly detection models to monitor airspace safety.

The goal of this work is to utilize machine learning to detect not just statistical anomalies, but safety anomalies that are operationally significant within the NAS. The anomalies must impact airspace safety. This poses many challenges, the first due to the lack of labeled airspace anomaly data for supervised learning. Second, the application of unsupervised methods yield results whose safety significance are hard to interpret. Using this approach, it is possible to identify anomalies that have no safety impact. In addition, recognizing airspace safety events from available data sources is only useful if the possibility of such events can be identified and mitigated before they occur. To avoid an airspace collision event, for example, the possibility of such an event must be identified before it occurs so aircrafts may be redirected in time. A precursor, therefore, is defined as a sequence of events leading to a safety event. A potential airspace safety event is one that exhibits the precursors.

In the literature, current flight anomaly detection methods focus on detecting single aircraft anomalies, such as an aircraft go-around near an airport [2, 3]. While these single-aircraft anomalies are important to detect from a flight safety standpoint, less research has been done using machine learning to find airspace safety events involving multiple aircraft. One of the more common airspace safety events is a LOS event, an event in which two or more aircraft come closer to each other than prescribed per safe separation standards in the given airspace class. These events are anomalous, safety-related, and involve multiple aircraft. We define an anomaly for the anomaly detection framework as a potential LOS event, that indicates higher likelihood of the manifestation of a LOS. Research on aircraft LOS in aerospace literature typically has been done using encounter models designed to avoid LOS from an onboard perspective [4]. We took the view of Air

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Traffic Control (ATC) and designed our model to operate from this standpoint.

Semi-supervised and unsupervised machine learning methods commonly used for anomaly detection classify individual data points as anomalies. While effective, the downside of this approach for time-dependent anomalies like LOS events is that precursors to the anomaly are not identified. Time series-based anomaly detection methods often rely on a single sequence of variable(s), which may flag indications of deviations from normal, but don't adapt easily to interactions between two unrelated sequences, such as two aircraft trajectories. A successful machine learning method for identifying precursors to LOS events must capture new and unseen dynamics between multiple aircraft. As such, a reinforcement learning method was implemented for solving the problem of detecting precursors to LOS events. While not traditionally used for anomaly detection, reinforcement learning lends itself to modeling movement of aircraft and assigning value to specific actions. We trained a reinforcement learning model to avoid potential LOS events between a set of two aircraft from the learned values of the model. In the following sections, we present the data preparation, reinforcement learning model, and demonstrate a precursor for a LOS interaction.

Data

To complete successful anomaly detection of LOS airspace safety events, a machine learning algorithm needs data cases either labelled or established within the set of available data as anomalies, or LOS events, to be detected. This type of information does not exist within the set of available data sources. The Aviation Safety Reporting System (ASRS) contains anonymous instances of safety events which are not tied to the specific aircraft identifiers. Consequently, it is necessary to identify and characterize airspace anomalies from available data.

Data Sources

The data sources available on this program include FAA SWIM sources such as Airport Surface Detection Equipment, Model X (ASDE-X) data and Time-Based Flow Management (TBFM) data. ASDE-X data contains aircraft track data within a 13-mile radius of an airport, useful for determining potential LOS events in the terminal airspace.

Identifying LOS Events

We worked with airspace safety experts to develop an approach for labeling anomalies for the supervised learning task. A technique using self-separation and separation calculations between aircraft in the data to tag anomalies was identified. These tags can be indexed by time and geography/airspace. An initial vision included using the above data sources in combination with FAA procedures as a means of filtering the ASDE-X data. Only the self-separation standards were used, however. Since ATC issues open-loop clearances to direct traffic, impacting aircraft trajectories in the terminal area and these communications are unavailable, the procedures cannot be used to label the data for violations.

