Review of Radar Classification & RCS Characterisation Techniques for Small UAVs or Drones

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Abstract: This review explores radar based techniques currently utilised in literature to monitor small UAVs or drones; several challenges have arisen due to their rapid emergence and commercialisation within the mass market. The potential security threats posed by these systems are collectively presented and the legal issues surrounding their successful integration is briefly outlined. Key difficulties involved in the identification and hence tracking of these 'radar elusive' systems are discussed, along with how research efforts relating to drone detection, classification and RCS characterisation are being directed in order to address this emerging challenge. Such methods are thoroughly analysed and critiqued; finally, an overall picture of the field in its current state is painted, alongside scope for future work over a broad spectrum.

1. Introduction

Micro Drones and UAVs have only recently been approved for integration in Low Altitude Airspace (LAA) by the Federal Aviation Administration (FAA) as of Nov. 2013 [1]. As a result of this, the number of registered drones have grown significantly throughout the years, with over 670,000 now registered in the US over 2016 [2]. According to the FAA annual forecast, they now project a total of up to 7 million registered drones in LAA by the year 2020 [3]. However, many other countries have yet to roll out such stringent laws and registration services governing the use of drones, with developed countries being the only exception [4]. A further issue to the large number of drones, is the lack of active enforcement personnel to police these laws, along with operational detection systems. Commonly leaving the police ill-equipped for dealing with such threats and emergencies [5]. The potential to misuse these widely available, easy to use and affordable platforms for serious crime is tremendous; to list a few examples: privacy violation, illegal reconnaissance of restricted areas, collision hazards, trafficking of illegal substances and deployment of explosive weapons or chemical agents [6]-[9]. Collision dangers involving aircraft and drones are one of the most commonly recurring events, where the authors in [10] proved by calculation that a 2 kg drone retains the equivalent kinetic energy of a 20 mm anti-aircraft shell (nearly twice as large as a .50 calibre), if it struck an aircraft flying at typical cruising velocity. We have been extremely fortunate that there have been no terrorist attacks or loss of life to this date involving these commercially available drones.

On the other hand, UAVs have found many positive applications in modern society, such as: remote inspection, agriculture, search and rescue, photography and package delivery. These systems particularly favour environments which are physically demanding for human work, costly to operate within, or consist of a large functioning volume. With the deployment of such systems, typical efficiency, cost effectiveness and overall range can be far surpassed [11]. The total value of the drone market is projected to be $127 billion [12], with the agricultural market contributing to 80% of this value [13] and predicted to be worth $5.6 billion by 2022 [14].

Radar systems can provide long range sensing capabilities in all-weather and light conditions, along with the possibility of quantifying range and velocity concurrently. However, UAVs exhibit characteristics which are difficult to detect by typical air surveillance radar, such as low: RCS, velocity and altitude [15]. Tracking systems incorporated in such radars may actively reject targets of similar properties to that of birds, as this could easily degrade tracking performance [16]. These technicalities have called for the opening of a unique area in the market, where new systems are being developed to actively detect, identify and track such targets [17][18][19]. However, these systems rely on optical sensors to achieve classification; this is undesirable as adverse weather conditions could easily cause principal responsibilities of the system to fail.

Research in both the characterisation and classification of UAVs and drones have increased drastically; with more than 40 publications emerging in 2017 and many more recently; whereas in prior years fewer than 10 had been published each year. The principal aim of such research is to develop an understanding of the radar signatures produced in the micro-Doppler domain and to also characterise the RCS perceived. This would ultimately allow it to be applied to real radars, where appropriate thresholds would be set, detection ranges determined and suitable parameters devised. There is also significant interest in the use of passive radars to detect and distinguish drones, as this does not require the deployment of expensive transmitting hardware, due to the ability to exploit illuminators of opportunity.

The rest of this paper is organised as follows: Section 2 investigates research efforts in the context of RCS characterisation, Section 3 is split into subsections and discusses drone detection and classification techniques, real implementations of classifiers, neural networks and analyses of micro-motions, Section 4 explores applications of passive radar, finally, Section 5 concludes the literature review and presents areas for future work across the field.

2. RCS Characterisation of Drones

There have been numerous papers which examine the RCS characteristics of various drones; many authors present their results in either received power or RCS magnitude. However, a common feature with the papers deliberated, is the difference in amplitude from the main body of the drone to the rotor blades. Since this is a relative measurement and all the examined plots in this literature are functions of RCS in some way or form, this feature will be termed 'relative amplitude' throughout this section and will be a means of drawing a common variable between the papers discussed.

The authors in [20] analysed the properties of the popular DJI Phantom 2, by means of utilising a hybrid Finite Element Method (FEM) and a Method of Moments (MoM) technique through simulation and compared this to experimental results obtained at 10 GHz. The study demonstrates close agreement to the principal reflecting components of the quadcopter and the assumptions made in simulation prove to be justified very well. These being: that the engine, battery and cable harnesses are assumed to be pure solid copper and the relative permittivity (ε_r) of the ABS in the simulation range from 2.4 to 3.3. Further to this, it is then proven ε_r values do not dramatically affect the simulation results. They have also shown that if the target is rotated about the z axis, the bistatic RCS analysis is significantly affected and the RCS estimation proves to be more complex. Nevertheless, RCS figures obtained through experiment indicate values in the region of -20 to -30 dBsm, which is between the RCS of a bird and an insect [21].

