GPS and ADS-B Dropout and Erroneous Data

Methods for Detection and Mitigation

Anton Skurdal[1], Niroop Sugunaraj[1], Zakaria El Mrabet[1], Jaya Preethi Mohan[1], Prakash Ranganathan[1]
Data, Energy, Cyber, and Systems (DECS) Laboratory
School of Electrical Engineering and Computer Science (SEECS), University of North Dakota

Abstract

Missing or invalid Global Positioning Systems (GPS) and Automatic Dependent Surveillance-Broadcast (ADS-B) data can be a safety and security risk for Unmanned Aircraft Systems (UAS) navigation and Detect and Avoid (DAA) operations [1]. Erroneous, spoofed, jammed, or drop outs of GPS data can result in UAS position, navigation, and timing (PNT) to be incorrect [2]. ADSB-In erroneous, spoofed, jammed, or drop outs can cause UAS to be unable to detect and avoid other aircraft or cause avoidance of aircraft that do not exist.
When these signals are delayed, interrupted, or modified the effects can range from minimal to severe. The detection, classification, and mitigation of data dropouts evaluates the integrity of the next-gen aircraft systems.

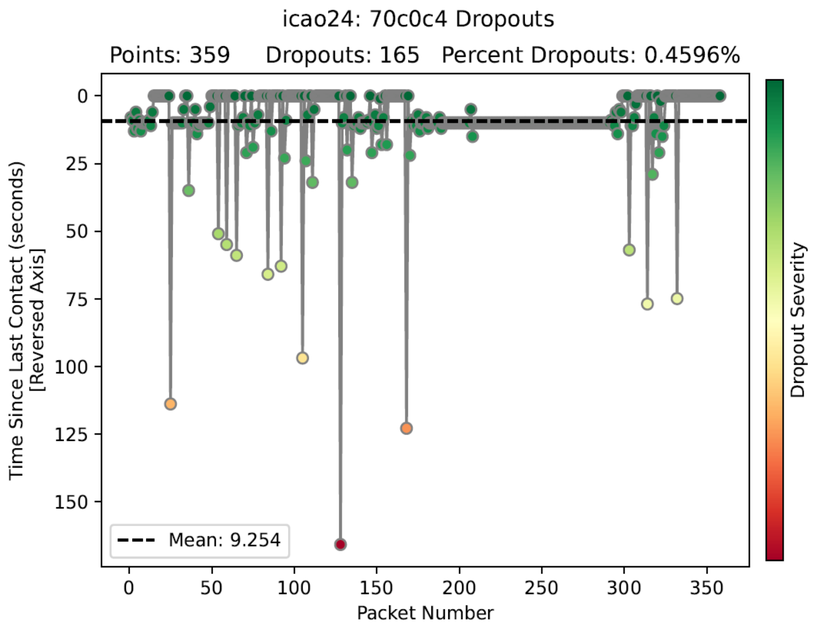
Data Acquisition

Data was obtained from the OpenSky Network, which provides live and historical ADS-B and Mode S sensor data for the aircraft they track, and the data from January 17, 2022 was used in this analysis. There are 7,304 unique aircraft in this dataset.

Dropouts

Dropouts are incidents where ADS-B failed to update within a specified rate [3]. Not all dropouts are severe, and some may be signal noise or a late update. Calculations were done by taking the difference between the time the previous message was received and the time the current message was received.

time since last contact [1] - time since last contact [0] = dropout length



Methods

Statistical mean was used as a threshold to classify data, but can easily be skewed by long dropouts. Several other statistical methods were also used as classification metrics to prevent misclassification. These methods include:

- Z-score
- Simple moving average
- Standard deviation
- Mode deviation, a novel method

Mode deviation is a measure of a point's deviation from the dataset's mode.

$$Z = \frac{x - \mu}{\sigma}$$

where:

Z = standard score
x = observed value
μ = population mean
σ = standard deviation

$$SMA_w = \frac{1}{w} \sum_{i=N-w+1}^{N} x_i$$

where:

SMA = simple moving average
w = window size
N = size of the population
x_i = each value from the population

