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Classification of Unmanned Aerial Vehicles (UAVs) Carrying Payloads with Polarimetric Radar

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***Abstract* —The ability of a fully polarimetric radar to discriminate between payloads carried by UAVs is demonstrated. A novel approach has been employed in the feature extraction algorithm, where features from individual and combined polarimetric channels are extracted for classification. Decision and ensemble fusions on the respective extracted features proved to enhance the classification performance. The method is validated on experimental radar data acquired in scenarios where the UAVs carrying payloads (a quadcopter and a hexacopter) are hovering, flying back and forth, and flying along rectangular waypoints. Initial results for the fusion methods provide 90%-95% classification accuracy.**

***Keywords* — polarimetry, radar, UAVs, payloads, feature extraction, classification.**

I. INTRODUCTION

With recent advancements in technology, the number of Unmanned Aerial Vehicles (UAVs), commonly referred to as drones, have massively increased, and they are now accessible to everyone. UAVs are used in multiple scenarios, ranging from defence purpose to commercial use, like photography, delivery of goods, inspections, agriculture and so on. The initial commercial application of UAVs can be dated back to the early 1980s for the purpose of spraying pesticides over rice fields, where remotely piloted helicopters rendered as a promising route of augmenting manned helicopters. In the domain of transportation, drones have become an integral component in e-commerce and many industries like Amazon and Domino's have launched the testing phase in the logistics of their goods. However, drones carrying payloads also pose threats, such as flying around prohibited areas, interfering with larger aircraft, and are more often than not used for illegal activities, such as smuggling of weapons or contrabands. Drones can be used for unintentional dangerous activities, or even enable criminal actions, hence there is a growing necessity to monitor them [1].

Radars with high resolution are increasingly used for drone detection and classification, thanks to their long-range, all-weather monitoring capabilities. Several techniques for binary classification of drone vs no drone, drone vs birds, and different models of drones, have been proposed based on relevant features extracted from the micro-Doppler signatures or from tracks' information [2].

Features related to the flight profile (maximum height, acceleration, jerk) for discrimination of the presence of hexacopters have been extracted from holographic L-band radar data [3], resulting in a classification accuracy of 88% with decision tree. Polarimetric features for distinguishing between birds and drones have been extracted from the BirdRad radar data [4], showing an optimal accuracy of 100% incorporating the Nearest Neighbour classifier. The classification of different types of drones has been carried out in literature, for example in [5-6] using a CW radar, where unique features were derived via spectrogram (blade flashes, body velocity), and cepstrogram (periodicity). Furthermore, neural network and deep learning, specifically adversarial auto-encoders, were used for denoising of spectrograms, producing an accuracy of 97% [6]. Properties of the linear micro-Doppler spectrum have been used for drone classification in [13].

Recently, more research is focused on the problem of classifying drone(s) carrying payloads. A novel micro-Doppler feature extraction technique, largely dependent on spectral kurtosis (SK) has been suggested in [7]. The idea is to use this 4^{th} order statistical parameter to characterise the different rotation regimes of the blades of the drones depending on the payload mass. SK is determined both on the narrowband and wideband spectrograms yielding an accuracy of 82%-97% for a k-nearest neighbour classifier. The same dataset with data collected at University College London is analysed in [8] using features based on SVD (Singular Value Decomposition) and centroid and bandwidth of spectrograms, with good accuracy reported. The effect of payload weights carried by drones on the micro-Doppler signature is presented in [9], which states that the flattening of the blade flashes in a spectrogram is the result of faster blade rotation in order to create adequate lift when the drone is carrying a payload of increasing weight.

In this paper, the problem of classifying drones carrying payloads is approached by combining polarimetric features and micro-Doppler signatures as the input to supervised machine learning classifiers. Initial results are presented based on experimental data collected using the TU Delft S-band polarimetric radar PARSAX for two different models of drones. Approaches using decision fusion and ensemble of classifiers to combine the polarimetric information are explored, and their effect on the performances are investigated.

The remainder of the paper is organized as follows. In Section II, the experimental setup, data collection based on the movements of the drone, FMCW data and signal processing for drone detection are presented. The proposed classification methods are shown in Section III and the subsequent results and conclusions are discussed in Section IV and Section V, respectively.