The authors in [22] performed an RCS analysis of two very different quadcopters available from the DJI series of drones, these being: F450 Flame Wheel (4 rotors) and the S1000+ Octocopter (8 rotors). Tests were performed in an anechoic chamber as a function of angle and frequency for two cases of front facing and rear facing configurations. Both measurements exhibit a distinct relative amplitude of approximately -20 dB, with a HH RCS of -17 dBsm for the quadcopter and VV RCS of -8 dBsm for the octocopter, these findings correspond well to the physical reflectors of the target. In the frequency plots which are swept over a 2.4 GHz bandwidth from 5.8 to 8.2 GHz, it is interesting to observe that there are no nulls in the VV polarisation, whereas when compared to the HH, trenches of up to 15 dB are measured. Acoustic measurements were also carried out, however the authors determined that ideal conditions would be required in order for this to be reliable in practice.

Khristenko, et al. [23], developed a fully calibrated system to measure the scattering properties of a Cheerson-CX-20 quadcopter with the rotors either on or off, this was done at 9 GHz in horizontal polarisation (H-Pol). The relative amplitude was measured to be -25 dB when the propellers are not rotating, corresponding to an RCS of -21 dBsm. When they were rotating, the relative amplitude is -22 dB and the RCS is -16 dBsm. From these results, the authors have shown that rotating elements are at least 20 to 25 dB weaker than the main body, hence the detection of blade signatures is complicated further since the main body RCS is already below typical target magnitudes.

Ritchie, et al. [24] undertook an examination into the dependencies of rotor blades of different materials on polarisation, frequency and azimuth angle. The study quantified differences in the RCS of H and V pols over a simulated 9 GHz bandwidth and concluded that HH is far more stable over the frequency range than VV (with VV components expected to be 40 dB below the HH). With respect to the material used, it was found that aluminium and carbon fibre behave very similarly; between 1 and 2.5 dB for L, S and C Band. Whilst reflections from the plastic blades were on average 10 dB lower (L, S band), however this gap was closed in HH measurements at C Band.

The authors in [25] performed a practical analysis on the effect of polarisation dependence on micro-Doppler signatures for two drones: the DJI Inspire 1 quadcopter and the HobbyLord F820 Hexacopter. This involved a heterodyne Ku Band FMCW radar, transmitting at 43 dBm over a bandwidth of 150 MHz [26]. The results obtained analyse all polarisation combinations and agree with Ritchie's findings, in that horizontal contributions of the rotating blade, produce a more stable return when compared to the vertical at low elevation angles (ϕ_{EL}). The work also determined that a Co-Pol configuration received a stronger return at a ϕ_{EL} of 0˚, whereas cross-polarisations (X-Pol) received a higher return when ϕ_{EL} is 90˚. It was also proven that the direction of rotation makes no difference and that an increase in the number of blades has little impact on the overall RCS (subject to relative size); though, extracting information regarding the rotation speed of the blade is far more complicated for the hexacopter case.

In [6], the authors gathered experimental data from a DJI Phantom and a wide variety of birds ranging from the 1.8 kg hooded vulture to the 280 g barn owl. This was performed with an S Band multistatic radar through six different flight paths, which intercept the transmitting beam of the monostatic node. These resulted in a multitude of unique range time intensity (RTI) and spectrogram plots, providing insight into the physical features exhibited by both bird (Fig. 1) and by drone (Fig. 2).

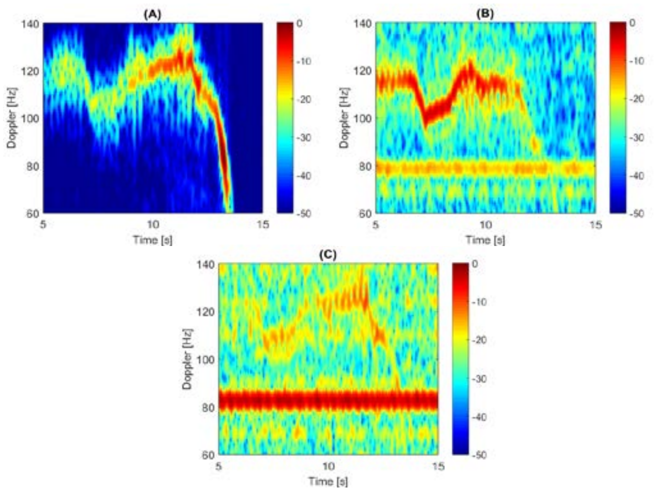

Fig. 1. Micro-Doppler signature of Barn Owl moving from A to B (A) Monostatic HH (B) Bistatic HH (C) Monostatic HV, Courtesy of M. Ritchie, et al. (UCL) [6]

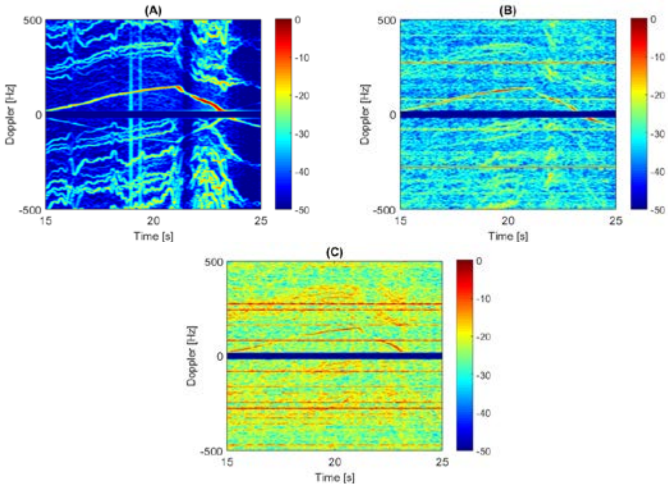

Fig. 2. Micro-Doppler signatures of DJI Phantom quadcopter drone moving from A to B (A) Monostatic HH (B) Monostatic HV (C) Bistatic HH, Courtesy of M. Ritchie, et al. (UCL) [6]

It was discovered that the RCS of the drone was in-between that of the barn owl and the vulture, however the contribution of the wings of the birds are far more significant than that of the blades of the drone. Most notably, birds do not produce as great Doppler components and reflections in the resultant spectrogram. If the influence of the wings or rotors are taken away, the resultant profiles would be practically identical and since these additional components have significant dependencies, it demonstrates that classification may be incredibly complicated outside of these ideal scenarios.