Specifically, we leveraged the Traffic Collision Avoidance System (TCAS) metrics as a means of finding potential airspace LOS events within the set of data sources. TCAS is an onboard system that calculates the Closest Point of Approach (CPA) for an aircraft and any aircraft within a range distance from that aircraft. TCAS utilizes separation standards within the given airspace class to do these computations. There are two advisories the TCAS may issue: Traffic Advisories (TAs) and Resolution Advisories (RAs). TAs are issued when a collision is possible whereas RAs are issued during potential critical collision events. The bounds of the TAs and RAs are shown in Figure 1.

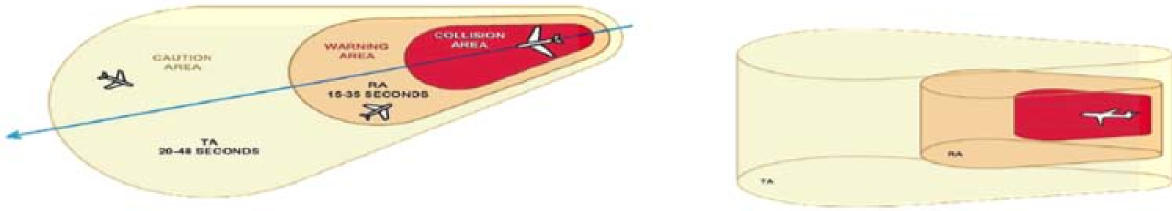

Figure 1. TCAS Envelopes for TAs and RAs

To perform the collision avoidance function, TCAS uses two calculations, range tau and vertical tau. Range tau is the time to CPA while vertical tau is the time to co-altitude between two aircraft. Consequently, range tau is focused on horizontal separation whereas vertical tau is focused on vertical separation. Each tau calculation is in seconds. TCAS alerts based on the values of both calculations and does so at different ranges based on the current airspace class and altitude location. Range tau is shown in Equation 1below.

Equation 1. TCAS Range Tau Calculation

$$Range\ \tau = \frac{3600\ x\ Slant\ Range\ (nm)}{Closing\ Speed\ (knots)} = \frac{Slant\ Range\ (m)}{Closing\ Speed\ (m/s)}$$

Since this work is focused on identifying precursors to safety events, range tau and Euclidean distance in meters were parameterized to find cases where aircraft may be approaching each other, but may have diverted prior to any TCAS alerts. Additionally, it helps us generate more labeled cased that can be used to develop and test this approach.

Data Examples

Separation calculations were completed using ASDE-X data from two weeks of data at LaGuardia (LGA) airport. ASDE-X gives aircraft position, speed, and heading at each time second. Calculations computed include closing speed, slant range, Euclidean distance, altitude difference, and range tau.

From the range tau and Euclidean distance computations, the complete set of separation data was filtered to those timestamps in which pairs of aircraft were less than 1 mile apart and the range tau was less than or equal to 90 seconds. In the remainder of this work we call this data the Potential Safety Event data. The range tau threshold chosen is approximately twice as much as the TCAS range tau for the airspace class of the ASDE-X data. While there is still significant distance at 1 mile apart, these are cases that could have led to a safety event, not those that resulted in a safety event, therefore they were included.

In all, there were 2,987 unique pairs of flights in the Potential Safety Event dataset, which involved 4,335 unique flights. Each pair of flights that met these criteria may have met the criteria for more than one second of time. Figure 2 highlights the range of time each pair of aircraft met the criteria. On average, aircraft in the Potential Safety Event data were within 90 seconds to CPA for 9 seconds, which isn't a significant period of time. It is clear there are cases where aircraft meet these criteria for more than 20 seconds, which may include more serious potential safety events.

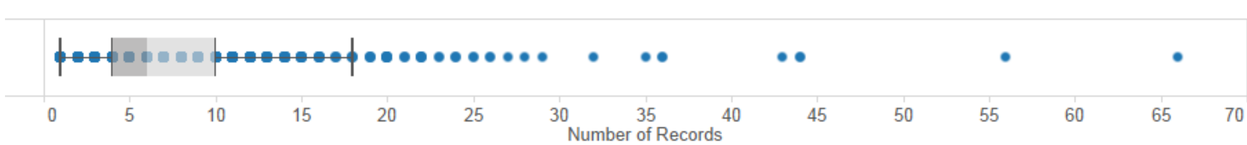

Figure 2. Number of Timestamps for Each Pair of Flights

To illustrate the contents of the Potential Safety Event dataset, Figure 3 presents a case identified as a potential safety conflict. A Runway 22 Arrival approaches a Runway 13 Departure. Most cases within the Potential Safety Event dataset involve larger aircraft coming close to smaller aircraft. Few cases involve two large passenger aircraft. In addition, many cases involve helicopters. The cases involving two helicopters are not necessarily significant from a safety standpoint.

