Classifying Aircraft using Velocity Data with Support Vector Machines and Likelihood Ratio Tests

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Timely classification of aircraft is important for small unmanned aerial system (sUAS) technologies, such as onboard collision avoidance systems, and aerial perimeter security for prisons and sports venues. This work uses velocity-based metrics to classify multi-rotor sUAS, fixed wing sUAS, and general aviation planes using two classification methods: Support Vector Machines (SVM), and Likelihood Ratio (LR) tests. We found that a 96% classification accuracy is achieved when either classifier is trained using average speed derived from flight controller data or radar data and tested with one second of radar data. Further, we show that LR tests perform similarly to SVM for single metric classification. In addition, we present two novel metrics for classifying aircraft: log variance of absolute change in speed, and log variance of relative change in speed. Finally, we discuss challenges associated with training classifiers with flight controller data but testing on radar data.

I. Introduction

Small unmanned aerial systems (sUAS) are projected to become widespread across many industries such as mobile delivery, agriculture, insurance, construction, mining, military, and law enforcement [1]. In 2021, over 873,000 sUAS were registered to fly in the United States [2] and the global market share of sUAS is projected to reach $279 billion by the end of 2032 [3].

While sUAS have the potential to benefit many fields, there are inherent dangers to sUAS, as outlined in [4]. Safety threats include unintentional collisions with other sUAS, aircraft, or persons, along with controlled attacks on targets. Security threats include smuggling contraband, unlawful surveillance, and stealing sensitive information such as trade secrets. As a result, the FAA has imposed airspace restrictions near airports, stadiums, emergency response operations, and directly above security-sensitive areas such as prisons [5]. In 2022, three televised sports events were delayed due to a rogue sUAS. This included a soccer match in England [6], and two football games in Seattle, Washington [7, 8]. Between May 2021 and February 2022, twenty arrests were made after over one hundred pounds of contraband were smuggled into Lee Correctional in Lee County, South Carolina including drugs, phones, weapons, and cash with sUAS [9]. To defend against future threats, security-sensitive areas need systems to detect and classify sUAS.

Wide adoption of sUAS technology also requires policies and tools for their safe integration into low-altitude airspace. To further this effort, the FAA and NASA created the Advanced Aircraft Mobility (AAM) project [10]. The success of the AAM project requires the development of onboard sense-and-avoid systems that achieve minimum operating performance standards (MOPS) proposed by the FAA and RTCA [11, 12]. Among these standards include the ability to detect aerial intruders such as other sUAS and small manned aircraft such as Cessna 172s at a range of 2.5 nautical miles [11]. sUAS detection and classification is a first step to meeting these proposed MOPS.

Many different methods have been proposed for detecting and classifying sUAS. Passive RF is the primary tool for detecting sUAS, but it requires the sUAS to be radio-controlled, is spoofable, and doesn't easily allow for classification. As alternatives, systems that use acoustics, object trajectories from radar/visual platforms, or object image recognition have been considered [4]. The main contribution of this work is to define and assess metrics for classification from

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velocity data, and to propose the use of likelihood ratio (LR) tests as an alternative to Support Vector Machines (SVM) for classifying aircraft from a single metric.

II. Related Works

We present a collection of works which detect and/or classify sUAS using a variety of methods related to this work. The first work [13] uses a ground-based radar to identify sUAS and predict their future path flight paths. The second work [14] uses ultra-wide band (UWB) sensing and advanced signal processing methods to detect the presence and movement of low, slow, and small UAS (LSS UAS). The third [15] and fourth [16] works use smoothness metrics to differentiate between birds and drones, with the latter testing over a radar dataset. The final work [17] uses an SVM and various velocity-based metrics to differentiate between three classes of aircraft: multi-rotor sUAS, fixed-wing sUAS, and general aviation (GA) planes. This work uses the same dataset as [17].

A complete proof-of-concept sense-and-avoid solution for sUAS was proposed in [13], which encompasses a method for the detection and identification of aircraft from radar data. Aircraft can be detected from the ground with high resolution in range, elevation angle, azimuth angle, and time by using a planar phased-array radar with beam-forming. Many such radars could be distributed into a cellular network to track multiple sUAS over large distances, which is useful for protecting restricted airspace. A communication link between the ground-based systems and nearby sUAS can also assist with collision avoidance, as a ground-based radar system has knowledge of the sUAS in area. A prototype system was implemented with an ownship sUAS and two intruder sUAS. The ground-based radar successfully detected a potential future collision and re-routed the ownship to avoid the collision in real-time.

A UWB sensing system was proposed in [14] for detecting LSS UAS, which are likely to be used in unauthorized surveillance schemes. LSS UAS are difficult to detect with traditional radar systems because the radar cross sections are small. In the paper, two PulsON 440 UWB sensors were placed at the same height in a room with a LSS UAS, transmitting and receiving 400 scan lines over 40 seconds. Advanced signal processing methods such as correlation, envelope detection, spectograms, wavelet transforms, and recurrent plot analysis were used to detect the movement of the LSS UAS. The authors found that recurrent plot analysis was especially effective at detecting the drone quickly enough for a real-time system.

