As UASs increasingly integrate into the US national airspace system, there is increasing need to characterize how UAS may encounter each other. To maintain safety and mitigate the risk of collisions during these encounters, vehicle to vehicle (V2V) technologies may be required. To inform the development of V2V and other safety critical technologies, we demonstrate a methodology to analytically calculate all potential relative geometries between different UAS operations performing inspection missions along three different types of linear infrastructure. This method is based on a previously demonstrated technique that leverages open source geospatial information to generate representative unmanned aircraft trajectories. Using high performance computing resources, we performed trillions of calculations to estimate the relative distance and azimuth between long linear infrastructure inspection missions across sixteen locations.

Introduction

The continuing integration of unmanned aerial systems (UAS) operations into the National Airspace System (NAS) is stressing the NAS’s ability to maintain safety and operate efficiently. The UAS ExCom Science and Research Panel (SARP) is supporting this UAS integration. The SARP identifies research gaps and focuses scientific and technical capabilities of member organizations to address clearly defined, quantifiable, implementable, and able to be validated capability gaps. One enabling technology to help address several gaps are airspace encounter models, which have been fundamental to quantifying airborne collision risk for manned and unmanned operations [1, 2]. These models represent how aircraft behavior and their relative geometries evolve during close encounters and have supported of surveillance and communication requirements [3, 4].

Motivation

Airborne collision risk and optimization of airspace operations are strongly dependent on the distribution of geometries and behavior of aircraft encounters. Characterizing relative positions between unmanned operations, as defined by encounter models, is critical for communications research, specifically vehicle to vehicle (V2V), due to potential frequent changes to the topology of operations across the airspace [5]. This has a direct impact on the development of routing protocols, link budgets, and energy requirements [5]. In response, the UAS ExCom SARP has been tasked to support the development and implementation of UAS-to-UAS V2V technologies.

About the UAS Science and Research Panel

The UAS ExCom SARP is an organization chartered under the ExCom Senior Steering Group (SSG), made up of senior managers in eight federal agencies – DoD, FAA, NASA, DHS, DOI, DOC, DOJ, and DOE. It was founded in 2011 by the Office of the Under Secretary of Defense for Acquisition, Technology, and Logistics for Unmanned Warfare to facilitate improved collaboration and information sharing between federal military departments and aviation focused agencies. It was realigned and expanded in 2013 under the ExCom SSG and membership was broadened to researchers, subject matter experts, policy makers, and managers across all ExCom agencies and their Federally Funded Research and Development Centers (FFRDCs) and University Affiliated Research Centers (UARCs). The SARP is led by a U.S. Government senior research advisor, currently Ms. Sabrina Saunders-Hodge of the FAA, and two co-chairs appointed by

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the SSG, currently Ms. Amy Baker of The MITRE Corporation and Mr. Dallas Brooks of Mississippi State University.

The SARP’s process involves collaboratively identifying key research needs, gaps, and overlaps through maintenance of a prioritized “gap” list and coordination of interagency resources and expertise. Gaps are scoped to be clearly defined, quantifiable, implementable, and able to be validated. The SARP’s primary goals support UAS integration into the NAS by focusing on the scientific and technical capabilities of a broad Federal technical community and aligning these capabilities with commercial and academic science and research efforts to avoid duplication and reduce cost. Prior to its V2V tasking, the SARP recently focused on recommending separation criteria to enable a sUAS to remain well clear of manned aircraft [6, 7]. These recommendations have been transitioned to standards development organizations (e.g. ASTM, RTCA) and FAA draft advisory circulars (e.g. AC-90-WCLR) for consideration.

Objectives, Scope, and Contribution

To support V2V research, our objective was to develop a method to characterize the relative geometries between two UAS during an encounter. We started this research with long linear infrastructure use cases but will extend to more use cases beyond this initial paper. The developed method will support future research estimating the probabilities associated with encountering low altitude aircraft based on geography and on total systems latency to maintain a target of level of safety. This future work will support identifying where V2V systems may be required.

The scope included United States airspaces with the exception of Classes A and E-above-A. Altitude was restricted to the higher of at and below 10,000’ mean sea level (MSL) or 2500’ above ground level (AGL). We primarily focused on UAS with wingspans of 25 ft. or less, which are similar to or less than those of manned general aviation aircraft; and UAS weighing less than 55 lbs. mean gross take-off weight (MGTOW). This wingspan limit was selected based on the previous SARP well clear research [6].

The primary contribution was an analytical method that uses freely available open source data to estimate range and azimuth between potential UAS operations. We adopted three long linear infrastructure use cases, the inspection of electric power transmission lines [10], railway inspection based on the UAS Focus Area Pathfinder Program [11], and oil pipeline maintenance [12], to guide development of this approach.

