

Drones Classification based on Millimeter Wave Radar Cross Section via Deep Learning

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Abstract—The wide use of drones is playing a vital role in the era of low-altitude economy, but meanwhile it also presents a threat to the privacy, property damage, health and safety of the public. Therefore, it's highly motivated to detect and recognize the flying drones, but this is challenging owing to the small size, slow speed and low altitude of typical drones. As the millimetre wave (mmWave) frequency band has been assigned to 5G communication as FR2 and will be continued in the 6G use, this provides a potential to turn the base stations into a network of mmWave radar for the drones' detection by leveraging the integrated sensing and communication (ISAC) techniques. This work aims to classify the drones based on their mmWave radar cross section (RCS) data that is converted to two-dimensional (2D) RCS images. Thus, 2D Convolutional Neural Network (CNN) is applied to the drone classification and the satisfactory testing results verify the proposed drone classification method.

Keywords—drone classification; mmWave radar; radar cross section; Deep learning; convolutional neural network

I. INTRODUCTION

Recently, drones have captured the interest of the academy, industry and general public due to their enormous potential applications, such as cinematography, agriculture, mapping, forensics, stockpile measurements, parcel delivery, mobile communication, military uses and many others. It is estimated that over 76,000 commercial drones will fly in the UK skies by 2030, which are expected to bring a £42 billion increase in the UK GDP [1]. However, as the use of drones expands and develops, they now pose evolving threats when they fall into the wrong hands, such as the air crash, air-to-ground/building crash and even terrorist attack. Therefore, it is important to recognize the misuse of drones that presents a real threats. With the typical features of 'slow-flying', 'low-altitude' and 'small-size', drones present a unique challenge when it comes to the enforcement of regulations that govern how a drone may behave, and also challenges the traditional surveillance capability. This shows the urgent need to develop better technologies to monitor the presence of drones and prevent possible threats.

Drones' recognition has attracted intensive research of radar target recognition. The radar target recognition can be classified into methods based on, such as radar cross section (RCS), micro-Doppler features, one dimensional high-resolution range profile, two dimensional synthetic aperture radar (SAR) or inverse SAR (ISAR) images. For drone targets, there are many ways to identify drones by using one

or more information sources in the field of drone identification [2], [3]. For instance, the micro-Doppler information of drone is used to identify the drones by convolutional neural network (CNN). In [4], a multi-layer classification system was designed based on multiple features of micro-Doppler, RCS, and micro motion, where the micro-Doppler and RCS obtained by the radar were used to solve drone classification. However, the method based on micro-Doppler requires high pulse repetition rate, and high complexity and cost of the systems. In contrast, RCS is the most common data that radar can easily obtain for the drone's classification.

RCS, also called radar signature, is a measure of radar energy reflected by the object back to the radar receiver, so it can be easily collected through measuring the radar received power. Therefore, it is possible to make an estimation of possible drone models, because different drones' shapes, materials and observation angles have different reflection ability and thus yield different RCS values [5].

Given that the spectrum is a scarce resource in telecommunications, the fifth generation (5G) and upcoming sixth generation (6G) mobile communication systems are expected to operate across a wide range of spectrum that includes not only the spectrum used by previous generations but also higher frequency bands such as millimetre wave (mmWave) to support 5G/6G applications with faster data rates, higher capacity, and lower latency. By using integrated sensing and communication technique, a mobile communication base station will be able to act as a radar to conduct the functions of sensing and detection in the meantime of communication [6]. In this way, the mmWave base stations enable high resolution sensing to make it possible to detect small drones, owing to the large frequency bandwidth. This paper aims to classify the drones through learning their RCS features at mmWave frequencies.

In this work, the drone classification is based on the mmWave RCS dataset collected in [7], where nine different drones' RCS was measured at mmWave frequencies from 26 GHz to 40 GHz, performed in an anechoic chamber at Aalto University, Finland, as shown in the schematic view in Fig. 1. In the lab measurement setting, the radar transmitter (Tx) and receiver (Rx) are separated but are deployed in the same place to act like a monostatic radar. By transmitting a signal from the Tx antenna and measuring the reflections that arrive

at the Rx antenna, the RCS data can be measured from varying observation angles. In [7], authors also did some basic analysis for the RCS features of the drones, while the drones classification wasn't included.