Closely related works [15, 16] explore using trajectory-based metrics to classify aerial objects such as birds from other sUAS. In [15], the sUAS were assumed to follow a constant-velocity nominal trajectory through a feedback control system. The model leads to a computationally efficient hypothesis test based upon two points in the sample autocorrelation of the data. In [16], smoothness metrics were created and tested on a dataset containing tracks of birds and sUAS.

The work in [17] proposed an SVM classifier to distinguish different types of aircraft between fixed-wing sUAS, multi-rotor sUAS, and a general aviation (GA) plane using the same dataset used in this work. The SVM used a total of 13 metrics, such as the mean and variance of velocity components, and the number of sign changes in vertical direction. The SVM was trained on velocity data derived from flight-controller logs and tested on radar data, since flight-controller logs are more abundant and less expensive to collect than radar data.

III. Contributions

First, we investigate the effectiveness of training an SVM using only Average Speed as a metric. Second, we propose the use of LR tests to classify aircraft instead of an SVM for single metric classification. LR tests are well-studied [18], and may be desirable for lightweight onboard collision avoidance systems, as LR classifiers can be trained easily, make decisions quickly, and implemented on inexpensive microprocessors.

Finally, we propose two novel metrics for classifying aircraft: log variance of absolute change in speed (Absolute Variance), and log variance of relative change in speed (Relative Variance). We later show why, although these novel metrics can be used to classify aircraft from flight controller data, they cannot be used to classify aircraft from radar data.

IV. Methods

A. Classifiers

The two types of classifiers used in our evaluation methodology are SVM and LR tests. Throughout our evaluation methodology, we investigate the performance differences between the two classifiers.

1. Support Vector Machines

SVM are a machine learning model which learns by constructing hyperplanes that subdivide feature space into different regions based on a labeled input dataset. The SVM classifies new data by comparing its location to a region in feature space. SVM have been commonly used to classify both low- and high-dimensional data [17, 19].

We choose to use an SVM in this work for two reasons. First, to make a comparison to the performance of [17], and second, to compare the performance of an SVM classifier to an LR classifier. In MATLAB, we use the command `fitcecoc` to train the SVM on the three classes of aircraft.

2. Likelihood Ratio Classifiers

An LR classifier uses a statistical classification method which compares the conditional probabilities that some hypothesis is true given that some event occurred. The hypothesis with the highest conditional probability is selected as the most likely. For example, an LR classifier answers the following type of question: given that the Average Speed of an aircraft was observed to be 27 m/s, was the object a multi-rotor sUAS, a fixed-wing sUAS, or a GA plane?

To train the LR classifier, the conditional Probability Density Functions (PDFs) of a metric are first estimated from a labeled dataset. Under the assumption that each hypothesis is equally likely (as assumed in this work), decision regions are found by finding which conditional PDF is the largest over a range of values. To test the LR classifier, an observed metric value is compared to these decision regions. We explore the use of an LR classifier since they are well studied [18] and could easily be implemented on a microprocessor onboard a sUAS. For our three chosen metrics, the distribution of each metric was assumed to be normal. The conditional PDFs for each metric are superimposed on Figs. 3-5.

B. Metrics

Three different metrics are defined for classification. These include Average Speed, log variance of absolute change in speed (Absolute Variance), and log variance of relative change in speed (Relative Variance). These metrics are each calculated over 1-5 second subdivisions of track data from both the radar and flight controller datasets.

1. Average Speed

Average Speed is defined as

$$m_1 = \frac{1}{N}\sum_{k=1}^{N} v_k \tag{1}$$

where

$$v_k = \sqrt{v_X^2[k] + v_Y^2[k] + v_Z^2[k]} \tag{2}$$

with v_X, v_Y, v_Z being the X, Y, and Z components of velocity from the radar dataset or

$$v_k = \sqrt{v_N^2[k] + v_E^2[k] + v_D^2[k]} \tag{3}$$

with v_N, v_E, v_D being the north, east, and down components of velocity from the flight controller dataset. In both cases, k is the discrete-time variable $k = 1, 2, \ldots, N$, and N is the number of data points in the track subdivision. Average Speed has units of meters per second.

2. Log Variance of Absolute Change in Speed

Log variance of absolute change in speed (denoted as Absolute Variance for brevity) is defined as

$$m_2 = \log\bigl(\mathrm{var}(v - \tilde{v})\bigr) \tag{4}$$

where v is a column vector $v = [v_k],\ k = 1, 2, \ldots, N$, where v_k is calculated with Eqs. (2) or (3), and $\tilde{v} = [\tilde{v}_k],\ k = 1, 2, \ldots, N$ is the best fit line to v, with

$$\tilde{v}_k = \beta_0 + \beta_1 k \tag{5}$$

where β_0 and β_1 are constants chosen to minimize the residual

$$r = \sum_{k=1}^{N} \left(v_k - \tilde{v}_k\right)^2 \tag{6}$$

The intuition behind Absolute Variance is that the speed of GA planes should vary less than the speed of the smaller aircraft because of the larger mass and inherent design of the GA plane. In addition, we observed the nominal speed of aircraft is roughly linear over short time intervals. We found that taking the logarithm made the distribution of Absolute Variance normal, removed the heavy tail from the original distribution, and made the histogram of Absolute Variance easier to visualize. Absolute Variance has units of $2\log(m/s)$.