Experiment Design

Our experiment was based on calculating the distance and azimuth between any given points along different long linear infrastructure surveillance missions. The experiment design was based on an approach to generate representative UAS trajectories that take into account their operational intent by leveraging OpenStreetMap (OSM), “a knowledge collective that provides user-generated street maps [9].” Instead of characterizing encounters between UAS trajectories in a six degree of freedom simulation, we processed the open source data used as input to the trajectory generation and determined the relative geometry interpolated points between different infrastructure line vectors. This closed form analytical approach is similar to what Edwards and MacKay used to determine surveillance requirements for UAS sense and avoid [4].

Long Linear Infrastructure Use Cases

All geospatial data used was freely sourced from the public domain. Electric power transmission lines operating at high voltages of 69-765 kV were sourced from the U.S. Department of Homeland Security (DHS) Homeland Infrastructure Foundation Level Data (HIFLD)1. Regular railway tracks were sourced from the Geofabrik OSM extracts2. Major crude oil pipelines were sourced from the U.S. Energy Information Administration (EIA)3. While electric power lines and railways are mostly above ground, majority of oil pipelines are buried underground. This results in relatively straighter infrastructure layouts.

We evaluated three pairs of railways and electric power lines; railways and oil pipelines; and oil pipelines and electric power lines. The results are relative to owncship operation and with respect to an intruder operation along a different type of infrastructure. We calculated, for pairs of use cases, the minimum longitude great circle distance, and then the azimuth for points at the minimum distance. The distance measurement corresponds to the worst case closet point of approach for any given point along the owncship vector.

| Id | Ownship     | Intruder     | Simulated? |
|----|-------------|--------------|------------|
| 1  | Railway     | Electric Power | Yes        |
| 2  | Oil         | Electric Power | Yes        |
| 3  | Railway     | Oil          | Yes        |
| 4  | Oil         | Railway      | No         |
| 5  | Electric Power | Railway   | No         |
| 6  | Electric Power | Oil       | No         |

Table 1 Pairings of long linear infrastructure use cases.

Locations and Administrative Boundaries

We evaluated use case pairs for sixteen locations. These areas include all the USA states associated with the UAS Integration Pilot Program (IPP), majority of states with FAA UAS test sites, a few states within FEMA Region 1, and the territorial island of Puerto Rico. These locations also include Urban Air Mobility (UAM) activities, as UAM aircraft may need to remain well clear of infrastructure inspection missions; however we only considered UAS vs UAS in this paper. While

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1 https://hifld-geoplatform.opendata.arcgis.com/datasets/electric-power-transmission-lines
2 http://download.geofabrik.de/north-america.html
3 https://www.eia.gov/maps/map_data/CrudeOil_Pipelines_US_EIA.zip
we did not consider UAM operations, the developed method is applicable for UAM V2V.

For these locations, their administrative boundaries were sourced Natural Earth Data at a 1:10m scale. Interpolation was calculated based on the arc length between points along the vector using a linear chordal approximation. This was more efficient than using a piecewise cubic Hermite interpolating polynomial (pchip) used by previous modelling efforts [1]. The spacing of 100 ft. was selected because it preserves details along curves and was also smaller than the 500 ft. horizontal component of the near mid-air collision (MAC) safety metric, which is commonly used to evaluate airborne collision risk.

### Processing

Prior to calculating relative geometry, we processed the geospatial data to enforce uniform spacing between points along a vector:

1. Download open source vector data for use cases
2. Filter data based on administrative boundaries
3. Interpolate data to have a fixed spacing of 100 ft.
4. Vector points are aggregated into a single array
5. Recheck and confirm that all points are within administrative boundary

After processing, we had over 18 million points uniformly spaced along each of the three long linear infrastructure use cases and sixteen locations, as reported by Table 2. Electric power lines had the most geographic extent and was the largest use case, whereas seven locations had no oil pipeline data.

### Results

We calculated for pairs of use cases, the minimum longitude great circle distance and the azimuth for points with the minimum distance using the MATLAB mapping toolbox’s distance function on the WGS84 reference ellipsoid. For example, assessing distance at the point of closest approach from railways to electric power lines in Alaska required approximately $7.9660 \times 10^9$ calculations. Across all locations, about $6.7615 \times 10^{12}$ discrete calculations were required in total for just the electric power lines and railway measurements. The computational scale necessitated the use of the MIT Lincoln Laboratory Supercomputing Cluster [13].