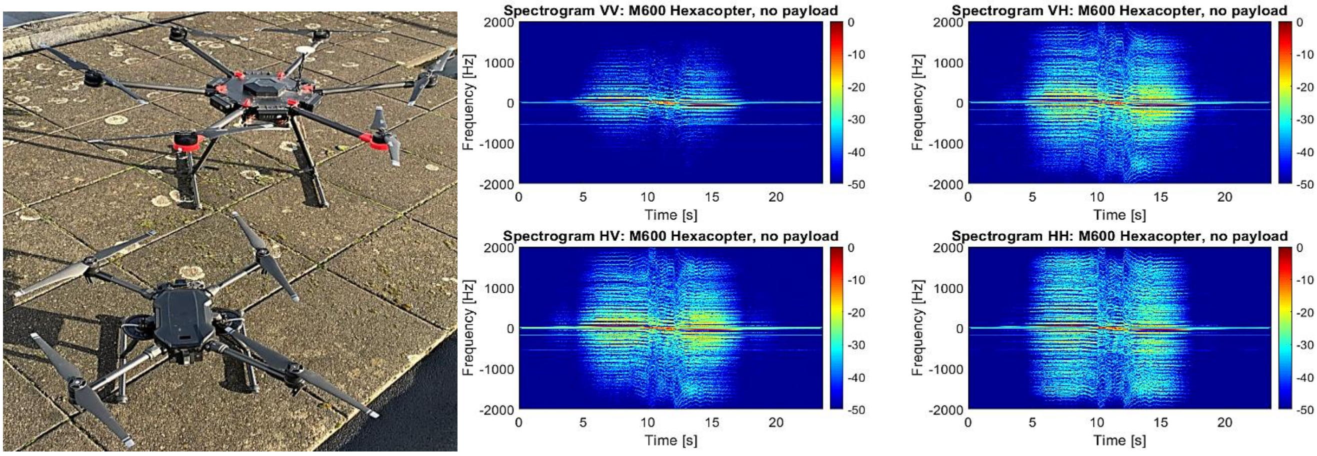


Fig. 1. Micro-Doppler signature of M200 quadcopter and M600 hexacopter (shown on the left) flying back and forth carrying no payload in (a) VV polarization; (b) VH polarization; (c) HV polarization; (d) HH polarization.

II. Experimental Setup and Data Analysis

A. Measurement

The data was collected employing PARSAX, which is S-Band polarimetric FMCW Doppler radar, where both the transceiver and receiver have two independent polarimetric RF channels, enabling to collect full polarimetric information simultaneously [12]. The bandwidth was 50 MHz with a Pulse Repetition Frequency (PRF) of approximately 4 kHz (240μs).

The data was collected in an open ground at the TU Delft campus, located at approximately 575m from the radar. Two types of drones were used, namely DJI M200 quadcopter and DJI M600 hexacopter, which were carrying 0kg/1kg and 0kg/2.35 kg, respectively (0kg means no payload present).

The data was recorded for approximately 30s for the scenarios where the drones M200 and M600 were (a) hovering in the same place, (b) flying back and forth in a 50m linear path, and (c) waypoints along a rectangular trajectory of dimensions 60m x 20m. Measurements were repeated for both cases of with and without payloads. The subsequent investigation also considered together the combined scenario of flying back and forth and rectangular waypoints in the feature extraction level.

B. Data Pre-processing

The FMCW data were processed to generate range-time maps, which were used to identify the range-bins containing the signature of the drones in the different recordings. After identifying the range bins containing the drones and extracting them, a Short-Time Fourier Transform (STFT) of 0.1s Hamming window and an overlap of 95% between adjacent windows is applied. An example of a spectrogram for the individual polarimetric channels for the M600 hexacopter flying is shown in Fig.1. Similar micro-Doppler signatures were obtained for the other scenarios of procured data. The blade flashes are distinct in HH polarization; however, they are also fairly significant in the cross-polarizations VH and HV as well. It was also noted visually that, for the same polarization, the extent of blade flashes in Doppler was larger when a payload is present, as expected from literature [7-9].

The spectrograms are then split into 30 blocks for feature extraction, each spanning 1s duration. As the drone signature is not continuous in the spectrograms because of the drone leaving the beam of the radar, only the spectrogram segments containing target signatures are considered in the classification process.

III. Proposed Classification Approaches

A. Decision Fusion of Separate Polarimetric Channels

In order to enhance the classification performance, different approaches for combining the data from the 4 channels of the polarimetric radar are investigated.

The first method is decision fusion that combines the 4 polarimetric channels independently, as if they were 4 separate simultaneous measurements. For this type of hard fusion, a specific model of classifier is imposed on all the polarization channels [11]. Then, the final performance metric is calculated by combining the confusion matrices of individual polarimetric channels. The classifiers used in this paper are Linear Discriminant Analysis (LDA), Naïve Bayes (NB), Decision Tree, and linear Support Vector Machine (SVM). The choice of these classifiers for this type of data is that they produce higher accuracy with lesser computational load in most scenarios, and in principle, they do not require a large dataset compared to deep learning approaches.