3. Log Variance of Relative Change in Speed

Log variance of relative change in speed (denoted as Relative Variance for brevity) is defined as

$$m_3 = \log\left[\mathrm{var}\left(\frac{(v - \tilde{v})}{\tilde{v}}\right)\right] \tag{7}$$

where $v = [v_k],\ \tilde{v} = [\tilde{v}_k],\ k = 1, 2, \ldots, N$ are calculated with Eqs. (2) or (3), and (5).

Relative Variance is related to Absolute Variance, but with a normalization term. In this way, Relative Variance focuses on the relative change in speed, rather than the absolute change in speed. Like Absolute Variance, we found that the logarithm made the distribution of Relative Variance normal, removed the heavy tail, and made visualizing the histogram of Relative Variance easier. Relative Variance is a unit-less value.

C. Evaluation Methodology

Two different types of tests are performed to evaluate the performance of the three metrics with the SVM and LR classifiers. The first type of test trains and tests the classifiers on radar data. The second type trains the classifiers on flight controller data and tests on radar data. For the latter test, we are interested in the performance of the metrics when given 1, 2, 3, 4, or 5 seconds of radar data. Classifying aircraft quickly is important for onboard collision avoidance systems, since the ownship needs to quickly move to avoid any oncoming aircraft.

1. Train on Radar Data, Test on Radar Data

We are interested in the performance of the three metrics for classifying the three types of aircraft using one second of radar data. The following tests are run for each metric and each classifier, for a total of 12 tests:

1) Train classifier with radar data, and test using the first second of each radar track.
2) Train classifier with radar data, and test using a set of random one-second intervals within the radar tracks.

The first test closely models a real-life situation, where the radar detects an aircraft and quickly classifies it. However, since the number of unique tracks in the radar data is small (the radar dataset consists of only 59 tracks), we included the second test to evaluate the performance of the metrics over a larger sample size. In the first test, the classifier is trained using every radar track, excluding the first second of each radar track. In the second test, we avoid testing and training on the same data by using 10-fold cross validation.

The K-fold cross validation technique is used to evaluate the metrics in this test. A dataset is subdivided into K equal-sized bins at random. Initially, the data in bin 1 is used for testing the classifier, while the other bins are used for training. The accuracy of the classifier on the testing data is recorded. Next, bin 2 is used for testing, while the other bins are used for training. This process repeats for each bin, and the classification accuracies in each test are averaged to give an overall accuracy.

2. Train on Flight Controller Data, Test on Radar Data
The work in [17] showed it was feasible to train a classifier on flight controller data and test on radar data. We run the following series of tests to directly compare the performance of a classifier trained on only Average Speed against the 13-metric SVM used in [17]. We perform the following tests on each classifier for each value of $T \in \{1, 2, 3, 4, 5\}$ for a total of 20 tests:

1) Train classifier with flight controller data, and test using the initial T seconds of each radar track.
2) Train classifier with flight controller data, and test using a set of random T-second intervals within the radar tracks.

The Absolute and Relative Variance metrics cannot be used to build on a classifier trained with flight controller data and tested on radar data for reasons discussed in Section VII.C.

V. Experimental Methodology

Two datasets were used in this work. The first consists of velocity tracks derived from an Echodyne radar. The second consists of velocity tracks derived from controller logs. In both datasets, the three classes of aircraft are multi-rotor sUAS, fixed wing sUAS, and GA plane. The two datasets used in this work were also used in [17].

A. Radar Dataset

In the radar dataset, the GA plane is a Cessna 172, the fixed wing sUAS is a USAUAS Tempest, and the multi-rotor sUAS is a Alta 8 Pro, as shown in Fig. 1. The Echodyne radar recorded the fixed wing sUAS and GA plane tracks onboard a BFD 1400-SE8 multi-rotor sUAS. The Echodyne radar recorded the multi-rotor sUAS from the ground. The radar dataset consists of a total of 59 tracks, totaling 0.48 hours across the three aircraft classes, as shown in Table 1. All radar tracks are recorded between 9 and 10 Hz. These radar tracks include estimated velocity components in three orthogonal directions: X, Y, and Z, where Y is upwards. The velocity estimates were performed by the Kalman filter in the Echodyne radar.

Table 1 Radar Dataset Overview [17]

Aircraft Class	Aircraft Name	Ownship Altitude (Meters)	Target Altitude (Meters)	Number of Tracks	Hours of Flight
Multi-Rotor sUAS	Alta X	Ground to Air Data	110	16	0.21
			80		
Fixed Wing suAS	USAUAS Tempest	190	190	22	0.13
			160		
			190		
GA Plane	Cessna 172	190	366	21	0.14

