Trajectory Analysis in a Lane-Based UAS Traffic Management System

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Abstract. The development of Advanced Air Mobility (AAM) systems requires not only a robust and safe approach to planning flights, but also a way to monitor Unmanned Aircraft Systems (UAS) flights in real-time to determine whether flights are deviating from their nominal flight paths or if there are rogue (i.e., uncoöperative) flights in the area. We have proposed a lane-based airways methodology for lane creation, scheduling and strategic deconfliction, and here we describe *Nominal vs. Anomalous Behavior* (NAB), an efficient and effective way to monitor flight trajectories to determine normal versus anomalous behavior.

1 INTRODUCTION AND BACKGROUND

The AAM community, including Providers of Services for Urban Air Mobility (PSU) and UAS Service Suppliers (USS)[4], operators and relevant government authorities, aims to provide a wide number of services (e.g., package delivery, air taxi, etc.) by means of robust and safe UAS Traffic Management (UTM) systems. The primary objective of UTM systems is to achieve large-scale (i.e., thousands per day) operations in urban areas without human control, but with reliable communications and contingency plans (see [1]). UAS Service Suppliers, for example AirMap [2] have dealt with the operational interfaces, integration of Geographic Information Systems (GIS), registration of flights, UAS communications, and monitoring UAS activity. These capabilities are all developed to operate as described in the strategic deconflicton context defined by NASA [3] which is defined in terms of a geographic grid (a set of cells). Each new flight must be deconflicted pairwise in terms of grid cells which have other scheduled flights. The trajectory of a UAS flight is a curve in 4-dimensional space (x,y,z,t). Given set of such curves, strategic deconfliction (i.e., make sure that no two flights are ever within a specified minimum distance called *spatial headway*) necessitates a pairwise comparison of the curves, and determining a good or optimal trajectory in this configuration space is in general P-SPACE hard. Moreover the Federal

[4] PSU interfaces and protocols fulfill a similar role as USS, the main difference being that PSU applies to a broadened scope of operations that include both manned and unmanned aircraft. USS and PSU will be used interchangeably.

Aviation Administration (FAA) and NASA have yet to specify contingency protocols, and some research suggests that all flights simply return to base in these scenarios (e.g., lost-link).

In previous work, we have proposed and studied various aspects of a lane-based approach [4–10]. This lane-based approach reduces strategic deconfliction complexity (to 1D from 4D) and makes the handling of contingencies a spatially local problem [5]. The use of lanes for commercial flights (Victor and Jet Routes) has a long-standing history [11]. However, human air traffic controllers manage commercial airway lanes, and this management function which must be automated if a large number of autonomous flights are to take place daily over major metropolitan areas. Given a lane-based UTM system, then lanes are created as a static structure (much like ground road networks) and all scheduled flights will follow a sequence of assigned (reserved) lanes from launch to landing. Figure 1 shows a lane-based airway over the Salt Lake City East Bench area in Utah.

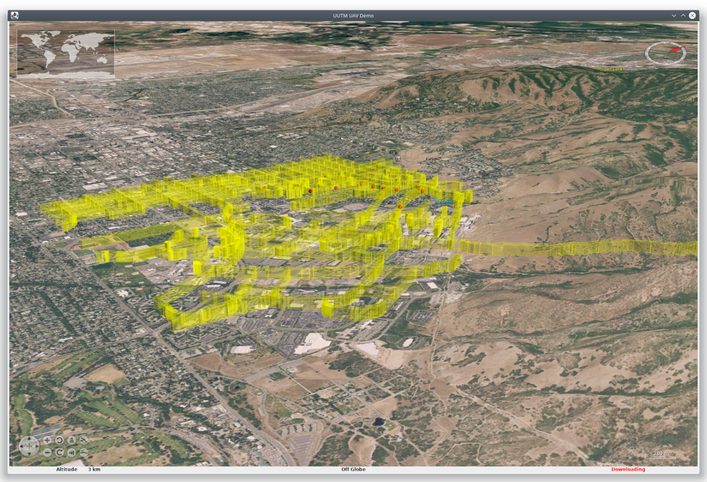

Fig. 1: Set of Airway Lanes Created over Salt Lake City, UT.

The basic problem addressed here is how a lane-based UTM system supports the recognition of rogue flights of a variety of sorts: amateur recreational hobbyists, UAS operators making an unscheduled up, over and down flight, malicious operators, etc. In order to detect such rogue flights, we propose the analysis of trajectories based on their deviation from the lane structure, including both location in space and direction of flight at that location. The basic idea is that a model can be produced directly from the lane structure and compared to any flight individually. The alternative FAA approach would require knowledge of all 4-dimensional flight trajectories, as well as target tracking to monitor the flights along those curves and a comparison of an unidentified flight to all of those curves. Thus, the proposed lane-based method is much more efficient and effective.