Suitable features are extracted by using SVD, centroid and bandwidth on the spectrograms, followed by the calculation of statistics such as the mean, standard deviation, skewness and kurtosis. These features are chosen as they can be linked to the significant components (notably the periodicity, vibrations, velocity) of the micro-drones' signatures [5,7-8]. The generated feature samples are split into training and testing sets of 80% and 20%. The classification algorithms are applied to the training data with a 5-fold cross-validation for assessing the effectiveness of the model, which helps in mitigating overfitting of the data. The performance metrics are Accuracy, Precision, Recall and F1 score.

B. *Classification based on Polarimetric Features*

In [4] polarimetric features contribute positively in improving accuracy for drone vs birds classification. Polarimetric features can be retrieved either in time-frequency domain (e.g., from spectrograms) or in time domain, and the latter is discussed in this section with an idea to analyse if meaningful features can be derived with a very short dwell time, shorter than the possible spectrogram window. The advantage of this approach would be overcoming the necessity to generate spectrograms for feature extraction.

Table 1. List of polarimetric features extracted, inspired by [4, 10]

Feature	Relation to matrix S	Explanation
δ	$2\,\langle\lvert S_{hv}\rvert^2\rangle\,/\,\langle\lvert S_{hh}\rvert^2\rangle$	Linear depolarization ratio
γ	$\langle\lvert S_{vv}\rvert^2\rangle\,/\,\langle\lvert S_{hh}\rvert^2\rangle$	Differential polarization ratio
ρ	$\langle S_{hh}S_{vv}^*\rangle/\sqrt{\langle\lvert S_{hh}\rvert^2\rangle\langle\lvert S_{vv}\rvert^2\rangle}$	Co-polarized correlation coefficients
β	$\langle S_{hh}S_{hv}^*\rangle/\sqrt{\langle\lvert S_{hh}\rvert^2\rangle\langle\lvert S_{hv}\rvert^2\rangle}$	Cross-polarized correlation coefficients
ε	$\langle S_{hv}S_{vv}^*\rangle/\sqrt{\langle\lvert S_{hv}\rvert^2\rangle\langle\lvert S_{vv}\rvert^2\rangle}$	

The polarimetric features in Table 1 are known as polarimetric inter-correlation parameters, which are applied on the range bins where the drone is present from the range-time plots. The operator <*> represents the spatial or temporal ensemble averaging considering the uniformity of random medium [10]. The bins where the drone is present in the range-time plot are split in this case into smaller segments of varying dwell time of 0.05s, 0.10s, 0.25s, 0.50s and 1s and the polarimetric features are extracted. In this scenario, an ensemble classifier is employed to enhance the classification performance, since the features from all polarimetric channels are combined as a single block. By fusing through ensemble of classifiers, the confusion matrices of the independent classifiers (LDA, NB, Decision Tree, Linear SVM) are multiplied elementwise to attain a greater classification performance.

IV. Results

A. *Decision Fusion on Individual Polarimetric Channels*

The results for measured polarimetric data were subjected to different parametric analyses such as varying dwell time, spectrogram window length, and SNR (by adding Gaussian noise to the original data), as depicted in Fig. 2. The results shown are only for the Linear Discriminant Analysis Classifier (LDA) and combined data for flying back and forth and along rectangular waypoints. A similar trend in variation was also seen with the other considered classifiers and flying scenarios.

The HH polarization produced the highest classification accuracy in all the parametric analyses and also the individual instance of each analysis. As for the case of varying the duration of the spectrogram split (i.e., dwell time), 1s has a better accuracy, indicating a comparatively faster dwell time is preferred for classification. Also, theoretically, as the dwell time is increased, the number of samples in each of the classes reduces proportionally as the dataset has a limited size. Thus, the number of training samples decreases, making it difficult for the classifier to get well trained, and hence resulting in poorer classification. Accuracy of ~87% is obtained for HH polarization at 1s. By fusing the information from the individual channels, a significant improvement in performance is achieved.

As the spectrogram window size is increased, the resolution in time becomes worse, and significant components in feature extraction may become spread out in different spectrogram splits. Though the number of samples in the dataset remains the same, the classifier gives a lesser accuracy by increasing the window size. So, in this scenario, the ideal window size is obtained to be 0.1s. Again, with fusion an optimum accuracy of ~100% is obtained at 0.1s and an overall accuracy increase is found at each instance of varying spectrogram window.