A unique approach was made by the authors in [27], where they undertook experiments with an ultra-wideband ISAR sensor over a bandwidth of 3 GHz, at two frequency bands: ~C and Ku Band. The purpose was to identify specific scattering locations and radar reflective surfaces of two aesthetically different drones, the DJI Phantom 2 and the Inspire 1, over a wide range of azimuth angles. The results show that even the non-metallic components can dominate the ISAR intensity plot, where the plastic rotor blades whether spinning or not, have minimal impact. The ISAR images for two different drones at two azimuth angles are shown in Fig. 3, it is interesting to observe the well-defined components of the drone in the image, immediately revealing the principle reflecting elements. This correlates well with previously mentioned works, where it has been consistently reported that propellers produce little reflection, whereas the body produces the majority.

Guay, et al. [28], undertook a different approach to analysing the RCS of a drone (Parrot AR), by means of describing it through a statistical model, due to the great number of variables involved. A fully calibrated RCS measurement environment was setup, operating at 8 to 9 GHz [29] and tests were carried out through a range of angles and flight patterns. The work produced a statistical description of the drone and then went on to generalise this with the radar equation. RCS values obtained were in the region of -21 dBsm. It was concluded that Probability of Detection (PoD) does not necessarily decrease with increase in frequency and the drone in dynamic flight produces a higher RCS than that in static flight, due to decreased likelihood of scattering from deep nulls.

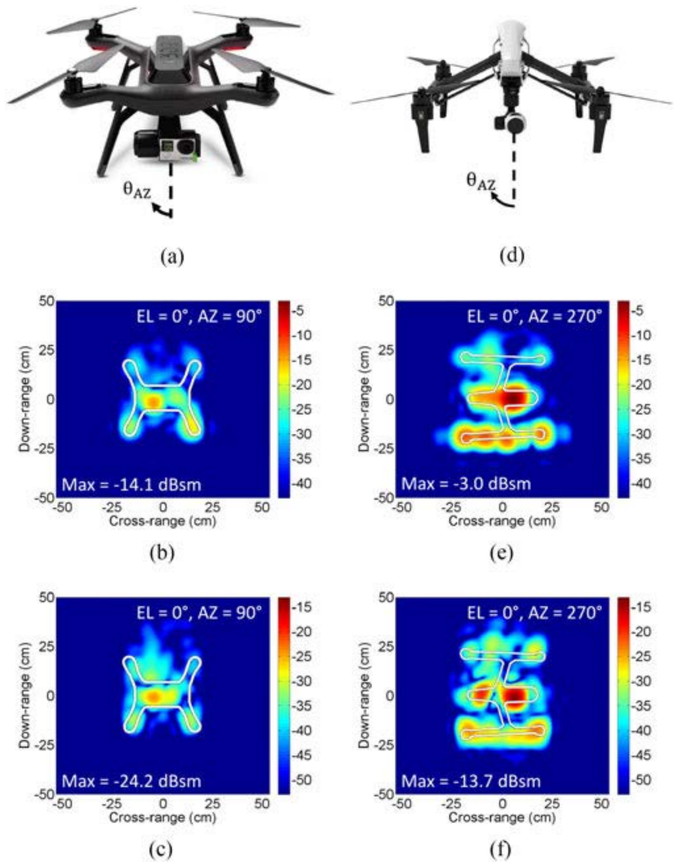

Fig. 3. (a) 3DR Solo, (b) Solo ISAR image at 90° (12–15 GHz), (c) Solo ISAR image at 90° (3–6 GHz), (d) DJI Inspire 1, (e) Inspire 1 ISAR image at 270° (12–15 GHz) (f) Inspire 1 ISAR image at 270° (3–6 GHz) Courtesy of C. Li, University of Texas (UT) [27]

A summary of the RCS figures and the relative amplitudes, as gathered from the field of drone RCS characterisation is presented in Table 1. The selected drones from the literature are similar in size and are of the quad-propeller variant, allowing comparison of the metrics. The measured RCS of the drone does not show an obvious trend with frequency, due to the array of materials and complex scatterers involved in the experiments. However, the relative amplitude remains moderately constant throughout, demonstrating that the discussed experimentations have been performed to a high standard.

Table 1. Summary of RCS values and amplitudes obtained in literature

Authors	Frequency / GHz	RCS / dBsm	Relative Amplitude / dB
A. Schroder, et al. [20]	10.0	-20 to -30	-20
A. Herschfelt, et al. [22]	5.8 to 8.2	-17	-20
A. V. Khristenko, et al [23]	9.0	-16	-22
M. Ritchie, et al. [24]	2.4	N/A	-17
B. K. Kim, et al. [25]	14.0	N/A	-20
C. Li, et al. [27]	3 to 6 12 to 15	-24.2 -14.1	N/A
R. Guay, et al. [28]	8.5	-20.9	N/A

3. Drone Detection & Classification Techniques

There has also been significant research undertaken regarding the classification of drones, this is widely considered to be the next logical step after successfully detecting the presence of such a vehicle. Aveillant [30], utilised their Gamekeeper 16U phased array radar, which operates at L Band and transmits at 1 KW, it is capable of extended dwell times in order to achieve fine Doppler resolution. The trials undertaken involved a DJI Phantom and a larger Aerosky 550 hexacopter fitted with GPS sensors to provide a ground truth during flight. Data was also captured involving birds, as they were within the surveillance volume during the time of the experiments. The staring capability of the radar allowed the trajectory of the targets to be analysed and predicted using a real time algorithm, which updates at 4 Hz. It is proposed that this track information is used as a feature to aid in the discrimination between birds and drones; as it was shown that drones exhibit a unique, ‘sharp’ flight pattern which is possible to recognise. It is also revealed that each drone produced a distinctive Doppler plot, due to the size of the drone, the rotors and the number of them. However, it is stated that the classification capabilities are strongly dependent on the stability of the rotors relative to the incident radar beam, hence a full quantitative analysis was not performed.