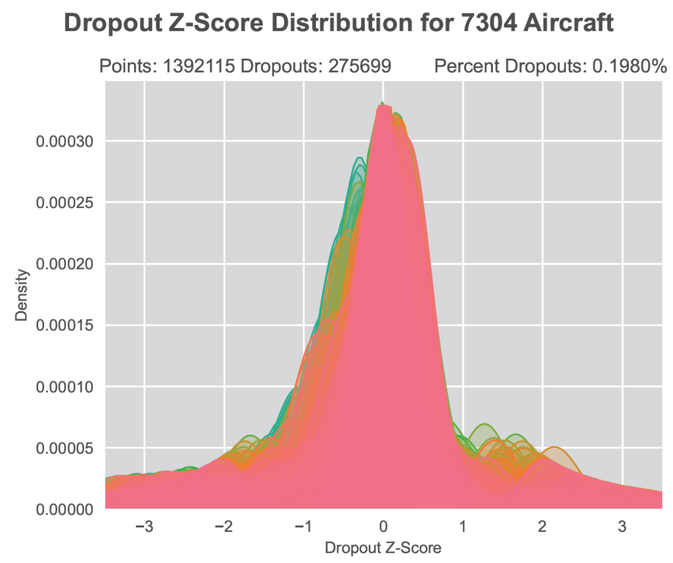
$$\sigma_{Mo} = \sqrt{\frac{\sum (x_i - Mo)^2}{N}}$$

where:

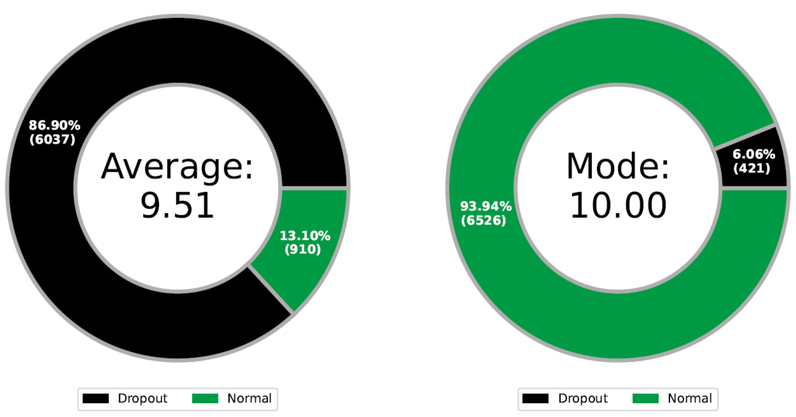
σ_{Mo} = population mode deviation
N = size of the population
x_i = each value from the population
Mo = population mode

Flight Analysis

Flight analysis was performed by separating aircraft using their unique ICAO24 tags. Once this was done, the dropout length was calculated and a plot of the signal delay was generated. This was done for every aircraft in the dataset and then used to calculate the mean, mode, standard deviation, and z-score for each dropout. Each flight had its own statistics calculated for analysis on an individual basis, but these statistics were also calculated using all of the flights. This produced a "holistic" analysis of the dropouts.



Holistic Percentage of Dropouts for 25 Aircraft



$$precision = \frac{TP}{TP + FP}$$

$$recall = \frac{TP}{TP + FN}$$

$$F1 = 2 * \frac{precision * recall}{precision + recall}$$

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

where:
TP = true positives TN = true negatives
FP = false positives FN = false negatives

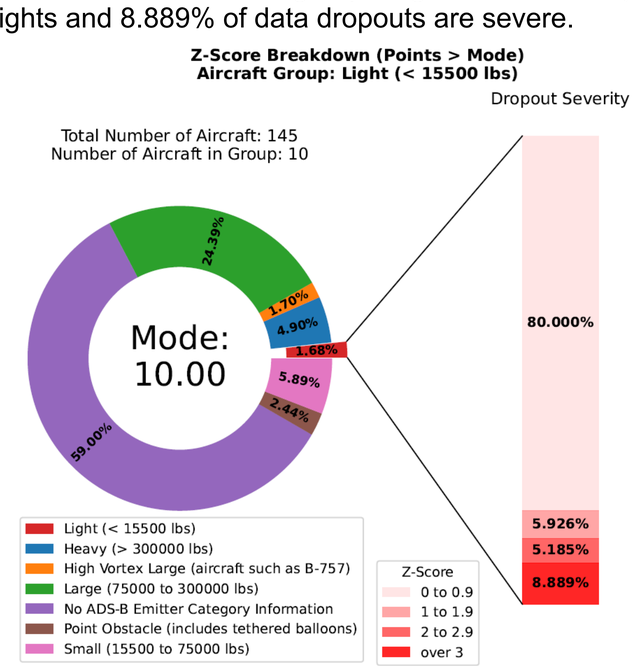
Maching learning performance metrics include:

- Precision
- Recall
- F-1 Score
- Support
- Accuracy

Support is the measure of the number of occurrences of the class in the dataset.