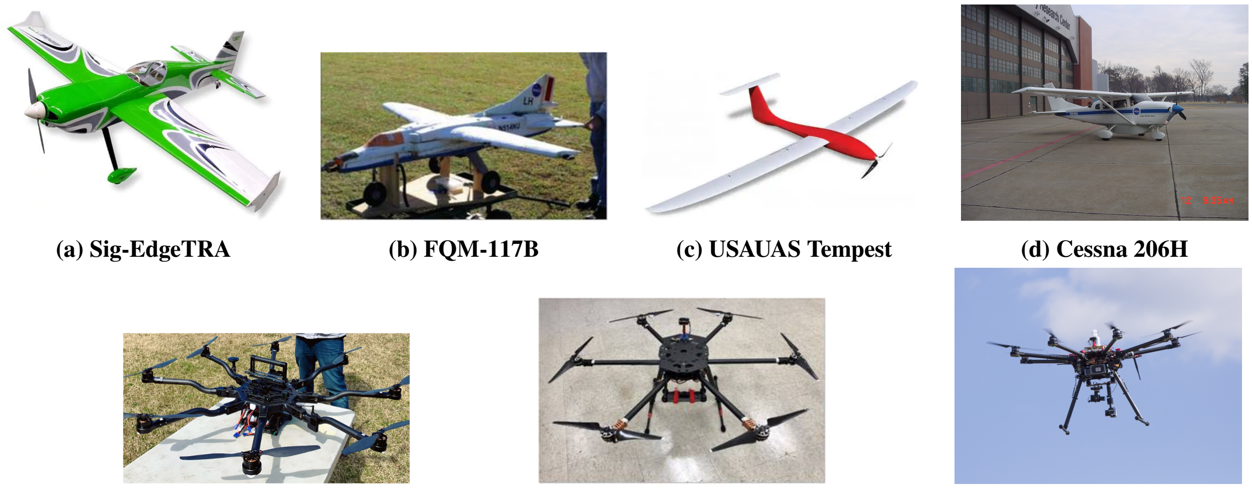
B. Flight Controller Dataset

In the flight controller dataset, the GA plane is a Cessna 206H. The fixed wing sUAS include a SIG-EdgeTRA, a Mig-27, and a USAUAS Tempest. The multi-rotor sUAS include an Alta 8 Pro Rotocopter, a Tarot T960, and ISAAC, as shown

(a) BFD 1400-SE8 **(b) USAUAS Tempest** **(c) Cessna 172** **(d) Alta X**

Fig. 1 Aircraft Used in Radar Dataset [17]

in Fig. 2.



(a) Sig-EdgeTRA (b) FQM-117B (c) USAUAS Tempest (d) Cessna 206H

(e) Alta 8 Pro (f) Tarot T960 (g) ISAAC

Fig. 2 Aircraft Used in Flight Controller Dataset [17]

Each type of aircraft used a variety of different sensors to provide velocity measurements. An extended Kalman filter was used to predict the north, east, and down components of velocity during each flight. The outputs from the extended Kalman filter were resampled to 10 Hz so the sample rate was uniform across all aircraft classes. After each down sampling operation, one second of data was removed at the start and end of each track to avoid edge effects. An overview of the flight controller dataset is shown in Table 2.

Table 2 Flight Controller Dataset Overview [17]

Aircraft Class	Aircraft Name	Flight Controller Sampling Rate (Hz)	Number of Flights	Hours of Flight	Number of Flights by Class	Hours of Flight by Class
Multi-Rotor	Alta 8 Pro	10	75	6.47	141	16.51
	Tarot	10	24	3.04		
	ISAAC	10	42	7.00		
Fixed-Wing	SIG-EdgeTRA	25	102	7.42	132	16.58
	Mig-27	25	14	2.25		
	Tempest	25	16	6.91		
GA Plane	Cessna 206H	200	1	1.60	1	1.60

C. Preprocessing

Short intervals of missing data were present in both datasets. To account for this, any track which exhibited missing data was split into two non-overlapping segments around the interval of missing data. This was especially important for the fixed wing sUAS flight controller logs. We additionally constrained the dataset to only include tracks where the Echodyne radar was facing the aircraft. Finally, tracks were subdivided into non-overlapping one second, two second, three second, four second, and five second intervals for further analysis.

VI. Results

Average Speed had the highest average accuracy across every type of test. Both the SVM and LR classifiers performed similarly between all tests when trained with Average Speed. Absolute Variance and Relative Variance had very low average accuracy when tested using the radar dataset.

A. Train on Radar Data, Test on Radar Data

1. Average Speed Accuracy — Testing on Initial 1-Second Interval

When the classifiers were trained with Average Speed from radar data and tested with the initial 1-second interval of radar data, the SVM and LR classifiers achieved 75% accuracy, as shown in Table 3. Both classifiers had perfect recall for the GA plane (all GA planes were properly identified), which is important for onboard avoidance systems, as unmanned aircraft need to yield to GA planes. From the confusion matrix in Table 3, the classifiers had a tendency to incorrectly predict a faster type of aircraft. For example, when a multi-rotor sUAS was actually flying, the classifiers incorrectly predicted a fixed wing sUAS was flying in 56% of the tests; when the fixed wing sUAS was actually flying, the classifiers incorrectly predicted the GA plane was flying in 13% of the tests. This is a result of the initial inflated speeds in the radar dataset, which is discussed further in section VII.B.