QinetiQ [31], explored the specific Doppler patterns of various drones during flight, this was done with their X Band FMCW radar, named Obsidian. A very interesting aspect of their analysis was the inclusion of a Doppler spectrum produced by the DJI Phantom, to which each contributing component is clarified clearly (Fig. 4). Zone ‘a’ represents the low offset frequencies, caused by the rotation at the blade root; zones ‘b’ are the mid offset frequencies caused by the length of the blade; and zone ‘c’ represents the higher frequencies caused by reflections at the blade tip. The negative side of the spectrum is when the blade is receding and has a larger return than when the blade is approaching [32]. This could potentially be caused by the disparity in blade pitch as the radar beam is scattered differently in the plane of rotation [33]. There are certainly unique features contained in this spectrum, therefore future identification opportunities are very promising.

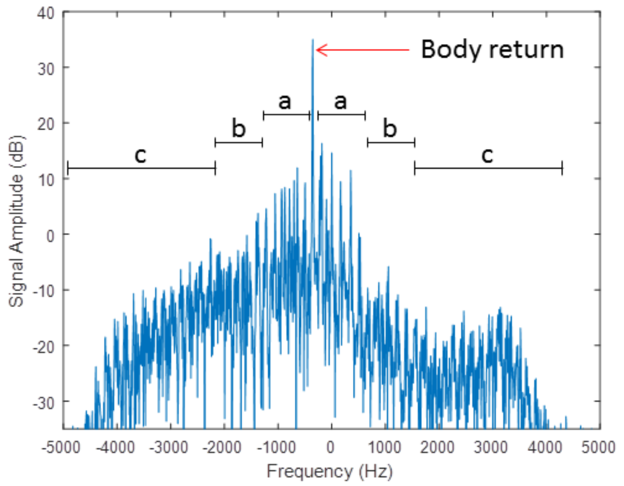

Fig. 4. DJI Phantom 2 Doppler spectrum signature, showing selected bands of interest, Courtesy of S. Harman (Qinetiq) [31]

Advancing from these observed signatures, further research has been undertaken into how novel features can be extracted or even potentially generated, by means of investigation into further transformation techniques. Thales, TNO [15], proposed suitable features to be used in a subsequent classification process. These features are: RCS, main velocity component, spectrogram periodicity, spectrum width (Doppler bandwidth) and spectrogram symmetry. A feature which is not typically analysed is the spectrogram periodicity; which extracts and quantifies periodic micro-Doppler modulations. This is achieved through the generation of a cepstrogram, which is the inverse FFT and log of the Doppler-time spectrum. For the extended dwell times or long integration intervals reported across literature [30][31], it would be advantageous to perform such a transform, as it further quantifies the repetitive nature observed in the spectrogram. In the context of the work undertaken, the authors have gathered the spectrograms for a variety of small aerial vehicles and have generated cepstrograms for each; the result of which show an obvious compression of an otherwise cluttered Doppler spectrum.

The same authors [34], have also proposed further extraction of information through the use of Singular Value Decomposition (SVD), a linear algebraic transformation which treats the entire 2D spectrogram as a matrix. This has been proven to produce extremely quantitative features as observed in similar radar classification problems, such as human micro Doppler, where near perfect classification between armed or unarmed individuals is reported [35]. Using this approach, they have demonstrated that SVD projects valuable time-frequency information into the **U** and **V** singular vectors, which classifiers can exploit readily.

Ancortek [36], undertook a detailed Doppler analysis using their 24 GHz interferometric radar with dual receiving channels, over a range of angles. Spectrograms were obtained for an increasing number of rotor configurations, this produced progressively complex spectrograms. Studies undertaken at higher frequencies are subject to increased atmospheric effects and distortion, the latter could see benefit from an EMD oriented analysis, allowing the spectrogram to be broken down prior to classification stages.

3.1. Classification Implementations

A complete classification framework is proposed in [37], to provide automatic and robust classification between a UAV and a non-UAV target. The novel signal processing algorithm developed is coined ‘2D Complex Regularised Spectral Analysis’ and it employs commonly discarded phase information to produce a complex log spectrum, which is carefully normalised to further benefit machine interpretation. Additional time-frequency transformations such as the cepstrogram and the Cadence Velocity Diagram (CVD) are used as sources of features to complement the traditional spectrogram, however the authors have adjusted these equations to exploit phase information, as it is not possible to take the log and absolute value, without otherwise discarding the phase. A Subspace Reliability Analysis (SRA) is also undertaken to assess and discard harmful features, detrimental to the classification process. This is identified through evaluation of the reliability of the class conditional covariance matrices and then removing the un-reliable feature dimensions, in order to maximise a derived reward function. The authors apply their proposed techniques to data provided by Thales Asia, of a low power X-Band radar monitoring a target scene, where a UAV and various other non-UAV targets are operating within, it should be noted that these other targets were mostly birds. This is also compared to state the art approaches in literature and is presented below in (Table. 2). ERR denotes Equal Error Rate and FAR denotes False Acceptance Rate, defined at a False Rejection Rate (FRR) of 1%.