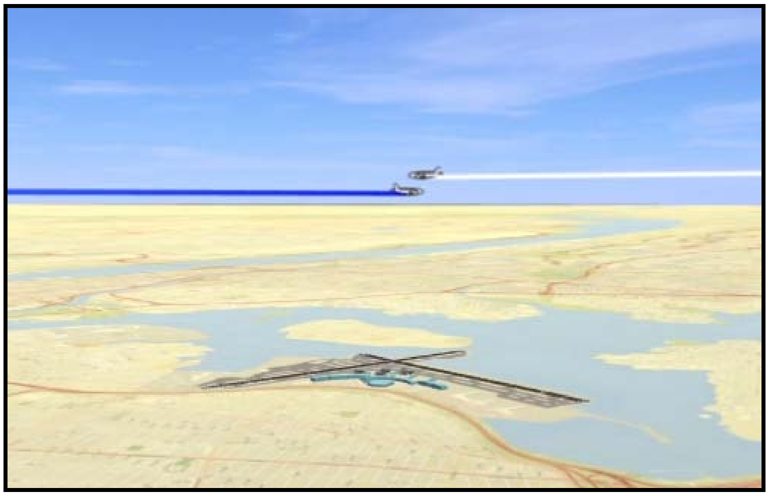

Figure 3. A Runway 13 Departure and a Runway 22 Arrival reach a Range Tau < 90 s, only 519 m Apart Near Laguardia Airport

The types of Arrival, Departure, or Other flight interactions in the given ASDE-X dataset are summarized in Table 1. The group Other includes anything in the air not flying to or from LGA, which includes GA aircraft, flights to and from JFK, and any other aircraft passing through the airspace. Most cases involve two Other types of flights or an arrival at LGA and an Other flight. The fact that there are fewer cases involving two departures makes sense since LGA does not have parallel runways and the departing aircraft leave the terminal airspace quickly reducing the opportunity window.

Table 1. Type of Flights in the Potential Safety Event Dataset

Flight Type 1	Flight Type 2	Percent of Flights
Arrival	Arrival	2.6%
Arrival	Departure	3.8%
Arrival	Other	33.4%
Departure	Departure	0.4%
Departure	Other	8.4%
Other	Other	51.3%

An analysis of airspace traffic by hour over the day revealed that a higher number of the Potential Safety Event cases occur during the afternoon, when LGA is operating at slightly higher traffic levels.

Since the goal of looking for safety events involves space and time dimensions, it is natural to analyze the data in terms of space. To do this, a 3-D mile-by-mile grid was created around LGA. Vertically, the grid was split in 1,000 ft. increments. Each data observation throughout the complete set of ASDE-X data was tied to its closest grid location. Figure 4 presents the 2-D version of the mile-by-mile grid. Each grid point is summarized by the number of flights that flew through it. All normal-operating data is shown on the left while the Potential Safety Event data is shown on the right. The dark blue regions highlight where a higher number of aircraft flew. High-traffic regions in the normal-operating data also show up in the Potential Safety Event data, specifically the area along the Hudson River.