2 NOMINAL VERSUS ANOMALOUS BEHAVIOR: NAB

Nominal coöperative flights report their telemetry at a pre-determined frequency (e.g., 1 HZ) to their associated PSU or USS, and this data from on-board sensors is expected to follow an approved trajectory (within reasonable constraints). Alternatively or in conjunction with telemetry, radar or other sensors may be used to monitor flights and provide an independent source for trajectory data. Various flight trajectory classifications are possible depending on the intentions of the flight operator, for example point-to-point delivery or reconnaissance operations may have different expected profiles. These data sources and the expected variability in trajectory behavior must be considered to develop an effective airspace monitoring system.

Consider a planned flight and its associated trajectory, where the UAS nominally sends telemetry data and a unique identifier for that aircraft. This makes it possible to determine if the flight is off-course and by how much. Independent verification of telemetry data is accomplished using external sensors for airspace monitoring, such as radar, which can produce locations of airborne objects. Assuming that it is possible to classify which objects are UAS with high probability (as opposed to birds, etc.), the expected result is that reported positions are consistent with ground sensor data.

In contrast to nominal coöperative flights, unplanned behavior produces classifiable trajectories in ground sensor data that may or may not have corroborating evidence in telemetry data. Misguided, malfunctioning, or malicious agents produce this class of behavior; more specifically, planned flights with unexpected trajectories are *anomalous* and unplanned flights with unknown trajectories are *rogue*. In practice, the Air Traffic Operations Center (ATOC) needs to detect anomalous flights as robustly as possible, and the NAB method is an approach for classifying Nominal versus Anomalous behavior, described in Figure 2.

For NAB to operate effectively, lane data is made available along with the UTM policy parameters and the set of scheduled flights. A spatial database is constructed from this data and consists of a set of 3D points sampled along each lane, and to each of these points is associated a nominal direction vector (recall that lanes are one-way directed paths). The lane model consists of this data organized so as to be efficiently exploited. The inter-sample distance must be selected so to minimize the number of points while at the same time allowing adequate discriminatory power to determine if a flight is near a lane and headed the right direction.

Next a set of NAB measures are determined which allow the discrimination of the different types of flights, both nominal and rogue. These are computed either by comparing the UAS trajectory to the lane data, or simply in terms of the trajectory itself. For example, two lane related measures are:

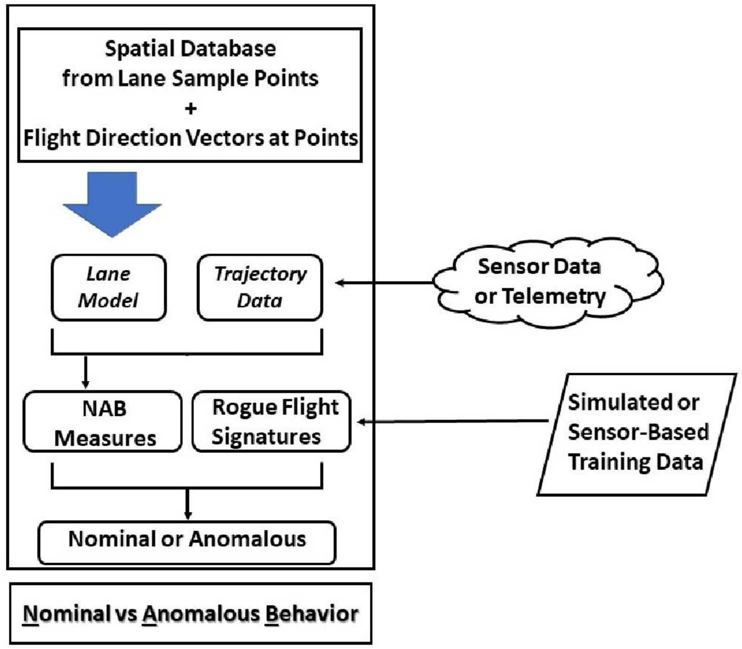

Fig. 2: The Nominal vs. Anomalous Behavior (NAB) Method.

1. M_{dist}: minimum distance to a lane at each time step, and
2. M_{dir}: cosine of the angle between UAS direction of travel and the lane direction of travel at each point.