Table. 2 Comparison between the authors approach and other state of the art methods [37]

Method	EER / %	FAR / %
Dynamic time warping (DTW) [38]	8.04	47.42
Principle Component Analysis (PCA) [39]	8.19	54.16
Spectrogram + PCA	7.75	27.00
CVD + PCA	6.68	28.41
Cepstrogram + PCA	10.17	48.07
Proposed Feature Representation (PFR) + PCA	3.98	4.50
PFR + Subspace Reliability Analysis (SRA)	3.27	3.89

The results reported demonstrate that their PFR and SRA analysis yields low error rates and has very good false alarm performance, when compared to the other methods implemented for this dataset. A key aspect to take away from this work is that it could be undesirable to immediately discard phase information as it could be interpreted differently by a machine, when compared to, for example a 2D visual plot which benefits a human operator.

There has also been research undertaken involving the possibility of classifying the case of whether a drone is carrying a payload or not. It is stipulated that the increased mass causes a different inertial response and subsequently the rotors are exerted further to achieve the equivalent manoeuvres [41]. This behaviour is directly observed in the micro-Doppler spectrum and the potential combination of this with a measured track of the drone [40], could perhaps be a viable candidate for reliable payload classification. The authors in [41], utilise centroid analysis, which determines the apparent centre of mass for the presented Doppler spectrum. SVD was also applied to the data sets and separate feature space plots were generated for the two groups of features. A Naïve Bayes classifier was employed and very good classification accuracy was reported, with results of at least 96% in the 5 classes of increased mass of the drone. However, a noteworthy conclusion from their analysis is that depending on the classification task, i.e. whether the drone is flying or hovering, the performance of the features varied. The SVD approach was more suited to classifying flying drones whereas the centroid analysis was more appropriate for the hovering case.

Torvik, et al. [42] studied how polarimetry could be exploited to aid in the classification between four classes of both birds and drones, these are already known to exhibit very similar RCS characteristics [43]. The work employed up to 12 extracted vectors from the radar signature across multiple domains as features for classification. The dataset consisted of over 8000 samples and accuracies around 99% were consistently reported using a linear discriminant analysis (LDA) classifier. It was discovered that there were systematic differences in the polarimetric eigenvector value and the co-polarised phase difference, which led to improved classification rates. It was postulated that these differences between the two cases were due to a decreased multi-bounce scattering effect and further creeping wave effects in the MIE resonance region, for the datasets involving birds. This shows that there is very useful information to be obtained regarding polarimetry, which can significantly aid in distinguishing between drones and birds.

P. Zhang, et al. [44], utilised two CW radars operating at K band and X band, to discriminate between three types of drones (helicopter, quadcopter and hexacopter). The spectrograms were decomposed using PCA and were presented across three dimensions, an SVM algorithm was then utilised to classify between the types of drones, through enclosing the clusters and defining a suitable hyperplane. Information from the two radar sensors was then exploited in order to improve the final decision, leading to an overall accuracy of 97.7% across all three classes. W. Zhang [45], then proceeded to undertake an analysis with the same drones operating together in the same target scene, in different combinations to see if it was possible to classify the type of drone from the unique CVD signature observed. A K-means clustering method was implemented in order to perform the classification and overall accuracies between the seven scenarios was on average 94.7%.

Given the highly unpredictable nature of drones in flight, techniques such as the Wavelet Transform (WT) may find direct applications in this field. The WT enables frequency variations to be analysed closely over time in a multiresolution space, as opposed to an STFT where resolution is determined by the depth of the FFT [46]. Other advantages also sported, are: suitability for non-stationary analysis, robust filtering through ability to approximate non-linear functions and also de-noising competencies [47]. WT's have witnessed successful applications in the radar detection of low velocity, small RCS targets amongst complex sea environments; sought after for their flexible configurability [48].

Rahman, et al. [49] applied WT's to radar data collected from a DJI Phantom and a bionic bird, using their phase coherent W-Band radar based on a DDS architecture. The wavelet approach was chosen due to the high Doppler resolution demands at high frequencies, offering lower equivalent computational complexity, when compared to the STFT (reduction by factor $log_2 n$). Tests were performed with a single propeller and then all four, at these frequencies it is interesting to see just how much the blade flash pattern changes between the two cases. The scalogram plots of the bionic bird exhibit far more prominent features compared to other spectrograms in literature at lower frequencies (< X Band), concluding that improved Doppler resolution does indeed provide more useful information that will hence benefit potential classification opportunities involving small drones.

3.2. Neural Network Implementations

There is a still great deal of research to be carried out in order to determine the most appropriate features and classification methods for every presented scenario. On the other hand, there are optimised and fine-tuned models readily available to be used for these complex classification tasks. For example, in 2016, the authors [50], exploited the famous pre-trained 'GoogleNet' Convolutional Neural Network (CNN) and applied it to spectrograms and CVD's collected from two flying drones. The experiment utilised the same bespoke sensor and the same drone models as in [25][26] and classification between the two types of drone, led to a solid accuracy of 94.7% being achieved.

The authors in [51], developed a Multi-Layer Perceptron (MLP) Neural Network (NN) based classifier and parameter estimator which can determine the number of propellers and the blades on a drone. The MLP network architecture consists of five individual pathways which accept complex IQ, time, frequency and also absolute data. There are two unique MLP classifiers which first analyse the propeller signatures and then the number of blades, this is then fed into an estimation algorithm. Classification accuracy achieved is very dependent on SNR but is near perfect, however this has been applied to synthetic data. This approach is unique and it would be very interesting to see how it performs on real drone data.