### Distance

Tables 3-5 report the minimum, mean, median, and maximum for closest point of approach for each pair of use cases for all locations rounded to the nearest tenth of a nautical mile (nm). The majority have a narrow peak and right tail that stretches more than 10 nm. We also calculated the bootstrapped distributions [14] for the mean and median using $1 \times 10^4$ samples for each location and determined that a subsample of results were not skewing the distributions. As an example, Table 3 supports the following colloquial statements for Alaskan railway operations:

- **Minimum:** “Railways and electric power lines are sometimes collocated.”
- **Mean:** “On average along a railway, a UAS comes within 3.8 nm from an electric power line.”
- **Median:** “At any given point along a railway, a UAS comes usually within 1.1 nm from an electric power line.”
- **Maximum:** “The closest point of approach between UASs inspecting a railway and electric power lines never exceeds 75.7 nm.”

| Administrative Boundary | Electric Power Transmission Lines | Railways | Oil Pipelines |
|-------------------------|----------------------------------|----------|--------------|
| Alaska                  | 134,962                          | 59,024   | 70,710       |
| California              | 2,311,446                        | 733,261  | 46,027       |
| Florida                 | 1,002,141                        | 279,511  | 0            |
| Kansas                  | 583,083                          | 437,236  | 81,993       |
| Massachusetts           | 214,503                          | 132,699  | 0            |
| North Carolina          | 896,262                          | 292,336  | 0            |
| North Dakota            | 848,685                          | 322,906  | 98,977       |
| New Hampshire           | 96,951                           | 34,668   | 2,373        |
| Nevada                  | 346,404                          | 127,855  | 0            |
| New York                | 1,000,564                        | 482,274  | 5,486        |
| Oklahoma                | 916,197                          | 271,276  | 125,356      |
| Puerto Rico             | 68,738                           | 760      | 0            |
| Rhode Island            | 21,876                           | 12,947   | 0            |
| Tennessee               | 709,717                          | 266,070  | 14,619       |
| Texas                   | 2,695,371                        | 1,043,943| 502,431      |
| Virginia                | 571,128                          | 310,504  | 0            |
| **Total:**              | **12,418,028**                   | **4,807,270** | **947,972** |

| Administrative Boundary | Minimum (nm) | Mean (nm) | Median (nm) | Maximum (nm) |
|-------------------------|--------------|-----------|-------------|--------------|
| Alaska                  | 0            | 3.8       | 1.1         | 75.7         |
| California              | 0            | 1.4       | 0.3         | 33.5         |
| Florida                 | 0            | 0.8       | 0.4         | 18.6         |
| Kansas                  | 0            | 2.6       | 1.4         | 19           |
| Massachusetts           | 0            | 1.2       | 0.7         | 14.6         |
| North Carolina          | 0            | 0.9       | 0.6         | 10.1         |
| North Dakota            | 0            | 1.4       | 0.7         | 14.9         |
| New Hampshire           | 0            | 2.6       | 1.3         | 13.9         |
| Nevada                  | 0            | 6.6       | 2.4         | 46.4         |
| New York                | 0            | 0.8       | 0.4         | 14.2         |
| Oklahoma                | 0            | 1.4       | 0.8         | 15.9         |
| Puerto Rico             | 0            | 0.6       | 0.6         | 1.7          |
| Rhode Island            | 0            | 0.6       | 0.5         | 2.0          |
| Tennessee               | 0            | 1.0       | 0.6         | 8.5          |
| Texas                   | 0            | 2.6       | 0.6         | 92.3         |
| Virginia                | 0            | 1.1       | 0.6         | 10           |

**Table 2** Total interpolated points for long linear infrastructure vectors for sixteen USA states and territories.
Table 3 Statistics for closest point of approach distance from a railway to an electric power line. Extremes are bolded.

| Administrative Boundary | Minimum (nm) | Mean (nm) | Median (nm) | Maximum (nm) |
|-------------------------|--------------|-----------|-------------|--------------|
| Alaska                  | 0            | 141.2     | 99.9        | 335.6        |
| California              | 0            | 1.1       | 0.6         | 9.8          |
| Florida                 | -            | -         | -           | -            |
| Kansas                  | 0            | 4         | 2.9         | 19.2         |
| Massachusetts           | -            | -         | -           | -            |
| North Carolina          | -            | -         | -           | -            |
| North Dakota            | 0            | 1.9       | 1.1         | 13.9         |
| New Hampshire           | 0            | 1.9       | 1.6         | 7.2          |
| Nevada                  | -            | -         | -           | -            |
| New York                | 0            | 1.4       | 1.1         | 5.2          |
| Oklahoma                | 0            | 1.7       | 1.1         | 15.7         |
| Puerto Rico             | -            | -         | -           | -            |
| Rhode Island            | -            | -         | -           | -            |
| Tennessee               | 0            | 1.6       | 1.1         | 6.8          |
| Texas                   | 0            | 2.5       | 1.6         | 17.6         |
| Virginia                | -            | -         | -           | -            |

Table 4 Statistics for closest point of approach distance from an oil pipeline to an electric power line. Extremes are bolded.