Based on the mmWave drones' RCS dataset [7], the statistical quantities of 1D RCS series (from a fixed observation angle) were calculated for the raw RCS data and concatenated in the feature vector to classify drones based on their RCS values in [8]. Various classification algorithms such as Support Vector Machines (SVM), Decision Tree, Naive Bayes Classifier, Neural Networks have been investigated for drone classification. In [9], the authors presented an improved long short-term memory (LSTM) with an adaptive learning rate optimising (ALRO) model that could reduce computation overhead. Experiment outcome showed the LSTM-ALRO method achieves much better drone detection accuracy of 99.88% when compared with the existing CNN-based drone classification model. This work performed drone classification based on the 2D RCS images at 26GHz, 28GHz and 40GHz, respectively. In [10], the authors utilised the advantages of 1D CNN and 2D CNN to improve the classification accuracy of drone by using the original 1D RCS data: 1) the 1D RCS series (from a fixed observation angle) were converted into 2D Gramian angular field (GAF) representation for 2D CNN; 2) the authors utilised a deep fusion network that fused the characteristics of 2D GAF representation with 2D CNN and 1D RCS series with 1D CNN to improve the classification accuracy of the drone. The drones are classified at 30, 35, and 40GHz, respectively.

Different from the above relevant work, this paper will investigate the classification for all the drones at all the frequencies in one shot. In this case, much larger 2D RCS image dataset will be used for model training instead of basing on the limited RCS images for only subset of drones and at a given frequency [8-10]. 2D CNN is applied to test the drone classification performance and accuracy.

II. RCS DATA MODEL AND ANALYSIS

A. RCS Data Measurement

As shown in Fig. 1-(a), the object under test is located on top of a rotating pillar on the opposite side of the chamber than antennas. Stepped motors allow two axes of rotation of the object. First, the object is rotated in the azimuth plane (θ -axis), then it is rolled around the centre axis (ϕ -axis). Angular ranges were set to $\theta \in [-90, 90]$ degree and $\phi \in [0, 180]$ degree with steps of 1 degree as shown in Fig. 1-(b).

In the measurement campaign [7], eight multi-rotor platforms and one radio-controlled helicopter were measured, as presented in Fig.1-(c). As the drones are likely observed from below, only the bottom hemisphere of the drones was measured. The radar transmitter (Tx) and receiver (Rx) are separated but are deployed in the same place to act like a monostatic radar. By transmitting a signal from the Tx antenna and measuring the reflections that arrive at the Rx antenna, the RCS data can be measured from the received radar power strength for the varying observation angles (θ , ϕ).

B. RCS Data Representation and Analysis

The RCS value is varying with the drone models and observation angles. The raw RCS data can be reshaped into a 181-by-181 matrix with the rows of $\theta \in [-90, 90]$ degree and the columns of $\phi \in [0, 180]$ degree. The 2D RCS images can be generated to displays the RCS data matrix, where each pixel of the image denotes the RCS value observed from given observation angles (θ , ϕ) at a certain mmWave frequency. A 2D RCS image example for drone 'M100' at 40GHz is shown in the Fig. 2.