Table 3 Average Speed Accuracy — Train on Radar Data, Test on Initial 1-second Interval of Radar Data

	Predicted (SVM)			**Predicted (LR)**		
Actual	MR	FW	GA	MR	FW	GA
Multi-Rotor sUAS (MR)	0.438	0.562	0.000	0.438	0.562	0.000
Fixed-Wing sUAS (FW)	0.046	0.818	0.136	0.046	0.818	0.136
General Aviation (GA)	0.000	0.000	1.000	0.000	0.000	1.000
Average Accuracy	0.752			0.752		

2. Average Speed Accuracy — Testing on Any 1-Second Interval

When the classifiers were trained with Average Speed from radar data and tested with any 1-second interval of radar data, the SVM and LR classifiers achieved 96% accuracy as shown in Table 4.

Table 4 Average Speed Accuracy — Train on Radar Data, Test on Any 1-second Interval of Radar Data

	Predicted (SVM)			**Predicted (LR)**		
Actual	MR	FW	GA	MR	FW	GA
Multi-Rotor sUAS (MR)	0.968	0.032	0.000	0.971	0.029	0.000
Fixed-Wing sUAS (FW)	0.046	0.932	0.022	0.046	0.929	0.024
General Aviation (GA)	0.000	0.022	0.978	0.000	0.017	0.983
Average Accuracy	0.959			0.961		

For both classifiers, the GA plane was correctly identified with 98% accuracy. The classifiers incorrectly predicted a faster aircraft was flying much less than in Table 3. For example, when the fixed wing sUAS was flying, the classifiers incorrectly predicted a GA plane was flying in only 2% of the tests, as opposed to 13%.

3. Absolute and Relative Variance Accuracy

The classifiers trained with Absolute and Relative Variance metrics both had poor averages accuracy across all tests, as shown in Table 5. This is because there is not enough separation between the distributions of the metrics, as shown in Fig. 4 and Fig. 5. Differences between the performance of the classifiers is not significant because of the low classification accuracy. For additional discussion, refer to Section VII.C.

Table 5 Absolute Variance and Relative Variance Accuracy — Train on Radar Data, Test on Radar Data

		Classifier	
Metric	**Test Type**	SVM	LR
Absolute Variance	Initial 1-Second Interval	0.302	0.333
Absolute Variance	Any 1-Second Interval	0.602	0.520
Relative Variance	Initial 1-Second Interval	0.333	0.519
Relative Variance	Any 1-Second Interval	0.347	0.427

B. Train on Flight Controller Data, Test on Radar Data

1. Average Speed Accuracy — Testing on T-Second Initial Intervals

When the classifiers were trained with Average Speed from flight controller data and tested with the initial 1-second interval of radar data, the SVM and LR classifiers achieved 72% accuracy, as shown in Table 6. These results are slightly worse than when the classifiers were trained with Average Speed from the radar data instead, as shown in Table 3. When the classifiers were tested with the initial T-second interval of radar data, the accuracy for the SVM and LR classifiers increased. This is expected, as the classifier has more data to predict the type of aircraft, and the initial spike in speed present in the radar data is averaged out over the longer time-horizon. Every additional 1 second of time-horizon adds about a 5% increase in classification accuracy.

Table 6 Average Speed Accuracy — Train on 1-second of Flight Controller Data, Test on Initial T-second Interval of Radar Data

	Classifier	
Time-Horizon (s)	SVM	LR
1	0.716	0.716
2	0.765	0.781
3	0.822	0.856
4	0.858	0.876
5	0.898	0.898

2. Average Speed Accuracy — Testing on Any T-Second Interval

When the classifiers were trained with Average Speed from flight controller data and tested with any 1-second interval of radar data, the SVM and LR classifiers achieved 96% accuracy, as shown in Table 7. This is similar in performance to the training with Average Speed on radar data, as shown in Table 4. When the classifiers were tested on the initial T-second interval of radar data, the performance increases, but with marginal gains. Every additional 1 second of time-horizon adds less than a 1% increase in accuracy.

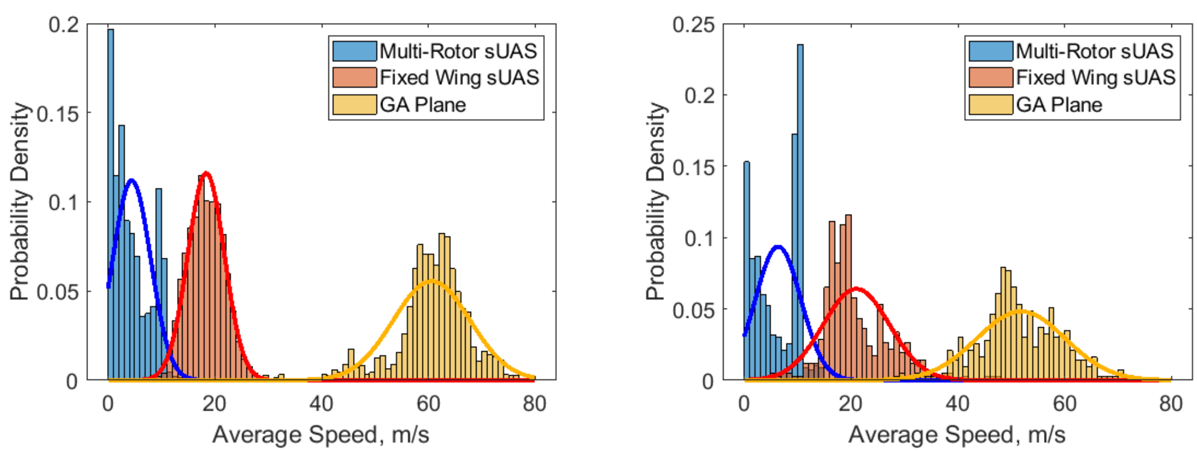
Table 7 Average Speed Accuracy — Train on 1-second of Flight Controller Data, Test on Any T-second Interval of Radar Data