Fig. 2 (right-hand side) shows the result of classification performance when noise is added to the spectrograms. The decision fusion of LDA classifier of each polarimetric channel outperforms the individual channel's accuracy. As the SNR is decreased, the classification performance also worsens as expected, about 20% below the optimal situation of high SNR.

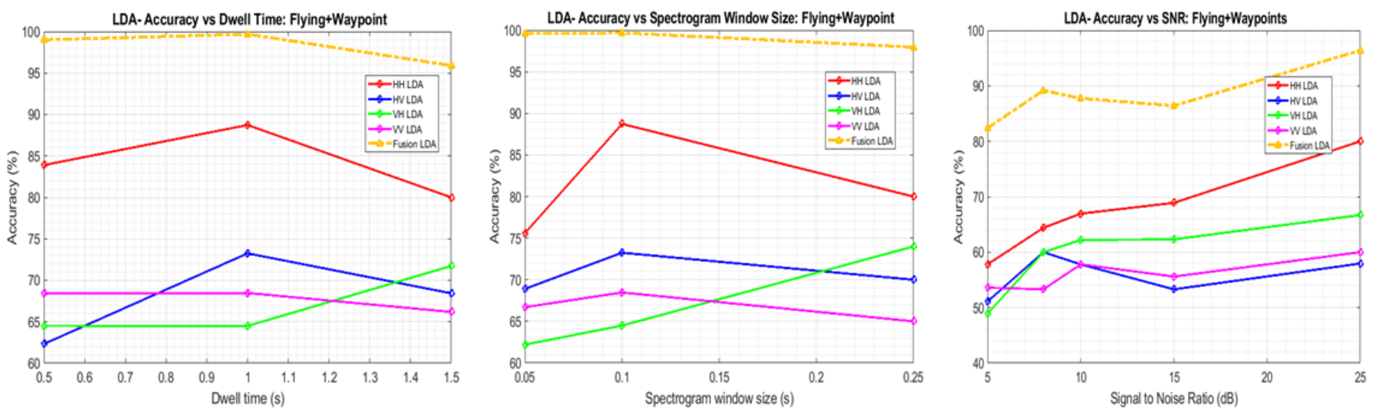


Fig. 2. Classification performance for the combined scenarios of drone moving along rectangular waypoints and flying back and forth. Individual polarimetric channels and their decision fusion compared for varying Dwell time (left-hand side); Spectrogram window (centre); and SNR (right-hand side)

B. Polarimetric Features

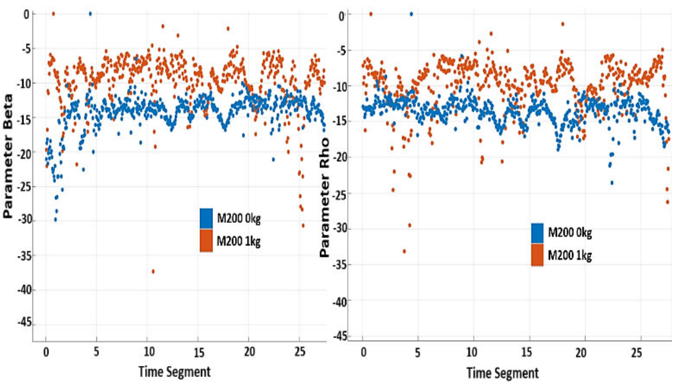
In this case, the polarimetric channels (VV, VH, HV, HH) are combined together into single polarimetric features. The dwell time, intended as the duration of the segment of data used for feature extraction, was varied from 0.05s, 0.10s, 0.25s, 0.5s and 1.0s. It was observed that for a faster dwell time, the classifier performs efficiently. A faster dwell time is often desirable as it proves the efficiency of the classifier's ability to distinguish between classes in the shortest time possible.

The classifiers in this case are able to attain a classification performance equivalent to that in Section IV (A), as also seen in Table 2. Moreover, at a shorter dwell time of 0.05s, an improved accuracy is obtained for the classification based on polarimetric features, whereas in Section IV (A) for features extracted from independent polarimetric channels, the ideal dwell time was 1s, which is comparatively longer.

In [8-9] it was shown how the presence of a payload would be visible in the faster rotation rate of the UAVs blades in the spectrograms, and this was exploited for classification. Similar separation for the payload vs no-payload classes can be seen in Fig. 3 for two examples of polarimetric features related to the hovering quadcopter. Unlike the easier kinematic interpretation of blade velocity in spectrograms, the EM interpretation of this separation seen in the polarimetric feature domain is still under investigation.