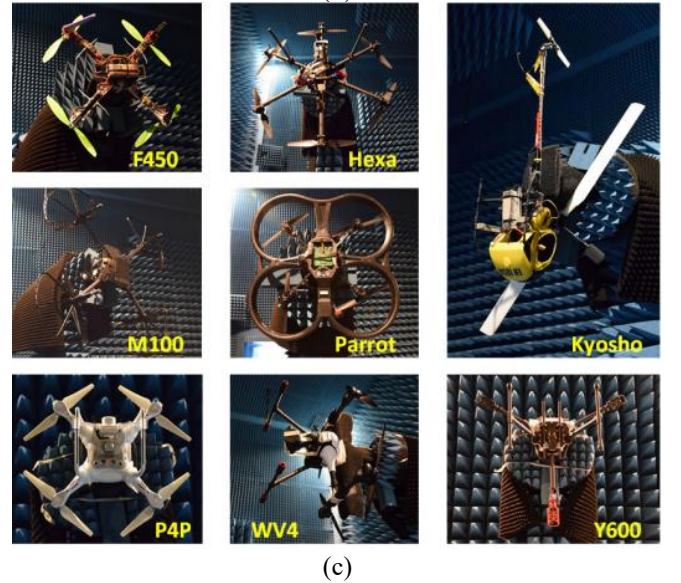
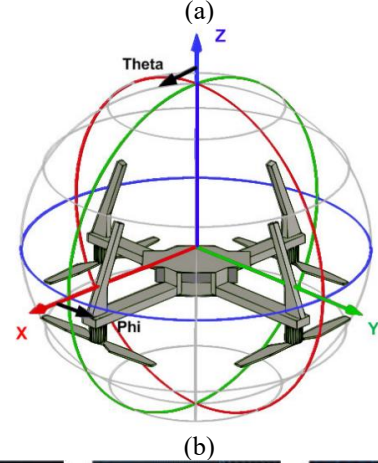
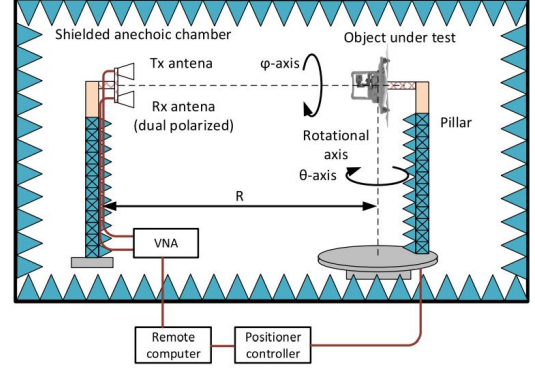


Fig. 1 (a): Schematic view of the measurement setup [7]; (b): Schematic view of the reference object: trapezoidal cuboid and the relevant coordinate system [7]; (c): Empirically studied drones (i.e. multi-rotor platforms, helicopter)

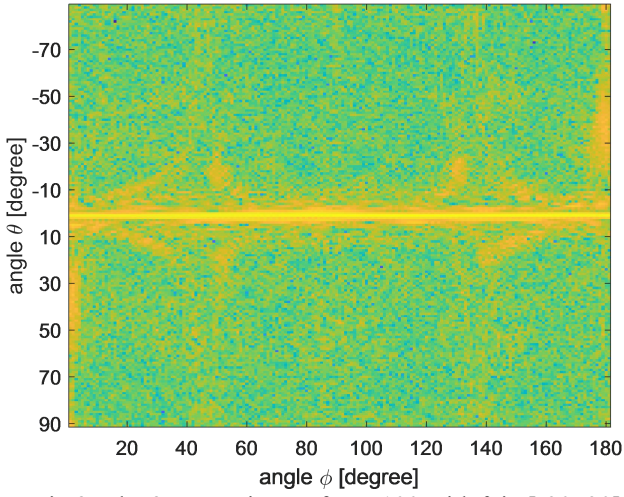


Fig.2. The 2D RCS image for M100 with θ in $[-90, 90]$ degree and ϕ in $[0, 180]$ degree at frequency 40 GHz.

III. DRONE CLASSIFICATION VIA 2D CNN

In this work, we consider the seven drone classification problem for the drones - “M100”, “F450”, “WV4”, “P4P”, “Heli”, “Hexa”, and “Y600” via 2D CNN. In total, we have 75 2D RCS images, where each drone has 15 RCS images for the frequencies from 26GHz to 40GHz. In the experiment, random 12 RCS images out of 15 RCS images per drone are used for the model training and the rest 3 RCS images are used for the blind testing.