	Classifier	
Time-Horizon (s)	SVM	LR
1	0.956	0.959
2	0.953	0.958
3	0.956	0.964
4	0.961	0.972
5	0.968	0.968

C. Visualizing Metric Distributions

This section provides histograms of the three metrics for both flight controller and radar data. In these histograms, larger separation between distributions correlates with higher classification accuracy. These histograms also show how Average Speed maps between flight controller and radar data well, while Relative Variance and Absolute Variance metrics do not map between flight controller data and radar data well. This result is further discussed in Section VII.C.

The two histograms in Fig. 3 show the distribution of Average Speed over 1-second intervals ($N = 10$). On the left is a histogram of Average Speed for the flight controller data. On the right is a histogram of Average Speed for the radar data. We make two observations. First, for both histograms, the distributions of Average Speed for different aircraft have little overlap, which leads to high classification accuracy between the three types of aircraft. Second, the minimum and maximum Average Speed for the multi-rotor sUAS and fixed wing sUAS are similar. This allows the classifier to train on flight controller data and accurately test on radar data.

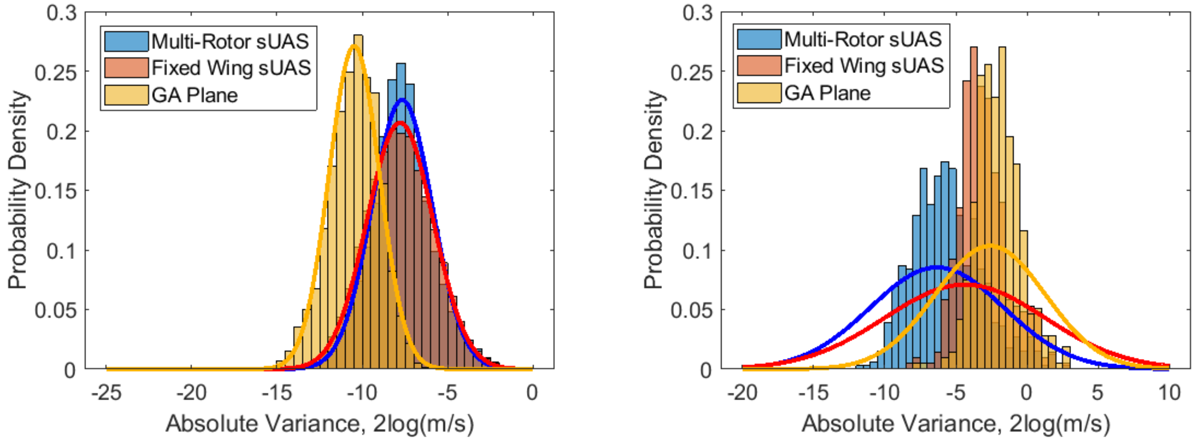


(a) Flight Controller Data **(b) Radar Data**

Fig. 3 Average Speed Histograms

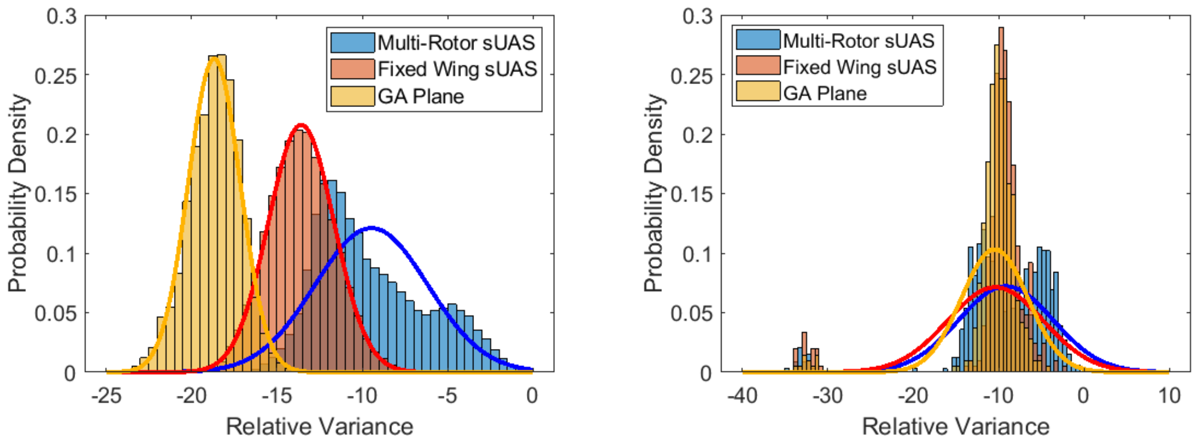
The two histograms in Fig. 4 show the distribution of Absolute Variance over 1-second intervals ($N = 10$). On the left is a histogram for the flight controller data. On the right is a histogram for the radar data. The means of the distributions for the flight controller data are different than the means of the distributions for the radar data. This shows that, for Absolute Variance, a classifier cannot be trained on flight controller data and then tested on radar data. This issue is explained greater detail in Section VII.B.