These measures are applied at each point in the trajectory to produce a temporal signature to represent the flight. An example of a measure based solely on the trajectory data would be the amount of time spent hovering (i.e., staying for some minimal duration in time in one place in space). Given a characterization of the types of flights of interest, then a set of trajectory signature templates can be constructed and used as class models. Such templates can be the result of a set of simulations or produced from data sets of actual flight trajectories. Given a new trajectory, its measured features are compared to the flight signature templates and matched to the closest in order to classify the type of trajectory (i.e., nominal or anomalous).

Consider a nominal flight which does not perfectly follow the lane but rather has some noise associated with it. Figure 3 top row shows the x values of a nominal flight trajectory (with Gaussian noise of 0.16 variance), and a smoothed version of that data (in red). The middle row shows the distance to the closest lane, and the bottom row gives the cosine of the angle between the direction of flight and the lane direction. This distance and direction difference are NAB measures. For the distance measure, over 96% of the trajectory points are within 1 unit of the lane, and for the angle difference measure, 70% are within 10 degrees. The large angle differences arise at lane changes.

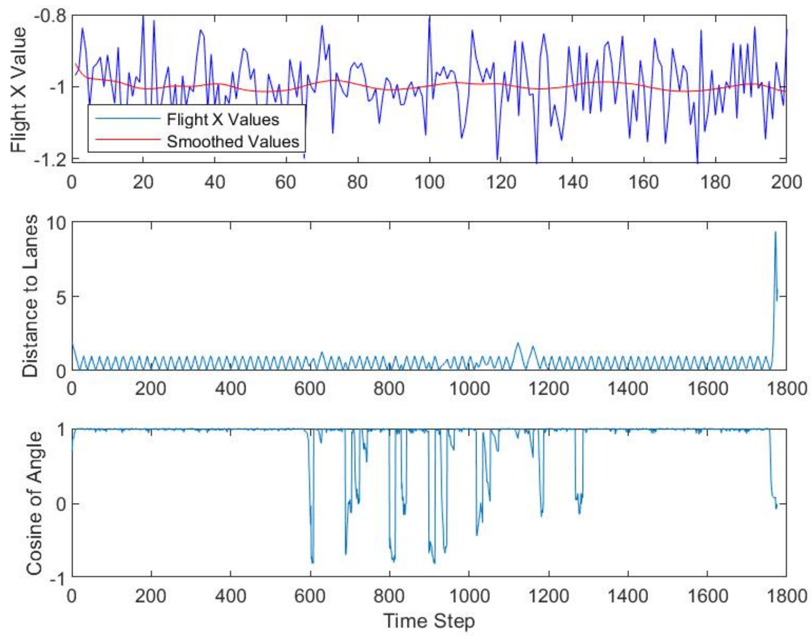

Fig. 3: NAB measures for a nominal flight.

Now consider rogue flights. Five categories are explored here:

– *Hobbyist Type I:* Flies up from one place and makes a few moves above the launch site, then eventually lands at the same site.
– *Hobbyist Type II:* Flies up from one place and makes a few moves above the launch site, hovers after each move, then eventually lands at the launch site.
– *Hobbyist Type III:* Flies up in a circular motion to some highest point then flies down in a circular motion to land.
– *Rogue Type I:* Flies up over and down as for a delivery.
– *Rogue Type II:* Flies up to a lane, flies along the lane to the end, then flies to another lane (not necessarily connected), and eventually flies down to land.

These anomalous flight patterns are representative of the types of flights to be expected. Figure 4 shows an example of these types.

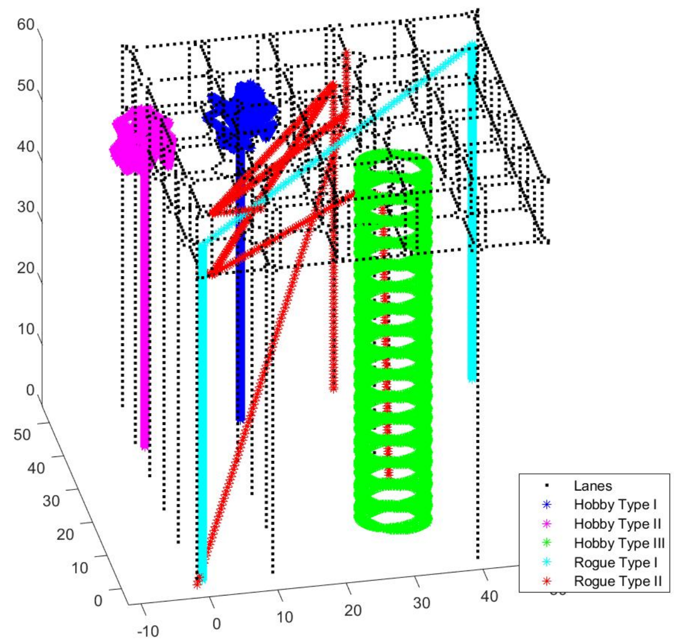

Fig. 4: Examples of the five anomalous flight trajectories.

