

UAS Flight Encounters at the DFW/Alaska Airport, it's Message Report Frequencies and Outlier Detection

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Abstract

One of the most recent problems in Unmanned Aircraft Systems (UAS) today, is message dropout. This occurs when a receiver fails to collect messages over a certain period. These messages typically contain important positional information such as latitude, longitude and the altitude of the aircraft. In this study, we develop a statistical framework for identifying an upper bound for acceptable time delays between consecutive GPS messages. If we receive time delays greater than this upper bound, we consider that to be an instance of message dropout.

Methodology

Any time delay greater than the mean time delay ($\hat{\Delta t}$) plus the root-mean-square-error (Δt_{RMSE}) of the time delay multiplied by a constant $k=2$ would be defined as a statistical outlier.

$$Outlier_{min} = \hat{\Delta t} + k \times \Delta t_{RMSE}$$

$$\Delta t_{RMSE} = \sqrt{\sum_1^N (\Delta t_i - \hat{\Delta t})^2}$$

Methodology Cont.

For both the DFW and Alaska data sets we have received, we primarily looked at the Mavic Air 2 drone. The messages within each of these data sets allowed us to perform statistical analysis with information regarding the time delay between consecutive messages with these flights. Using built in libraries in python, we gathered mean, median, and mode statistics that give us general areas within the flights where dropouts could be occurring.

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References

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Results and Discussion

Figure 1 shows that all flight durations did not exceed 30 minutes, with an average flight time nearing around 16 min. The average maximum altitude was near 375 ft, and a typical time delay after outlier removal was approximately 3.5 seconds. The average upper bound for determining dropout instances was near 6.25 seconds for the flights analyzed. The mode and median time intervals were relatively consistent at 4 seconds. This data was gathered from P4 Series, Mavic Mini 2, Mavic Air 2, M300 RTK, Mavic 2, Mavic Mini, and FPV Drones.

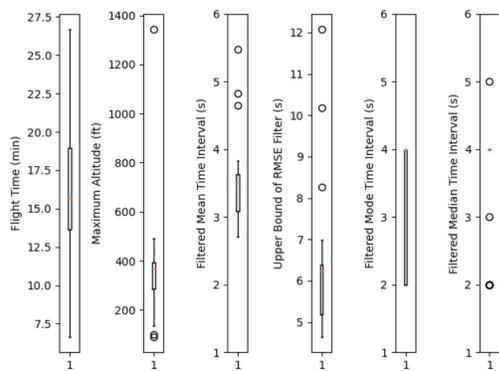


Figure 1: Statistics Gathered for DFW Flights

Figure 2.

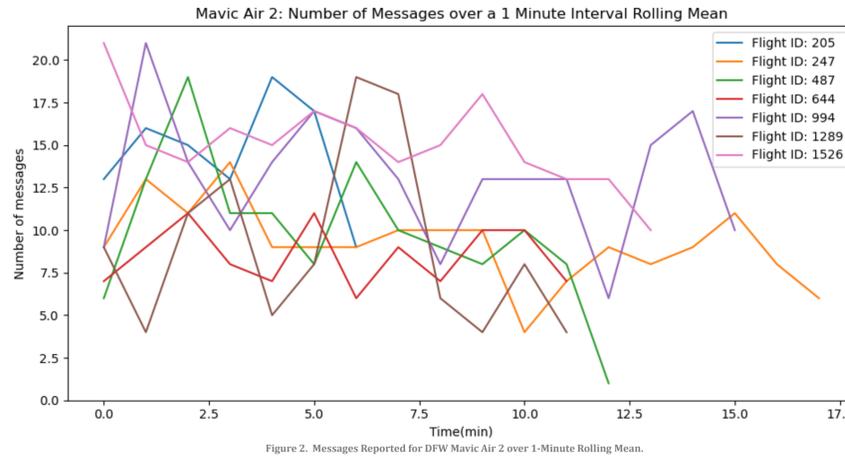


Figure 2. Messages Reported for DFW Mavic Air 2 over 1-Minute Rolling Mean.

Figure 3/Figure 4

Drone Type	Num. of Flights	Flight Time	1 Minute Mean/Average No. of Messages		2 Minute Mean/Average No. of Messages		3 Minute Mean/Average No. of Messages		Total No. of Messages
Aggregate Value			6.4075	11.6	6.1414	21.8	6.0655	30.1	169.0
Mavic Air 2	16	0:6:38	4.1252	14.6	4.0018	25.5	3.9858	34.0	102
	17	0:18:59	7.5923	9.2	7.0802	18.5	7.0994	23.7	166
	18	0:13:39	6.8513	9.8	6.6455	18.3	6.3794	25.6	128
	19	0:12:56	8.0372	8.5	7.8029	14.6	8.0008	20.4	102
	20	0:16:26	5.0192	13.0	4.9076	26.1	4.7372	34.8	209
	21	0:12:16	9.1065	9.1	8.1710	18.2	6.8722	27.3	109
	22	0:13:48	4.0079	15.1	3.9473	30.1	3.9381	42.2	211
Aggregate Value			6.3914	11.6	6.0795	21.6	5.8590	30.0	146.7

Figure 3. DFW Mavic Air 2 Mean Time Intervals

Results and Discussions Cont.

Figures 3 and 4 show the mean time delay gathered, as well as the average number of messages reported within each rolling mean time interval tested. The data we received for the Alaska Mavic Air 2 flights, had time delays as little as 100 milliseconds, while DFW Mavic Air 2 flights had delays between 2 seconds to 15 seconds per message. Therefore, the mean calculations are much more precise in the Alaska set comparatively to the DFW set. We can see for both sets, however; as the minute interval increases, the mean time delay typically decreases slightly.

Date	Flight	Flight Duration	Rolling Mean every 1-minute interval: [mean, Average No. of messages]		Rolling Mean every 2-minute interval: [mean, Average No. of messages]		Rolling Mean every 3-minute interval: [mean, Average No. of messages]		Total No of Messages
02/21/2022	1	0:09:50	0.130919	458.2	0.130681	918	0.130545	1372.7	4498
	2	0:08:41	0.132212	456.8	0.132185	912.8	0.132636	1362.5	3967
	3	0:08:36	0.127716	466.4	0.127810	932.3	0.127683	1407.5	4005
	4	0:09:08	0.131027	454.2	0.130861	908.3	0.131061	1362	4146
Aggregate Statistics			0.130468	458.9	0.130384	917.8	0.130481	1376.2	4154
02/22/2022	1	0:09:23	0.131029	458.2	0.130984	916	0.130853	1373.3	4288
	2	0:13:11	0.132405	454.5	0.132524	908	0.132246	1361.5	5983
	3	0:17:50	0.133003	453	0.132882	904.3	0.133084	1356	8082
Aggregate Statistics			0.132146	455.2	0.13213	909.4	0.132061	1363.6	6117

Figure 4. Alaska Mavic Air 2 Mean Time Intervals.

Conclusions/Future Work

With the data and calculations gathered, we now have a better way to locate where dropouts would most likely be occurring. Being able to break down each flight by the minute, gives us a more in-depth analysis of each flight, so we can see where these dropouts could be occurring. In order to take this research further, we would need to require more data sets with these similar drones, to compare and see which drones are most susceptible to message dropout. If we can receive data with smaller differences between each time delay, this would allow us to obtain more accurate and precise results on where dropout would be occurring.