| Administrative Boundary | Minimum (nm) | Mean (nm) | Median (nm) | Maximum (nm) |
|-------------------------|--------------|-----------|-------------|--------------|
| Alaska                  | 0            | 79.7      | 87.5        | 558.3        |
| California              | 0            | 52.5      | 31.9        | 252.6        |
| Florida                 | -            | -         | -           | -            |
| Kansas                  | 0            | 22        | 18.3        | 112.8        |
| Massachusetts           | -            | -         | -           | -            |
| North Carolina          | -            | -         | -           | -            |
| North Dakota            | 0            | 17.5      | 14.3        | 60.6         |
| New Hampshire           | 0            | 49.5      | 51          | 105.1        |
| Nevada                  | -            | -         | -           | -            |
| New York                | 0            | 151.9     | 176.1       | 321.8        |
| Oklahoma                | 0            | 19.5      | 14          | 89.7         |
| Puerto Rico             | -            | -         | -           | -            |
| Rhode Island            | -            | -         | -           | -            |
| Tennessee               | 0            | 89        | 60.8        | 246.3        |
| Texas                   | 0            | 15.3      | 6.10        | 175.8        |
| Virginia                | -            | -         | -           | -            |

Table 5 Statistics for closest point of approach distance from a railway to an oil pipeline. Extremes are bolded.

Railway and oil infrastructures both come within a few nautical miles of electric power lines, yet railway and oil infrastructure are often have points of closest approach that are large. This is exemplified by the geospatial distribution of infrastructure in northern Kansas, Cushing, OK, and San Antonio, TX. First, notice in Figure 1 that the oil pipeline bisects the region and has multiple intersections with electric power lines, while the railways generally run in parallel to the specific sections of the power grid. The railways and oil pipeline are often tens of nautical miles apart at the point of closest, resulting in a great distance between potential closests point of approach between UASs. Second, observe in Figure 2 that while the electric power grid permeates across the region, the railways are limited to two general tracks and have different orientation and intents than the pipelines converging in Cushing. Lastly, across all regions, the railways have similar spatial orientation for sections of the power grid. This is illustrated by Figure 3 where the railway moves through the city but not around it as the power grid topography.
Azimuth

Azimuth, the relative angle between sampled points along the infrastructure vectors and was measured clockwise with respect from ownship to the intruder. We illustrate azimuth illustrated with a bin size of 15 degrees in Figures 4 and 5. This discretization accounts provides sufficient encoding for aircraft right-of-way rules with a left or right sense [15].

When evaluating all locations in aggregate in Figure 4, the azimuth distributions with respect to electric power were similar. The azimuth distribution for an oil pipeline had greater peaks. We partly attribute the azimuth homogeneity and small peaks to urban planning, in that there is some underlying structure to how long linear infrastructure is spatially distributed, as already noted in Figure 3.

Discussion and Conclusion

We demonstrated an analytical method to characterize potential UAS encounters. By characterizing encounters, we can develop and evaluate systems, such as V2V, that mitigate airborne collision risk. The distance distributions will inform the initial conditions for encounters and when considering reasonable UAS airspeeds, can provide estimates for the rate in which aircraft move closer to each other and the time prior to closest point of approach.

We establish that requirements may be dependent upon UAS use cases. For UAS operations near electric power lines, we analytically demonstrate that other long linear infrastructure UAS operations can be within a few nautical miles of other infrastructure. With completion of future work, this may justify the need for V2V systems, as these infrastructures are often spatially co-located and that coordination is required to, either strategically or tactically, mitigate airborne collision risk. Suppose, a V2V system is intended for a UAS inspecting a railway, a practical V2V requirement could be based on the mean or median closest point of approach distances in Table 3. However for some encounters, such as an UAS inspecting a railway and an UAS inspecting an oil pipeline, the relative geometries can be tens of nautical miles apart and a V2V system for tactical coordination may not be required.

Regarding azimuth, while there is variability across locations, the location specific and aggregate distribution indicates a need for an omnidirectional V2V system.

Future work will expand upon this analytical approach to include more UAS operations and characterizing how relative geometry can change over the length of an encounter. Lastly the underlying analytical distributions used to generate the figures in this paper are intended to be released open sourced on the MIT Lincoln Laboratory website.
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Acknowledgements

The authors greatly appreciate the support provided by Sabrina Saunders-Hodge, Adam Hendrickson, and Bill Oehlschlager from the Federal Aviation Administration. The authors wish to acknowledge the support of all the SARP team members, especially Amy Baker, Dallas Brooks, Rodney Cole, and Ngaire Underhill. The authors also acknowledge the MIT Lincoln Laboratory Supercomputing Center for providing high performance computing resources that have contributed to the research results reported within this paper.

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