The two histograms in Fig. 5 show the distribution of Relative Variance over 1-second intervals ($N = 10$). On the left is a histogram for the flight controller data. The means of the distributions for the flight controller data are



(a) Flight Controller Data **(b) Radar Data**

Fig. 4 Absolute Variance Histograms



(a) Flight Controller Data **(b) Radar Data**

Fig. 5 Relative Variance Histograms

different than the means of the distributions for the radar data. This shows that, for Relative Variance, a classifier cannot be trained on flight controller data and then tested on radar data. This issue is explained greater detail in Section VII.B.

VII. Discussion

Three discussions are included. First, [17] is compared to the SVM trained with Average Speed. Second is a discussion of the inflated initial speeds found in the radar dataset, along with some plots of the recorded radar speeds. Third is an explanation for the motivation behind Absolute Variance and Relative Variance, which details why Absolute Variance and Relative Variance metrics are not suitable for classifying aircraft in radar data, and highlights potential issues caused by training with flight controller data but testing on radar data.

A. Comparison of the Performance of Average Speed to Previous Work

We make a comparison to the performance of the SVM used in [17], which used 13 different metrics including Average Speed, to the performance of the SVM classifier in this work, which was trained using only Average Speed. Both SVM were trained on flight controller data and tested on radar data from the same datasets. We acknowledge that the any

T-second interval test is not an ideal comparison, as both papers randomly assigned data into bins for 10-fold cross validation testing.

We compared the performances for the initial T-second intervals and any T-second intervals, as shown in Table 8. The higher accuracy is shown in bold font. The SVM in [17] performed better than the SVM in this work on the initial 1, 2, 3, and 4-second intervals. The SVM in this work performed better for the any T-second interval tests.

Table 8 Comparison of Average Speed to Prior Work

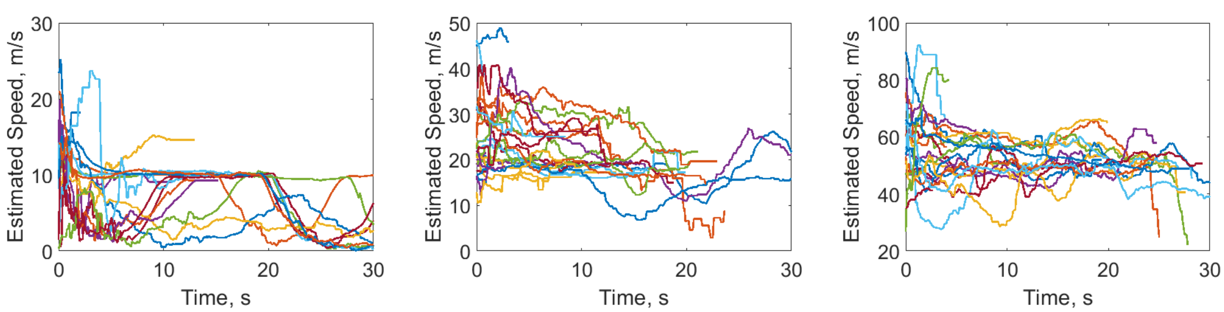
	Initial T-second Interval		Any T-second Interval	
Time-Horizon (s)	SVM in [17]	SVM in This Work	SVM in [17]	SVM in This Work
1	**0.797**	0.716	0.877	**0.956**
2	**0.810**	0.765	0.881	**0.953**
3	**0.860**	0.822	0.887	**0.956**
4	**0.889**	0.858	0.886	**0.961**
5	0.865	**0.898**	0.886	**0.968**

We suspect that the SVM in [17] was more robust to the inflated initial velocities present in the radar data, since 13 metrics were used instead of just Average Speed. However, when analyzing any T-second interval, Average Speed is strong predictor of the type of aircraft, and the SVM in this work performed best. In the latter case, the additional 12 metrics in [17] may have reduced the accuracy of the SVM.

In datasets where multiple types of aircraft fly at similar speeds, Average Speed will not be as effective for classification. However, Average Speed can be useful in onboard collision avoidance systems to quickly predict whether an aircraft is a GA plane or an sUAS.

B. Increased Initial Speed in Radar Data

Estimated aircraft speed in the initial seconds of radar data tracks was larger than subsequent measurements, as shown in Fig. 6. Every line corresponds to a different radar track. We believe that the Kalman filter on the Echodyne radar initially overestimates the speed of the aircraft, and as more data is collected, the Kalman filter obtains a better and lower estimate for speed. This behavior is present for all three types of aircraft, but this not a explicit rule in the data, as there are a few instances with the multi-rotor sUAS where the estimated speed increases with time. The increased initial speed is responsible for the difference in average accuracy when testing Average Speed over the first 1-second interval versus any 1-second interval, as shown in Tables 3 and 4, and in Tables 6 and 7.