3 NOMINAL VERSUS ANOMALOUS BEHAVIOR ANALYSIS

Given a set of UTM lanes, a convenient model is just a set of point samples on the lanes, each with an associated direction of travel in the lane. Figure 5 shows a set of sample points from the lanes given in Figure 1. These provide a good model since any nominal flight (i.e., following its assigned lane sequence) should be near a lane and headed in the direction of the (one-way) lane. As part of the model, the direction vectors can also provide significant information about a flight. Figure 6 shows a subset of the trajectory direction vectors used in the model.

The trajectory model is then just the set of 3D sample points along the lanes and the direction of travel vector at each of those points. In the example here, for the Salt Lake City East Bench airways, an inter-sample distance of 2 meters produces a set of 454,331 points. The model is organized as a kd-tree using the 3D points. Any nominal flight should be near one of the sample points and headed in the appropriate direction. Of course, a temporal analysis can be performed by checking the associated Space Time Lane Diagram (see [6]) which specifies the position of each flight in a lane at each time instant. Also, with the

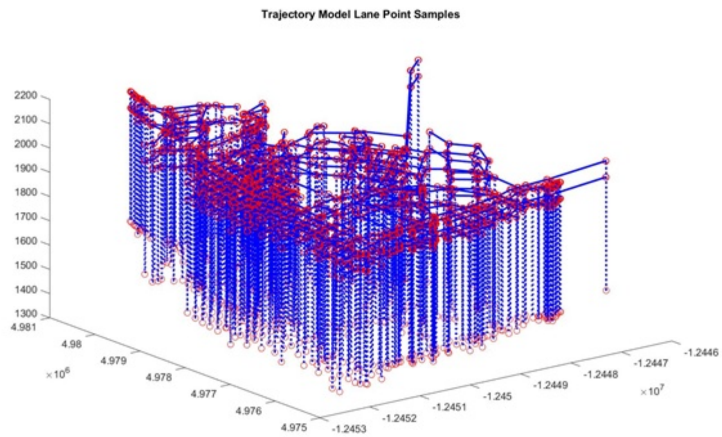

Fig. 5: Trajectory Point Set Model of Airway Lanes over East Bench of Salt Lake City, UT. Red circles are lane endpoints; blue points are samples along lane.

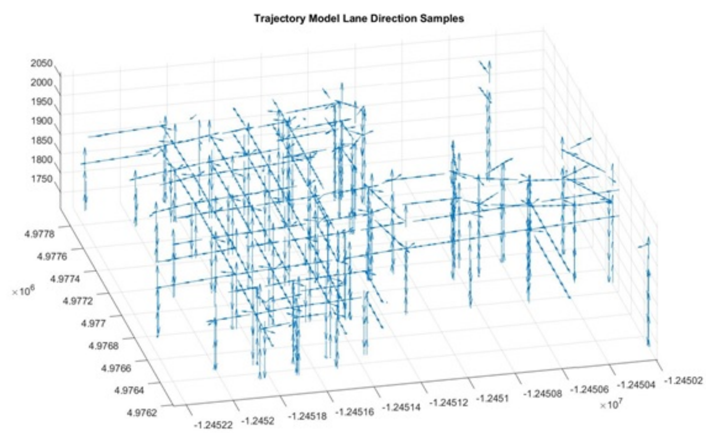

Fig. 6: Trajectory Direction Vector Model of Airway Lanes over East Bench of Salt Lake City, UT.

FAA-NASA unstructured airspace approach, there is no fixed set of lanes, and therefore, every existing flight would require target tracking against the set of all flights.

The two NAB measures given previously allow the discrimination of nominal from anomalous flight trajectories in almost all cases. This is due to the fact that anomalous flights, generally speaking, do not stay near the lanes nor do they fly in the same direction as the nearest lane. However, trajectories (i.e., x,y,z,t 4-tuple sequences) are of variable length depending on the distance of the flight and the sampling rate. Thus, in order to compare trajectories, it may be necessary to normalize the length of each trajectory to some standard length.