The authors in [52], developed an S band CW radar featuring a 90˚ hybrid IQ receiver stage; this was used to distinguish between three very different types of micro drone (AirHog Firewing Bird, Skyrover helicopter and a Radioshack quadcopter). The Spectral Correlation Function (SCF) which is the Fourier transform of the Autocorrelation Function (ACF), was employed to identify unique modulations caused by the many dynamic components of the target of interest. A Deep Belief Network (DBN) is utilised as the classifier in this work, unlike typical Deep Neural Networks (DNNs) the layers are interconnected rather than the individual units, resulting in a very hierarchical and modular design. The data gathered from the trials is passed through four SCF pattern reference banks (generated before the trials and are unique to each class), finally these are weighted and summed before being fed into a classifier to make a final decision on the target. Classification accuracies are in the region of 97% between the two models of drone and 99% for the artificial bird.

3.3. Micro-Motion Analyses

In areas which have not yet been copiously applied to the context of drone classification, significant mathematical effort has been directed into understanding the micro-motions of rotating elements [32][53] produced by a broad range of aircraft, beyond the cases of drones or UAVs. The formulations presented in [53] are resilient to the number of blades, through utilising the Rényi entropy of the time-frequency distributions captured. Such a capability is essential, as the number of blades which are observed on any given drone is highly variable, hence resistance to this technicality is strongly desired.

A detailed method involving Empirical Mode Decomposition (EMD) to separate micro-motions from the main body for ISAR applications can be found in [54]. In this work, a signal model for a rotating element is derived for an LFM chirp, to which a bespoke micro Doppler selection algorithm is designed around, this is based on direct analysis of the intrinsic mode function (IMF). The implementation of this technique is pursued for its suitability in decomposing data which is non-stationary and potentially non-linear [55]; hence the suitability for application in drone classification.

Authors in [56] developed a bespoke homodyne W-Band radar, assembled and attached at the microscopic level (because of losses), to automatically measure blade length and rotation rate of a drone's numerous rotors. The DJI phantom was placed at a distance of 1.5 m away from the radar and data was recorded for a different number of active propellers. Information was extracted through detecting the envelope of the signatures in the Doppler spectrum, this was possible as SNR was sufficient to allow reliable thresholding. Blade length could be accurately calculated to within an average error margin of: 0.96%, 2.15% and 1.3% for single, double and quad rotors respectively.

A brief summary of the aforementioned classification methods discussed throughout this entire section, is detailed in Table 3. Important and noteworthy keywords to the works have been signified through bold font.

Table 3. Summary of classification techniques used throughout literature

Authors	Purpose
Aveillant [30]	Investigate Doppler components produced by drones at **L Band**
QinetiQ [31]	Investigate signals produced by drones at **X Band**
Thales, TNO [15]	Explore relevant features and **Cepstrograms**
TNO, Thales [34]	Explore relevant features and **SVD**
Ancortek [36]	Interferometric analysis at **K Band**
J. Ren, et al [37]	**Complex Log** spectral analysis including **Phase**
M. Ritchie, et al [41]	Payload classification with **Centroids** and **SVD**
B. Torvik, et al [42]	**Polarimetric feature** injection into **LDA** classifier
P. Zhang, et al [44]	**PCA** with **SVM** classifier
W. Zhang, et al [45]	**CVD** analysis with **K-Means** Clustering
S Rahman, et al [49]	**Wavelet** Decomposition and Analysis
B. Kim, et al [50]	**'GoogleNet' CNN** with merged Doppler
N. Regev, et al [51]	Combination of **MLP** NNs for blade estimation
G. Mendis, et al [52]	**DBN** with **SCF** reference banks
M Adjrad, et al. [53]	Signal component estimation using **Rényi Entropy**
X. Bai, et al. [54]	Imaging of micro-motion targets using **EMD**
A. Singh, et al. [56]	Determine blade properties with **W-Band** radar

4. Passive Radar Detection

Research involving the passive detection of drones have also begun to emerge in parallel with that of active radars. Passive Radars (PR) have a number of advantages over their active radar counterparts, being: lower cost, reduced energy consumption, covert operation and less frequency limitations, due to unrestricted band licensing [57]. Good autocorrelation properties are present in the inherent transmitted waveform, due to channel specifiers, scrambling codes and error control measures; this minimises the necessity of waveform design. However, it does come with some disadvantages these being: dependence on transmitters usually a significant distance away and out of the control of the user, reliance on continuous transmission and clear line of sight (LoS), there are also limitations in the maximum detectable range [58].

Authors in [59], developed a Passive Bistatic Radar (PBR) to receive digital television signals at 685 MHz and 738 MHz simultaneously. Extensive signal processing is applied to filter, compensate and beam form, in this case an Extended Kalman Filter (EKF) is employed to track the target trajectory. A diagram of the complete configuration implemented is shown in Fig. 5, this is akin to the subsequently discussed PBR architectures. This arrangement has proved to be very effective in detecting and tracking a DJI Phantom 4 across a relatively large volume. Interestingly, a bird of a comparable size to the drone, seemed to have entered the search volume and consequently captured the track and lured it away [60]. This, having an identical effect to that of a decoy target, in the context of radar countermeasures and radar warfare [61]. This work emphasises the importance of being able to classify and reject false targets, to prevent such undesirable effects from occurring.

