Classification of Loaded/Unloaded Micro-Drones Using Multistatic Radar

F. Fioranelli, M. Ritchie, H. Borrion and H. Griffiths

This letter presents preliminary results on the use of multistatic radar and micro-Doppler analysis to detect and discriminate between micro-drones hovering carrying different payloads. Two suitable features related to the centroid of the micro-Doppler signature have been identified and used to perform classification, investigating also the added benefit of using information from a multistatic radar as opposed to a conventional monostatic system. Very good performance with accuracy above 90% has been demonstrated for the classification of hovering micro-drones.

Introduction: In the past few years the number of micro-drones, i.e. small Unmanned Aerial Vehicles (UAVs), available to civilian users has largely increased due to low price and ease of use. These platforms can be privately used for filming and leisure, for applications such as agriculture and surveillance, and for search and rescue in disaster response operations. However, these platforms can also be misused to conduct anti-social, unsafe, or even criminal acts, including hostile reconnaissance, collisions (with people, other micro-drones or larger aircraft), and transport of explosives or biological agents [1].

The suitability of conventional radar systems to detect and identify micro-drones has been investigated in recent years. This task is expected to be challenging as micro-drones have low Radar Cross Section (RCS) and fly at lower altitude and slower speed in comparison with conventional aircraft. There is little available research on radar detection and classification of micro-drones. In [2-4] the micro-Doppler signatures of different models of micro-drones collected using a continuous wave radar at X-band have been analysed to discriminate between different models and also between micro-drones and large birds. In [5] other features extracted from tracks rather than from micro-Doppler signatures have been proposed to classify micro-UAVs and distinguish them from other aircraft, birds, or atmospheric phenomena. Our work in [6] investigates the variation of the RCS of micro-drones and their blades through simulations and controlled experiments.

The main objective of this work is to analyse the micro-Doppler signatures of a micro-drone hovering while carrying different payloads, and investigate the suitability of features to classify and distinguish between the different cases. Knowledge that the drone is carrying extra payload may be an indication of suspicious and potentially hostile activity, and cue other surveillance sensors for improved identification or trigger some form of countermeasures if required. Two features based on the centroid of the micro-Doppler signature are proposed, and the classification benefit of combining data from a multistatic radar rather than a conventional monostatic radar are discussed. These experimental data from a multistatic radar system measuring micro-drones carrying different payloads are believed to be significantly novel and provide preliminary results to address the open challenge of micro-drone detection via radar.

Experimental setup and radar system: The data presented in this paper were collected using the University College London multistatic radar system NetRAD [7]. NetRAD is a coherent pulsed radar consisting of three separate but identical nodes that operates at 2.4 GHz, S-band. The transmitted power was approximately +23 dBm, with horizontally polarized antennas with 24 dBi gain and approximately 10°×10° beam-width. The RF parameters chosen for the experiment described in this paper were linear up-chirp modulation with 45 MHz bandwidth and 0.6 µs duration, 5 kHz pulse repetition frequency (PRF) which allows the whole micro-Doppler signature of the micro-drone to be included in the unambiguous Doppler region, and 30 s duration of each recording. The experiment took place in July 2015 in an open football field at the UCL Sports Ground to the north of London. Fig. 1 shows the geometry of the experiment with the three NetRAD nodes deployed along a linear baseline with 50 m inter-node separation and the micro-drone hovering at approximately 60 m from the baseline. Node 1 was used as monostatic transceiver, with Node 2 and Node 3 as bistatic receivers. The bistatic angle was approximately 40°. The micro-drone used in the tests was the quadcopter DJI Phantom Vision 2+. The camera provided with the micro-drone was removed for these tests, and the micro-drone was fitted with different payloads made of small metallic disks, each weighing 10 g, placed in a plastic tray mounted below the drone. Three datasets were recorded for no payload, 200 g and 500 g payload which was the limit for take-off.

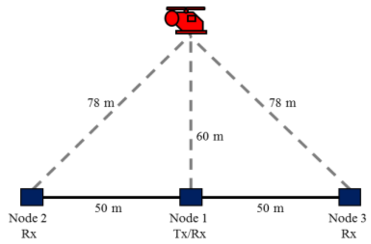

Fig. 1 *Geometry of the experimental setup*

Data analysis and classification: The recorded data were processed using Short Time Fourier Transform (STFT) to characterize the micro-Doppler signature of the micro-drone for different payloads. Firstly the range bin where the drone was present was isolated. Then each 30 s recording was divided into fifteen 2 s blocks and the STFTs were calculated on each block using 0.1 s Hamming window with 95% overlap. Fig. 2 shows four micro-Doppler signatures of the drone hovering in case of no payload and 500 g payload with data recorded at monostatic and bistatic nodes. The horizontal lines related to the rotation of the blades are clearly visible in the spectrograms and are consistent with the literature [2-4]. The difference in spectrograms between the no payload and 500 g payload cases can be empirically appreciated, with the blade Doppler lines appearing more uniform and straight, and reaching higher positive and negative Doppler values, for the 500 g payload case. This is thought to be related to the higher rotational speed of the blades when the micro-drone is loaded in order to get higher lifting power to cope with the payload.