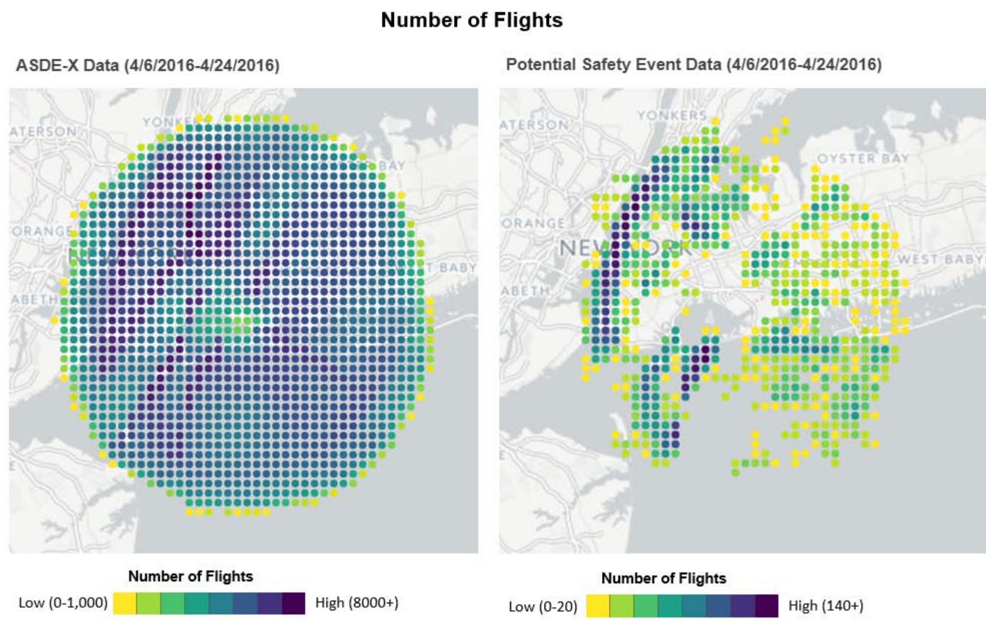

Figure 4. Number of Flights by Mile-by-Mile Grid

Along with the 2-D version of the grid, the altitude facet of the problem is highlighted in Figure 5. Most of the flight data for both cases are located within the lower two altitude levels. In the terminal area, more flights fly between 750-1850 m, which corresponds to ~2,000-6,000 ft.