The nominal flights can be distinguished from the anomalous flights by means of a simple feed forward neural network. First, the trajectory lengths are normalized. Next, the NAB measures are computed at every point on the trajectory, and finally, the measures are concatenated into one vector (in this case, distance measure followed by cosine measure). A trajectory generator is created for each flight type based on random launch-land sites (uniformly selected over flight area), and appropriate parameters for the type of flight. Noise is added to the trajectory as follows (the same type of noise is added to all trajectories). First, the ideal trajectory is created. Then starting with the first point and moving to the second point, the error is defined by a circle around the goal point (the circle in the plane normal to the vector from the first point to the second point). A point in the circle (uniformly selected) is chosen as the target point. Next, a point on the line between the starting point and the circle point is chosen using a half Gaussian distribution centered at the circle point; this is the next point in the modified trajectory. When the circle has radius zero, and the Gaussian has zero mean and variance, then the resulting trajectory is the same as the original.

A set of 100 sample trajectories was generated for each flight type, including nominal, for a total of 600 trajectories; half of these were used to train the network to classify nominal versus anomalous flights (two classes), and half were used to validate the result. Figure 7 shows the training performance (from Matlab) as well as the 100% correct classification results on the test set.

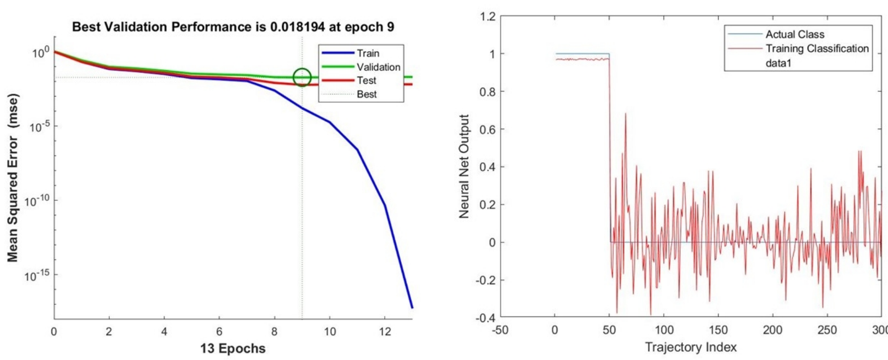

Fig. 7: Results of feed forward neural net classification of flight trajectories into two classes: nominal (first fifty) and anomalous (remaining 250). On the left is the network learning performance data, and on the right is the classification result.

Once an anomalous flight has been identified, it is possible to develop more refined and model-based techniques to distinguish between the sub-classes. Some characteristics of anomalous flights are:

- *Hobbyist Type I:* not on lanes, not in correct direction, change of altitude in non-vertical direction, launches and lands near same site.
- *Hobbyist Type II:* not on lanes, not in correct direction, change of altitude in non-vertical direction, launches and lands near same site, hovers for short periods of time.
- *Hobbyist Type III:* not on lanes, not in correct direction, change of altitude in non-vertical direction, launches and lands near same site, makes circular motion.
- *Rogue Type I:* not on lanes, only goes up, over and down, middle segment may not align with lane, may not be at normal lane altitude, launch and land sites may not be near lanes.
- *Rogue Type II:* not on lanes some of the time, not in correct direction some of the time, lanes followed may not be connected in lane network, some changes of altitude not vertical.

These characteristics are used to develop models of the various trajectories, and a classifier built based on them. Using the same set of simulated trajectories already described, the classification confusion matrix is given in Table 1 are achieved. From these results it can be seen that the trajectories of the Hobbyist Type I and the Rogue Type II are similar and require further refinement for discrimination.

	1	2	3	4	5	6
1	100	0	0	0	0	0
2	0	92	0	3	2	3
3	0	0	100	0	0	0
4	0	4	0	83	10	3
5	0	0	0	0	100	0
6	0	14	0	0	0	86

Table 1: Classification results. The 6 trajectory types are (1) nominal, (2) hobbyist type I, (3) hobbyist type II, (4) hobbyist type III, (5) rogue type I, and (6) rogue type II.

4 CONCLUSIONS AND FUTURE WORK

The lane-based UAS traffic management approach supports efficient and effective trajectory analysis of UAS flights in the airspace. This allows the straightforward detection of unplanned flights through the airspace without having to compare to every existing flight at the time of occurrence. In addition, it is possible to distinguish different types of rogue flights according to the trajectory distance and direction measures.

Several new avenues of investigation are under consideration:

– model updates due to dynamic lane creation and deletion
– how to exploit knowledge of UTM parameters (e.g., UAS speed limits, lane network topology, 3D corridor constraints, etc.)
– any influence on trajectory measures due to weather, congestion, or other environmental or contingency effects
– the constraints on sensor data to ensure effective identification of anomalous flight patterns
– the role of communications in UAS flight trajectory analysis.

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