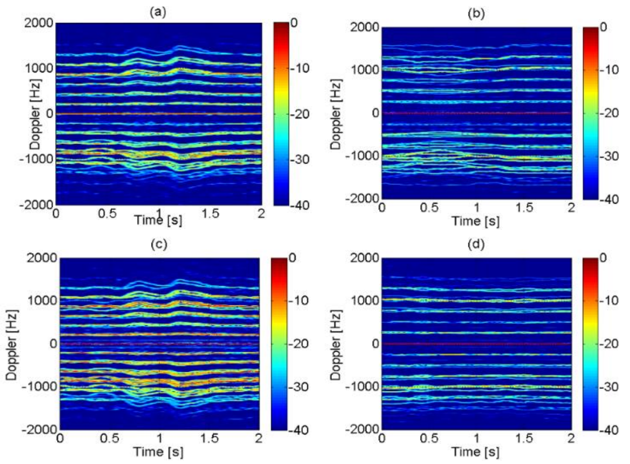

Fig. 2 *Micro-Doppler signatures for the drone hovering: (a) monostatic no payload, (b) monostatic 500 g payload, (c) bistatic no payload, and (d) bistatic 500 g payload*

Following the same approach used to classify human micro-Doppler signatures, feature samples have been extracted from the spectrograms [7-8] and used as input to a classifier. Two features based on the Doppler and bandwidth centroid of the micro-Doppler signatures have been identified as suitable for the loaded/unloaded classification [9]. The first parameter gives an indication of the centre of gravity of the micro-Doppler signature, and the second provides an estimate of the signature bandwidth around the centroid. The parameters are calculated as in (1) and (2), where *S(i,j)* represents the value of the spectrogram for the i^{th} Doppler bin and the j^{th} time bin.

$$f_c(j) = \frac{\sum_i f(i) S(i,j)}{\sum_i S(i,j)} \tag{1}$$

$$B_c(j) = \sqrt{\frac{\sum_i (f(i) - f_c(j))^2 S(i,j)}{\sum_i S(i,j)}} \tag{2}$$

One feature sample has been extracted from each 2 s block of spectrograms. The total number of feature samples is therefore 45 per recording, assuming 3 radar nodes and 30 s overall duration of each recording. Fig. 3 shows bi-dimensional scatter plots of the feature space from the three radar nodes. The classes are micro-drone hovering with no payload, 200 g payload, and 500 g payload. A good separation between the three classes can be seen in the data recorded at each different radar node, hence good classification performance is expected using these features.

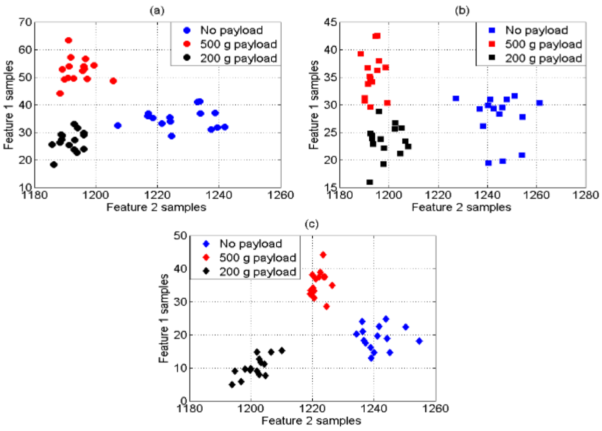

Fig. 3 *Feature samples for micro-drone hovering with different payloads as extracted from: (a) Node 1, (b) Node 2, and (c) Node 3*

The classifiers used here are the Naïve Bayes and the diagonal-linear variant of the discriminant analysis classifier, described in more details in [7, 10]. The classifiers are trained with 10% to 30% of the overall samples available, and the remaining data are used to assess the accuracy and calculate the classification error. This process is repeated 50 times with random changes in the set of samples used for training in order to test the consistency of the classifiers behaviour, and the classification error averaged over these 50 repetitions is calculated. The classification error is defined as the total number of misclassification events divided by the total number of samples. The average accuracy is simply 100% minus the average error and is reported in this work. Multistatic data have been combined in two different ways and the resulting classification performance compared with the use of monostatic data only, as for a conventional radar. In the first approach samples from all the three nodes are given to a single, centralized classifier which provides the final decision. In the second approach separate classifiers process the samples extracted at each node and provide partial decisions, which are then combined in a voting procedure to reach the final decision, i.e. the decision which gets the majority of 2 out of 3 classifiers. Table 1 shows the classification accuracy for different sizes of the training set and different methods of combining multistatic information. The three classes considered are the micro-drone hovering with no payload, and with 200 g and 500 g payload (same as in Fig. 3). Some trends can be extracted from the table, such as the increasing accuracy with increasing size of the training set (as expected), and the increase in accuracy when combining multistatic data through the separate classification and binary voting approach, in comparison with using only monostatic data or a single classifier. The overall classification results have an accuracy consistently above 90% and reaching 100% when the binary voting approach is used.

Conclusion: This letter has presented preliminary results of using micro-Doppler features extracted from multistatic radar data to discriminate and classify between micro-drones hovering while carrying different payloads. It has been shown that the proposed features provide a classification accuracy consistently above 90% when multistatic data are used in separate classification at each node, which can be regarded as sufficient for a screening security system. Further work will aim at collecting additional data in different conditions to validate these preliminary results, including for instance different models of micro-drones, different payload size and shape, and diverse operational scenarios where one or more micro-drones are flying.

TABLE 1: Classification accuracy as function of size of the training set and methods of combining multistatic data for micro-drone hovering with different payloads

Classification Accuracy [%]		10% train	20% train	30% train
Discriminant Analysis	**Mono data only**	97.6	98.3	98.4
	All multi data	86.1	87.1	87.6
	Binary voting	99.5	99.9	100.0
Naïve Bayes	**Mono data only**	82.0	94.5	99.4
	All multi data	81.7	85.7	87.7
	Binary voting	90.0	98.4	99.7

Acknowledgments: This work was funded partially by the IET A F Harvey Prize awarded to Prof Hugh Griffiths (2013), and the Engineering and Physical Sciences Research Council [EP/G037264/1].

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