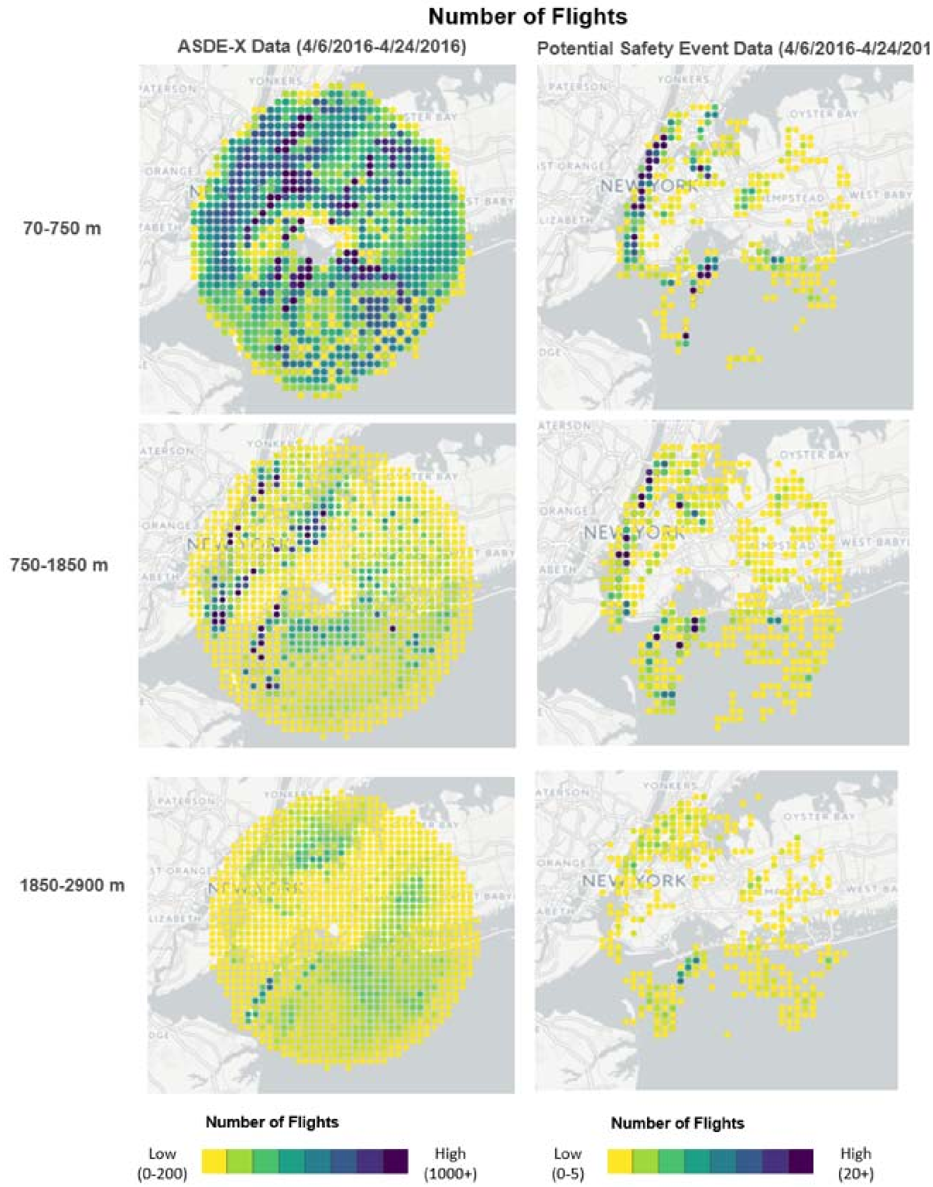

Figure 5. Number of Flights by Mile-by-Mile Grid and Altitude Level

While the number of flights flying through a grid point indicates the level of traffic associated with that space, this does not give an indication to what additional traffic may have been flying in the region at that same point in time. A traffic metric was created which measures for each flight-timestamp how many other aircraft were also observed in the airspace at that time. Figure 6 presents the summarization of this traffic metric. A dark blue dot, for example, indicates that on average for flights going through that grid point there were only 0-11 other aircraft flying in the LGA airspace at the same time. These correspond to low-traffic time periods. Yellow dots indicate that when flights flew close to that grid point, there were on average 35-50 other flights in the airspace at that same time. This indicates that traffic in the airspace was high when flights flew through that region of the airspace. High-traffic time periods below do not correlate with the patterns observed in Figure 4 and Figure 5, as traffic in general is high in the LGA airspace. More high-traffic times are observed in the Potential Safety Event data. Some regions have flights which are located away from the high-flight regions. This is rational in that if there are more aircraft in the airspace, not all aircraft will fit within the more frequently flown parts of the airspace therefore pushing aircrafts to less frequently flown areas of the airspace.