A. 2D CNN Model for RCS Images Classifications

Different from the references [9-11] that only consider drone classification for the subset of drones at a certain frequency, i.e., each classification study only for a single frequency, we plan to study the drone classification performance based on the 2D RCS images for multiple drones at all the frequencies in one shot.

For the 2D RCS image-based drone classification, the typical multi-layer 2D CNN model training is set as the following procedure in Fig.3.

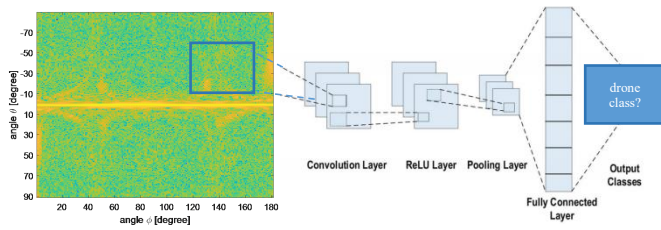


Fig. 3. 2D CNN architecture for drone classification

In order to evaluate the performance and accuracy of the drone classification when all the frequencies are considered, different case studies of drone classification have conducted in this work.

B. Case Study of Two Drones Classification

This case study considers the two drones, both of which are metal and with four rotors, i.e., “M100” and “WV4” as shown in the Fig. 1-(c). Also, Fig. 3 shows both drones have the similar RCS patterns.

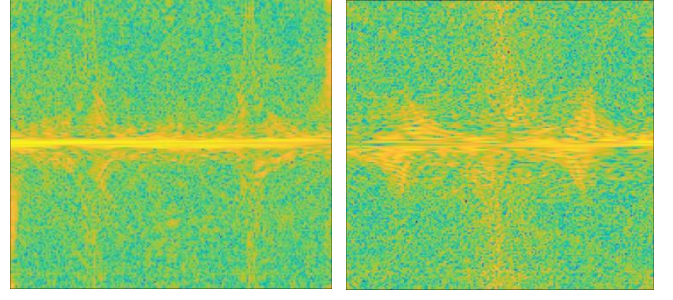


Fig. 3. Left: “M100” 2D RCS image example at 26GHz; Right: “WV4” 2D RCS image example at 26GHz.

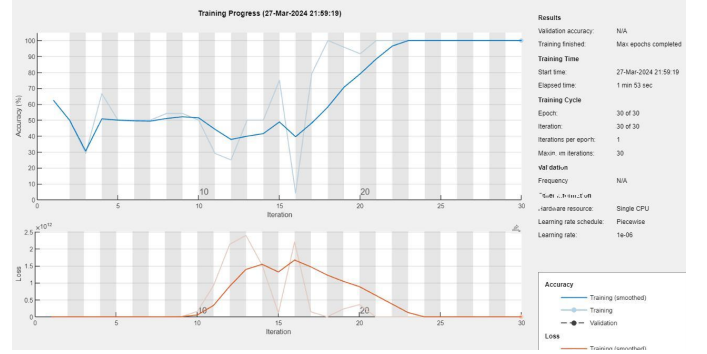


Fig.4. CNN model training performance

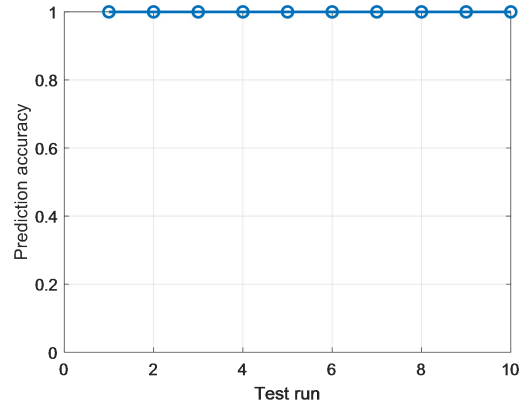


Fig. 5. Test results for 10 times run of the training & testing, and each run with random image splitting.