Categorization

The FAA aircraft registration database was used to classify aircraft by category description, which enabled dropout analysis by group.This information was added to the analysis flight data and then used to show z-score distribution. The aircraft group "Light < 15500 lbs)" comprises 1.68% of flights and 8.889% of data dropouts are severe.



Aircraft Counts by Category Description

Category Description	Count
No ADS-B Emitter Category Information	67
Large (75000 to 300000 lbs)	35
Small (15500 to 75000 lbs)	17
Heavy (> 300000 lbs)	11
Light (< 15500 lbs)	10
High Vortex Large (aircraft such as B-757)	4
Point Obstacle (includes tethered balloons)	1

Discussion, Results, Conclusion

Statistics were calculated for each data point and scored based on the previously mentioned threshold metrics. Labels were then applied to the score for training. A threshold of score of 4 was common and was used to label dropouts. Once labelling was complete, three machine learning methods were applied to predict the labels from features "lat", "lon", "velocity", "geoaltitude", and "dropout length". Labelled datasets were divided into three batches. Batch 1 was the training set, Batches 2 and 3 were testing sets. The models tested include Random Forest Classifier, K-Nearest Neighbor, and Support Vector Machine. Of these, the Random Forest Classifier performed the best over all on both batches of test data.

The Random Forest Classifier achieved an accuracy of 96.2% on Batch 2 and 87.7% on Batch 3, outperforming the KNN and SVM in terms of performance and accuracy for classification.

Batch	Unique Aircraft	Data Points	Dataset Type
1	55	691,764	Training
2	2	201,624	Testing
3	2	241,891	Testing

Model	Metric	Batch							
		batch_2				batch_3			
RF	index	precision	recall	f1-score	support	precision	recall	f1-score	support
	dropout	0.396	0.466	0.428	1093	0.590	0.459	0.516	4029
	erroneous	0.986	1.000	0.993	17872	0.996	1.000	0.998	62434
	noise	0.963	0.957	0.960	93078	0.792	0.877	0.833	83828
	normal	0.964	0.965	0.965	89581	0.892	0.810	0.849	91600
	accuracy	0.962				0.877			
KNN	index	precision	recall	f1-score	support	precision	recall	f1-score	support
	dropout	1.000	0.014	0.027	1093	1.000	0.011	0.023	4029
	erroneous	0.451	0.211	0.288	17872	0.449	0.141	0.214	62434
	noise	0.493	0.483	0.488	93078	0.362	0.509	0.423	83828
	normal	0.463	0.527	0.493	89581	0.398	0.452	0.423	91600
	accuracy	0.476				0.384			
SVM	index	precision	recall	f1-score	support	precision	recall	f1-score	support
	dropout	0.922	0.218	0.352	1093	0.898	0.255	0.397	4029
	erroneous	0.988	0.623	0.764	17872	0.998	0.871	0.930	62434
	noise	0.490	1.000	0.657	93078	0.449	0.999	0.620	83828
	normal	0.000	0.000	0.000	89581	0.000	0.000	0.000	91600
	accuracy	0.518				0.575			

References

[1] Federal Aviation Authority. "Unmanned Aircraft Systems (UAS)."
[2] U.S.D. of Transportation. "What is Positioning, Navigation and Timing (PNT)?".
[3] Federal Aviation Authority. "ADS-B Ins and Outs".

Acknowledgement

This research work is supported by both the FAA and NSF under NSF EPSCoR Track-1 Cooperative Agreement #UND 0026829 and A44 #UND0026156 respectively.

Contact Information

Anton Skurdal
M.S. Computer Science Student
anton.skurdal@und.edu

OPENSKY NETWORK
ND EPSCoR
C2SR CENTER FOR CYBER SECURITY RESEARCH
FEDERAL AVIATION ADMINISTRATION
NSF
DECS DATA, ENERGY, CYBER AND SYSTEMS
UND School of Electrical Engineering & Computer Science
UNIVERSITY OF NORTH DAKOTA