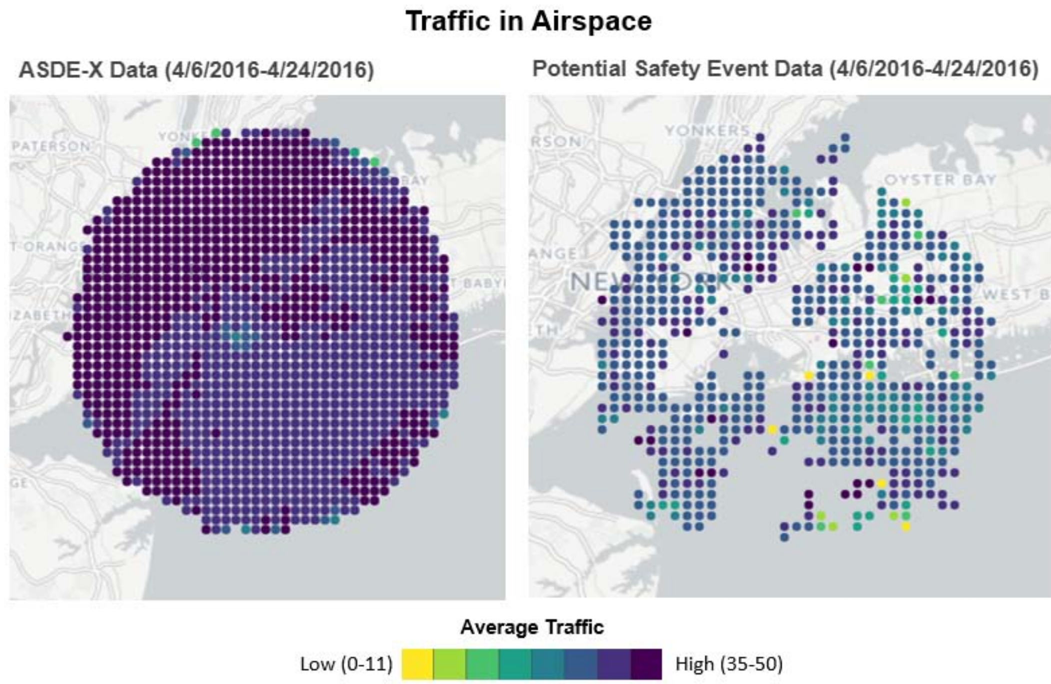

Figure 6. Traffic in Airspace observed when flights fly through each grid point

Model Formulation

Multiple conditions must be met to create an effective approach for detecting precursors to the airspace safety events identified above, some of which have been highlighted by the data analysis presented thus far. The requirements of a successful supervised anomaly detection approach include: accurately modeling space-to-time relationships, predicting events before they occur, and detecting events involving multiple aircraft. A reinforcement learning approach was implemented for detecting precursors to LOS events. The approach is set up to decide which actions should be taken at which point in time for an "Aircraft of Interest" to avoid LOS with another aircraft. We define this approach in the following subsections.

Model Parameters

We first define the model parameters of the Reinforcement Learning model by the following set of data created from the ASDE-X data:

- *Trajectory Database:* A trajectory database of historically flown trajectories segmented by aircraft type, runway, and intent (arrival/departure).
- *Set of Aircraft Interactions:* Within the trajectory database, this consists of the set of Intent-Runway scenarios at LGA (i.e. a Runway 22 Arrival or Runway 13 Departure)

From the set of aircraft interactions, we choose two specific flights and define the following:

- One aircraft, m – Aircraft of Interest, movement is tracked and rewarded in the model

- Other aircraft, n – Intruder Aircraft, movement is tracked in the model
- Generated Plans, p_m and p_n – For a specific aircraft interaction, these are the planned trajectories of each aircraft, which consist of specific trajectories, p_m and p_n in the trajectory database where *m* is allowed to make changes in movement from this plan and *n* is not. Each plan contains speed, heading, latitude, longitude, and altitude along the track.
- Trajectory Set, S_m – This contains a set of trajectories with the same intent as the Aircraft of Interest and within which this aircraft can make movements.
- *Separation Threshold* θ *:* The minimum separation distance for *m* and *n*, in meters.

Figure 7 shows an example of the definitions of *m, n,* and the trajectory set S_m, in green, for an Arrival-Departure scenario from LGA. The Aircraft of Interest *m*, in orange, is heading to land on Runway 22 at LGA while the Intruder Aircraft, in blue, departed from Runway 13.

Figure 7. Illustration of Model Parameters

Reinforcement Learning Model

Given the model parameter definitions above, we define the reinforcement learning problem. The goal of the reinforcement learning problem is to learn the optimal policy for the Aircraft of Interest to take to avoid LOS within separation threshold θ with the Intruder Aircraft.

The environment of the reinforcement learning model is defined as follows:

- *State:* The current state is described by the location of each aircraft within the airspace and the agent's current plan trajectory in S_m.
- *Agent Actions:* The agent is the Aircraft of Interest, which can stay on its current trajectory path or move to a trajectory to the left, right, up or down of that trajectory within S_m. The movement is constrained by an allowed heading deviation, current aircraft position, and current speed. If the agent chooses to switch trajectories, the new trajectory becomes the updated plan in the model. Actions occur at fixed time increments of *t*.