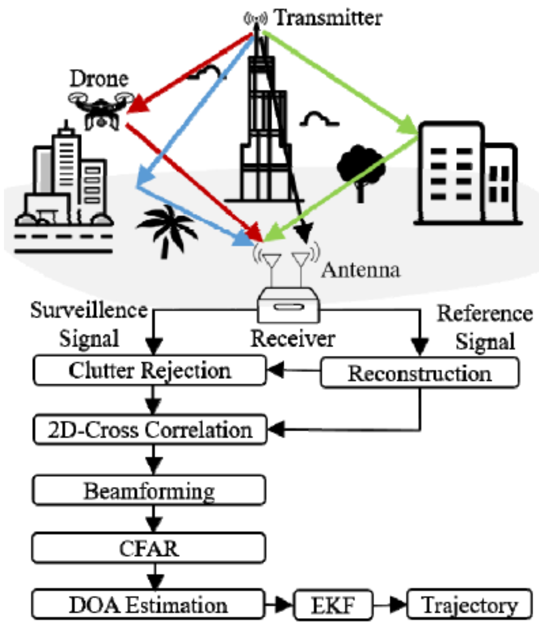

Fig. 5. Passive Radar Signal Processing Flow Diagram, Courtesy of X. Wan (Wuhan University) [59]

Fraunhofer [62], utilised their Passive Coherent Location (PCL) GAMMA-2 radar system, which has the ability to intercept the GSM 1800 communications band (1.8 GHz), through eight 200 KHz wide channels, within a bandwidth of 30 MHz. In the experimental trials a 380 g Parrot AR drone and an Amos X4 drone, weighing more than 5 kg is used as targets for detection. Due to the increased availability of GSM stations, up to three Base Transmitting Stations (BTS) can be exploited simultaneously, forming a multistatic radar scenario; this has been shown to enhance performance, especially if data fusion techniques are realised [63].

Roke Manor [64], used a COTS USRP to obtain 3G signals in the UTRA 1 band (2110 MHz to 2170 MHz on the downlink and 1920 MHz to 1980 MHz on the uplink). This yielded a coarse bistatic range resolution of 64 m, but a relatively fine Doppler resolution of 7 Hz / ms^{-1} adequate for the detection of drone size targets. Three variations of experiments were performed: mobile phone illumination providing the reference signal on the uplink, micro base station providing a continuous downlink pilot channel and finally base tower illumination. Through these tests, very clear spectrograms were generated, demonstrating the precise motion of both a quadcopter and a helicopter style drone (Fig. 6). It is certainly interesting to see the direct benefits of exploiting inadvertent mobile phone illuminators in the vicinity to enhance signal purity. The calculations explored by the author reveal that the system is indeed limited in detection range, to within an order of 100 meters, due to environmental path loss and also the minimum RCS of the target. Although, detection of targets could still be very well functional beyond this; however, classification abilities would be severely hindered at these further ranges.

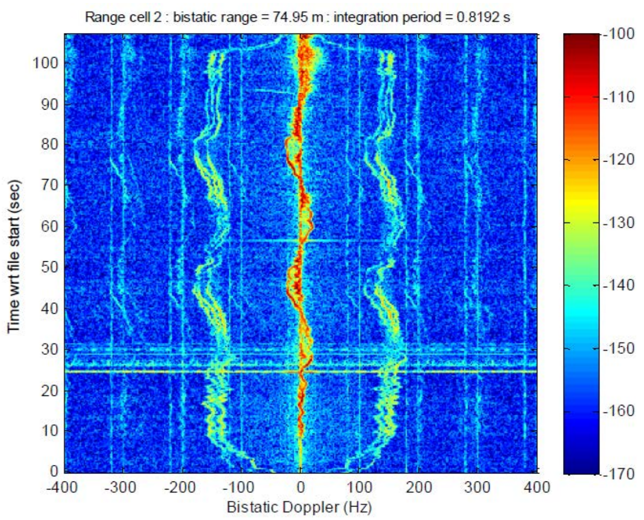

Fig. 6. Micro Base Station Illuminator, Quadcopter Target, Courtesy of A. Chadwick (Roke Manor Research) [64]

Authors in [65], utilised emissions from a Wi-Fi router to detect and track both a small light aircraft and a very lightweight drone consisting mainly of carbon fibre, through three spatial dimensions. Rigorous signal processing techniques were employed to improve the quality and resilience of the received Wi-Fi signal, most notably against interference from other access points (AP). Sidelobe control measures are taken to mitigate complex structures in the Ambiguity Function (AF) of the reference signal. An Extensive Cancellation Algorithm (ECA) is applied to suppress the direct breakthrough and multipath effects. Finally, a Cell Average Constant False Alarm Rate (CA-

CFAR) is implemented to track the target through the range and velocity planes. The results demonstrate a non-spurious, stable track of the drone through 3D space, however there is no ground truth to verify the accuracy of the passive radar system.

In [66], the authors derived the Doppler offset induced in an OFDM signal and then took this further to describe how this could be applied to a circular array of transmitters. Typical target velocities are grouped and a CFAR algorithm is designed to enable appropriate detection and track. Initial classification abilities were demonstrated through simulation; however, this was not performed over real target data. The analysis presented in this work can be applied to any OFDM transmission system, this is of interest as 5G services are expected to operate between 3 and 4 GHz in the low bands and 24 GHz or more in the high bands [67]. This area of research is open for development and there is scope for investigation into Doppler signatures produced in passive radar systems.

A summary of important measures extracted from the aforementioned literature is stated in Table 4. along with whether the work has demonstrated either detection and/or classification.

Table 4. Summary of passive detection techniques and corresponding frequencies – (‡indicates that there is immediate potential for classification)

Authors	Frequency Range	Detection /Classification
Y. Liu, et al [59]	685 – 738 MHz	Detection
Fraunhofer [62]	1800 MHz	Detection
Roke Manor [64]	2110 -2170 MHz	Detection/Classification‡
T. Martelli, et al [65]	2400 – 2500 MHz	Detection
X. Yang, et al [66]	N/A	Detection/Classification‡

5. Discussion & Conclusion

In this literature review, the research efforts in the context of drone characterisation and classification using radar sensors have been thoroughly reviewed, including exploration into various nuances and techniques to each approach. This is an emerging field of research, which takes into account the challenges posed by the potential misuse of these platforms. The following section deliberates noteworthy elements from each topic and highlights aspects which could systematically advance the research efforts in the overall field.