Table 2. Classification accuracy for polarimetric features (dwell time = 0.05s)

Classifier	Hovering	Flying	Rectangle Waypoints	Flying + Rectangle Waypoints
LDA	86.5%	52.8%	57.4%	48.4%
Naïve Bayes	79.1%	45.3%	34.2%	42.0%
Decision Tree	89.6%	66.0%	76.1%	67.2%
Linear SVM	87.7%	61.2%	60.0%	50.9%
Ensemble Fusion	99.9%	90.5%	95.9%	75.8%



(a) (b)

Fig. 3. Feature samples for the case of Quadcopter M200 hovering for (a) Feature β; (b) Feature ρ, dwell time = 0.05s. Red (payload); blue (no payload)

V. Conclusion

In this paper, two approaches for classification of UAVs with payloads using polarimetric radar information are investigated. These are demonstrated on experimental data at S-band with two types of drones, a quadcopter and a hexacopter. It was shown that feature extraction from independent polarimetric channels produced higher classification for HH polarisation for different combinations of dwell time, spectrogram windows and SNR. Both decision fusion and ensemble fusion generate promising outcomes. With the former, an accuracy of 95%-100% is reached, at least 20%-30% above over only using one of the polarimetric channels. The latter achieved about 90%-95% accuracy. A hard decision fusion between the 4 channels significantly improved the classification performance. For polarimetric features extracted combining the raw data from the four channels, performances were nominally lower but could be enhanced to over 90% via ensemble of four different classifiers.

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References

[1] PWC. Global report on the commercial applications of drone technology, 2016. url: https://www.pwc.pl/pl/pdf/clarity-from above-pwc.pdf.

[2] Patel, J., Fioranelli, F., and Anderson, D.; 'Review of radar classification and RCS characterisation techniques for small UAVs or drones', *IET Radar, Sonar & Navigation*, vol. 12, no. 9, pp. 911-919, August 2018.

[3] M. Jahangir and C. Baker, ''Robust detection of micro-UAS drones with L-band 3-D holographic radar,'' in Proc. IEEE Sensor Signal Process. Defence (SSPD), Sep. 2016, pp. 1–5.

[4] B. Torvik, K. E. Olsen, and H. Griffiths, ''Classification of birds and UAVs based on radar polarimetry,'' IEEE Geosci. Remote Sens. Lett., vol. 13, no. 9, pp. 1305–1309, Sep. 2016.

[5] R. I. A. Harmanny, J. J. M. de Wit, and G. P. Cabic. "Radar micro-Doppler feature extraction using the spectrogram and the cepstrogram". In: 2014 11th European Radar Conference. 2014, pp. 165–168.

[6] A. Huizing et al. "Deep Learning for Classification of Mini-UAVs Using Micro-Doppler Spectrograms in Cognitive Radar". In: IEEE Aerospace and Electronic Systems Magazine 34.11 (2019), pp. 46–56.

[7] L. Pallotta et al. "A Feature-Based Approach for Loaded/Unloaded Drones Classification Exploiting micro-Doppler Signatures". In: 2020 IEEE Radar Conference (RadarConf20). 2020, pp. 1–6.

[8] M. Ritchie et al. "Multistatic micro-Doppler radar feature extraction for classification of unload-ed/loaded micro-drones". In:IET Radar, Sonar Navigation11.1 (2017), pp. 116–124.

[9] J. J. M. De Wit, D. Gusland and R. P. Trommel, "Radar Measurements for the Assessment of Features for Drone Characterization," 2020 17th European Radar Conference (EuRAD), Utrecht, Netherlands, pp. 38-41.

[10] J. S. Lee and E. Pottier, Polarimetric Radar Imaging: From Basics to Applications. Boca Raton, FL, USA: CRC Press, 2009.

[11] H. Li, A. Shrestha, H. Heidari, J. Le Kernec, and F. Fioranelli, "BiLSTM network for multimodal continuous human activity recognition and fall detection," IEEE Sensors J., vol. 20, no. 3, pp. 1191–1201, Feb. 2020

[12] O. A. Krasnov, L. P. Ligthart, Z Li, P. Lys, and F. van der Zwan, "The PARSAX - full polarimetric FMCW radar with dual-orthogonal signals," in 2008 European Radar Conference, 2008, pp. 84–87.

[13] Y. Cai, O. A. Krasnov, A. Yarovoy, "Radar Recognition of Multi-Propeller Drones using Micro-Doppler Linear Spectra," 2019 16th European Radar Conference (EuRAD), 2019, pp. 185-188.