The reward structure for the Aircraft of Interest is as follows:

- Maximum negative reward is given for actions that brought the aircrafts within the separation distance θ apart, -10,000
- Small negative reward for the Aircraft of Interest switching plans, encouraging the Aircraft of Interest to stay its course unless necessary, -50
- Minimum negative reward for each time step, -1

The value function of the model represents state-action values and is defined by $\hat{v}(s_t, a_t) = r_{t+1} + \gamma\hat{v}(s_{t+1}, a_{t+1}, w_t)$ where w_t is the set of parameters of the function approximation technique used to represent the state space to the learning algorithm and all other parameters are listed above [5].

Results

Three common interactions where two aircraft come within separation threshold θ in the ASDE-X data were found and used as training and testing scenarios for the reinforcement learning model. We present the results for one of these scenarios, a Runway 22 Arrival – Runway 13 Departure interaction. In the original ASDE-X data, the Runway 22 Arrival and Runway 13 Departure aircrafts came 519 m. Using the model description in the previous section, the Runway 22 Arrival was set as the Aircraft of Interest and Runway 13 Departure as the Intruder Aircraft. The model parameters used were: a time step of $t = 10$ seconds, a heading deviation of 30 degrees for actions where the aircraft chose not to stay on its current plan, and a separation threshold of $\theta = 800$ m (~0.5 mile). The Aircraft of Interest was given a set of $|S_m| = 10$ trajectories.

The results of the model are presented in Figure 8. Following the model policy with a separation threshold distance θ = 800 m, the two aircrafts come 1,300 m apart. The model found a policy in which the aircraft would have maintained the θ separation threshold and avoided a LOS event.

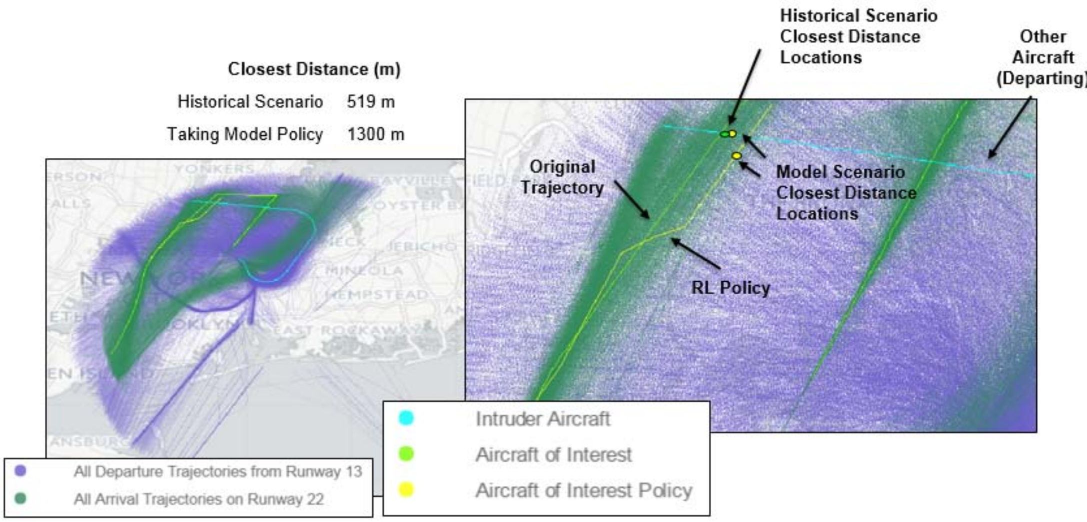

Figure 8. Result of the Reinforcement Learning Model for Runway 22 Arrival – Runway 13 Departure

The point in time where the reinforcement learning policy chooses a path that differs from that of the Aircraft of Interest's plan is the point in time where a precursor may be defined. Identification of the precursor is important since if the Aircraft of Interest is notified and switches its path accordingly, a LOS event is less likely. Figure 9 highlights a comparison of the reinforcement learning policy to the set of the trajectories in $\boldsymbol{S_m}$ given to the Aircraft of Interest. The left plot shows the sum of the distance to the policy over time increments *t* vs. the minimum distance to the Intruder over the whole trajectory. The right plot shows the trajectory set $\boldsymbol{S_m}$, the original scenario, and the model policy.