(a) Multi-Rotor sUAS **(b) Fixed Wing sUAS** **(c) GA Plane**

Fig. 6 Aircraft Speeds in Radar Data

To compensate for the initial increased estimated speed, the following steps could be taken. First, the radar should be tested on aircraft flying a constant speed. If a sharp decline in speed is observed after the initial seconds, this could be accounted for in one or more of the following ways:

1) Apply a normalization term $\eta(t)$ to the initial seconds of the radar speed data, defining estimated speed as $\hat{v}(t) = \eta(t)v(t)$.
2) Apply a bias term $\beta(t)$ to the initial seconds of radar speed data, defining estimated speed as $\hat{v}(t) = v(t) - \beta(t)$.
3) Instead of averaging speed over the time period $T \in [0, n]$, consider an average over the time period $T \in [m, n]$, with $n > m > 0$.
4) Use a moving average over $T \in [m, m + \Delta T]$ for some $\Delta T > 0$.

C. Explanation of the Poor Performance of Absolute Variance and Relative Variance

Absolute Variance and Relative Variance are not suitable for classifying aircraft from radar data. A detailed explanation of why they are included in this work follows.

1. Background on the Design of Absolute Variance and Relative Variance

Initially, this work aimed to create new metrics that could be used as additional input to the SVM in [17]. The work in [17] was trained on flight controller logs as a proxy for radar data because flight controller logs are more abundant and less expensive to collect than radar data. As a result, metrics were developed that differentiated between aircraft in the flight controller data. Of these, the Relative Variance metric performed the best, achieving an 80.4% classification accuracy when tested on any 1-second interval of flight controller data.

2. Why Absolute Variance and Relative Variance Did Not Successfully Classify Aircraft from Radar Data

After these metrics were developed for the flight controller data, they were applied to the radar data. We found that unlike Average Speed, the distributions of Absolute Variance and Relative Variance did not map from the flight controller data to the radar data, as shown in Fig. 4 and Fig. 5. We give three possible reasons for this behavior, but acknowledge that other explanations could exist.

First, the distributions of Absolute Variance and Relative Variance depend on the sensors and filters used to estimate the velocity of the aircraft. For example, the addition of a low-pass filter to a speed signal would greatly reduce the values of Absolute Variance and Relative Variance, as the higher frequency components of the speed signal would be reduced. Second, the precision of the sensor is important for calculating Absolute Variance and Relative Variance. A less precise sensor would likely produce a larger value for Absolute Variance and Relative Variance than a more precise sensor because the variance of the less precise sensor is larger. Third, the flight controllers on the multi-rotor sUAS are different from the flight controllers on the fixed-wing sUAS or GA plane, which may have caused additional separation between the distributions of Absolute Variance and Relative Variance in the flight controller data. In the radar data, the same radar sensor is used to track every type of aircraft, and the separation between distributions of Absolute Variance and Relative Variance is greatly reduced.

For Absolute Variance and Relative Variance to be useful for classifying aircraft, sensors and filters would need to be chosen carefully to accurately estimate velocity trajectories without removing information embedded in the true perturbations of the velocity signal.

3. Summary

The poor performance of Absolute Variance and Relative Variance have shown that metrics developed for one type of data source do not necessarily map to other data sources well, i.e. metrics developed for classifying aircraft using flight controller logs will not necessarily classify aircraft from radar data well. In future work, it should be determined whether metrics map from training data to testing data appropriately before a classifier is trained and tested with different data sources.

VIII. Conclusion

Average Speed computed using 1 second of radar or flight controller data is an effective metric for training a classifier, achieving 96% classification accuracy when tested with 1 second of radar data. The LR classifier had similar performance to an SVM when training with Average Speed for all tests throughout this work, which shows an LR classifier may be used instead of an SVM for single metric classification. We compared the 13-metric SVM in [17] to an SVM trained on just Average Speed from flight controller data, and found little differences in their average classification accuracies when tested with radar data. We also provided rationale for why the two novel metrics — log variance of absolute change in speed, and log variance of relative change in speed — had low classification accuracy when training and testing with radar data.

While Average Speed has shown great potential for quickly classifying aircraft, classification error was greatest between quicker multi-rotor sUAS and slower fixed wing sUAS. Future work may combine Average Speed with other heterogeneous features, such as image recognition, to improve the classification accuracy for objects flying near cutoff speeds. Average Speed could also be tested on a dataset derived from a camera source, rather than a radar.

Additional metrics should be developed to accurately classify aerial objects which fly at similar speeds, such as birds and sUAS. In security perimeter systems which sense sUAS, classifying birds from sUAS would reduce false alarm activations. In onboard sense-and-avoid applications, avoiding birds may require less evasive maneuvers than avoiding other sUAS, as birds typically distance themselves from sUAS.

Finally, it would be insightful to analyze more radar datasets and determine whether increased initial speeds are present for other models of radar. If present, the methods suggested in Section VII.B could be implemented to increase the accuracy of classifier trained with Average Speed.

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