Fig.4 shows the training performance when 2D CNN is used to train the model based on 80% RCS images from 26GHz to 40 GHz. Test results in Fig.5 are for 10 times run of the training & testing, where each run is with random RCS image un-overlapped splitting (80% for training and the rest 20% for testing – 12 images for training and 3 images for testing for each class). In Fig. 5, it is shown that the 2D CNN can always achieve prediction accuracy: the prediction accuracy: 100% runs with 100% accuracy.

C. Case Study of Three Drones Classification

Three-class drone classification for “M100”, “F450” and “WV4” is studied in this case study. The total 36 RCS images will be used for the training and the rest 9 images for the testing.

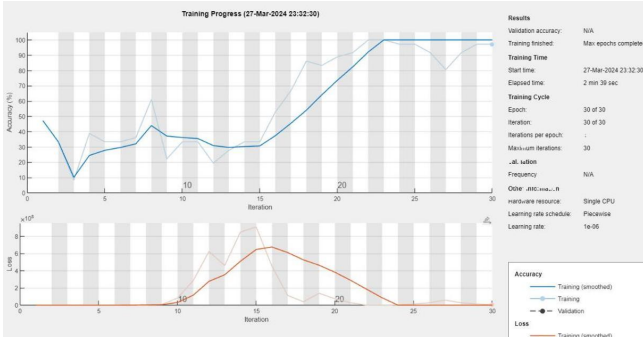


Fig. 6. CNN Model training performance.

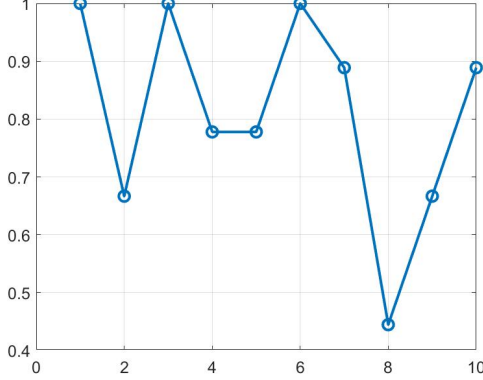


Fig. 7. Test results for 10 times run of the training & testing, and each run with random image non-overlapped splitting.

The three-class 2D CNN simulation results have been shown in Fig. 7. The 2D CNN has a very good convergence of the model training accuracy during the model training. Fig. 5 shows the prediction accuracy: 30% runs with 100% accuracy, 20% runs with 8/9 accuracy, and 20% runs with 7/9 accuracy, and 20% with 6/9 accuracy, and 10% with 5/9 accuracy - with an prediction accuracy of 82.2% in average.

D. Case Study of Seven Drones Classification

The seven-class drone classification of “M100”, “F450”, “WV4”, “P4P”, “Heli”, “Hexa”, and “Y600” is considered in this case study. In each simulation, 12 random images per drone is for training and the rest 3 images for testing - 60 RCS images for training and 15 RCS images for testing in each simulation. In this seven-drone classification case study, more epochs are needed for the training convergence, while the training performance has a usually very good convergence of the training accuracy close to 100%.

		PREDICT						
A C T U A L		M100	F450	WV4	P4P	Heli	Hexa	Y600
	M100	3,3,3						
	F450	1	2,2,2		1			1
	WV4	1		3,2	1		2	
	P4P				3,3,3			
	Heli					3,1,3		2
	Hexa				1		3,1,3	1
	Y600	1			1			3,3,1

Table 1. Confusion matrix for the seven-drone classification performance (black, red, and green colour denotes the three times different simulations).

The confusion matrix in Table 1 summarize three different simulation tests, where the digits in black, red and green colour denotes the three times independent simulation tests. In average, the predication accuracy in the Table 1 can be calculated as 79.4%.

IV. CONCLUSIONS

The 2D CNN has been applied for the drone classification based on 2D RCS images through evaluating different case studies of two-class, three-class and seven-class drone classification, respectively, at all the frequencies from 26GHz to 40GHz in one shot. The experiment results shows that our method can provide a reasonably high prediction performance in most of the case studies.

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