The model found a policy that meets the minimum threshold distance θ, but does not give much more margin than that required to avoid the worst-case LOS scenario. The set of trajectories to the right of the policy in the left plot may also be considered valid for avoiding LOS since they avoid crossing the threshold distance θ. In addition, the model avoided choosing Trajectory H, which does not meet θ. The original trajectory of the Aircraft of Interest may have switched to any of the trajectories to the right of the θ line in the left plot and we consider the model's optimal policy as the actions to take to minimally avoid a LOS event.

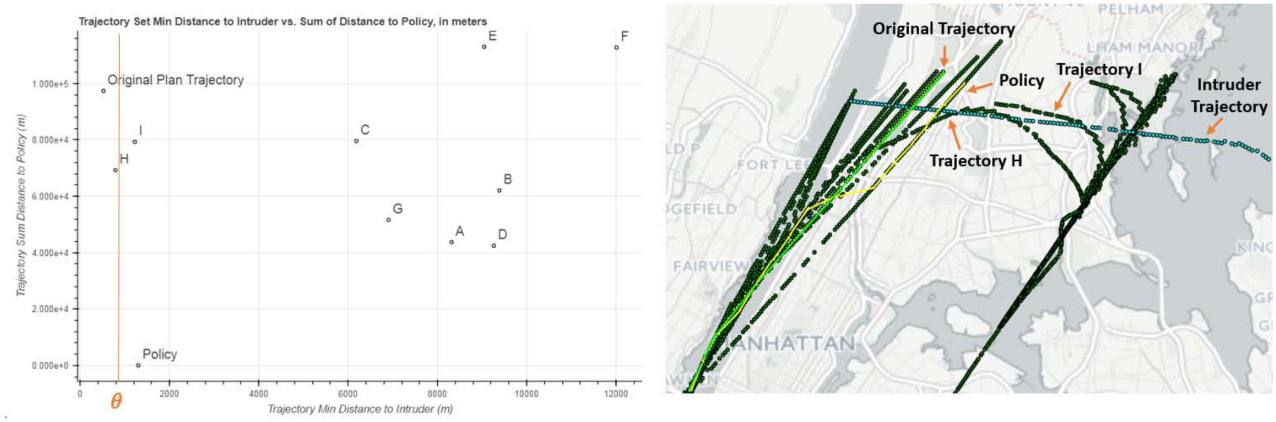

Figure 9. Comparison of the Policy Trajectory vs. Others Given in the Trajectory Set S_m

Conclusion

The airspace anomaly detection framework described here successfully applies reinforcement learning to find potential airspace LOS events. Solving the reinforcement learning problem to detect airspace anomalies required finding potential LOS events within ASDE-X data. Finding these events was done using the TCAS range tau metric on ASDE-X data from LGA. The calculated separation data was then filtered to cases where aircraft came within one mile of each other at a range tau of less than or equal to 90 seconds, which we termed as the Potential Safety Event dataset. More common historical interactions in this dataset were chosen as the training space for the anomaly detection framework. We presented the results for a Runway 22 Arrival – Runway 13 Departure scenario.

Given the potential LOS events in the data, a reinforcement learning model was built to find an Aircraft of Interest's set of actions to take to avoid a potential LOS with an Intruder Aircraft. The results demonstrate the ability to learn a policy that meets the self-separation criteria, detects the anomalies, and identifies the corresponding precursors. Next steps include testing the model with additional trajectories and scenarios and changing model parameters to understand solution robustness.

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Acknowledgements

This research was completed as part of the NASA Big Data Analytics in Aeronautics program (NNA16BF04C), worked in partnership with Mosaic ATM and Purdue University.

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