5.1. RCS Characterisation

Researchers in the field of RCS examination have undertaken EM simulations to a high degree of accuracy and have verified acquired results with real experimental data; in all cases correlating well and are justified appropriately. Bistatic RCS estimation proves to be more challenging to predict, due to large dependencies on object alignment and related angles; in addition to this, the calibration methods utilised for the monostatic approach were not transferable to the bistatic scenario. A relative amplitude disparity of approximately -20 dB between the drone body to the blade was witnessed across multiple papers where RCS was assessed [20]-[25].

The dependency on the visibility of drone blades for improved detection and classification against non-drone objects or of different models, raises significant issues. The main being that the large variability in the materials and shapes used in the construction of these drones has to also be taken into consideration, this in turn has an effect on the range of RCS values that a radar might expect for a drone. The simple use of a plastic rather than a carbon fibre blade has already been shown to have an impact [24], however there are still many materials, sizes, shapes and blade configurations to be explored. With this in mind and the scope of the entire issue, it would not be impossible to imagine the emergence of drones exhibiting true ‘stealth’ characteristics, in ways more so than they already are. This encourages further work in improved detection capabilities through adaptations in perhaps, radar parameters such as centre frequency, bandwidth and polarisation [68].

Studies regarding polarimetry and bird discrimination have concluded that horizontal polarisation is preferable, as it simultaneously observes rotor modulations from the drone and the flapping of the bird’s wings. However, at high elevation angles vertical and cross polarisation combinations are shown to provide improved SNR. Low frequency measurements at L Band are established to be not as useful as S Band, nevertheless classification performance is improved [42][69]. In the context of a real drone surveillance radar, very high elevation angles would be uncommon as, drones typically operate at low to medium altitude (below 100 m).

5.2. Drone Classification

Research in drone classification practices have largely been successful through the transfer of established techniques migrated from other Automatic Target Recognition (ATR) problems. However, the entirety of the mathematics behind the observed signatures and also the development of a resilient model has not been fully investigated; this is due to the incredibly complex dynamics and nature of the target. The main contributing factors being the number of fast rotating blades and the wide range of angles incident to the radar, especially during manoeuvres. It is therefore difficult to reproduce the pure mathematics behind it, whilst also applying reasonable assumptions to get there. Such an analysis is crucial as it could potentially be a strong factor in drone detection and hence classification, as they will exhibit unique signatures associated to that type or model of drone. This is analogous to Jet Engine Modulation (JEM), which is sometimes used to detect the presence of aircraft from the signatures produced by the jet engines [61].

The classification techniques demonstrated in open literature usually assume that the drone is visible to the radar for sufficient time in order to extract segments of micro-Doppler signatures. This assumption is not always appropriate, either for the drone navigating outside of the main radar beam, or for the need of steering the beam in other directions for concurrent radar tasks. To address this issue, techniques that employ compressive sensing and interpolation of 'punctured' signatures [70] are of great interest due to agile nature of the target. A noteworthy addition to this is that: most of the discussed work in classification has been undertaken within ideal scenarios and usually at close range, real operation of a drone introduces a dynamic which is otherwise difficult to reproduce, simulate or predict, certainly having an effect on classification performance. A further complication to the research, is that the collection of original radar data with drones in operation demands significant space, resources and bespoke radar sensors; the entirety of which is challenging for a university to obtain for research purposes.

Substantial work has been undertaken regarding the selection of the most appropriate features through diverse representations and across many domains. Conversely, great success has been attained through utilising algorithms which intelligently decompose datasets, such as CNNs. This alleviates time spent in fully understanding and extracting the appropriate features, but instead leaving it to the neural network training process to determine. As radar systems become increasingly adaptive and 'cognitive', it is reasonable to assume that they will be able to fuse more information to enhance their classification capabilities, whilst also exploiting the latest developments from the artificial intelligence and deep learning community.

Multilayer classification procedures are a robust measure for ensuring the validity of a final decision within a network [15][52][63]. This could be employed over a multitude of domains, such as the cepstrogram, spectrogram, range time or even through track temporal evolution [30][71]. In addition, during training a bespoke cost function could be implemented to oversee and encapsulate the overall classification process across multiple unique classifiers, potentially indicating locations of performance bottlenecks.

5.3. Passive Radar Detection of Drones

Passive radar in the context of drone detection and classification is certainly a viable endeavour and is becoming increasingly attractive with the advancement of communication technologies and interest in higher transmission frequencies. Passive systems also provide capabilities without modifying existing radar transmitters or installing new sensors, benefitting from reduced cost and spectral compliance. However, there are certainly notable drawbacks such as the limited channel bandwidth, leading to poor range resolution, maximum detectable range which is restricted by the receiver design hence sensitivity and finally the inability to experiment with polarisation combinations. As a result of these issues, classification between types of drones or other targets is far more challenging compared to the equivalent for an active radar, further research needs to be undertaken to investigate this prospect.

To potentially mitigate such disadvantages, it could be favourable to develop and deploy a multistatic radar system, this being a combination of both active and passive sensors, therefore benefiting from techniques used in both research areas. This would: decrease the reliance on the illuminator, since the user has direct control, waveforms could be tailored to suit the mission at hand, the passive nodes could preserve covert operation and opportunities for data fusion immediately arise [72][73]. Given this, there is scope to research novel adaptive and diverse waveforms [74][75], coupled with an intelligent resource management system [76][77]. This would allow optimal detection and classification of low RCS targets, through the hardware and also software. Through this complete architecture, there are significant advantages to be gained and potential too substantial to be ignored.

6. Acknowledgments

The authors would like to thank Leonardo Airborne & Space Systems and the EPSRC for funding this research; and also: Matthew Ritchie, Chenchen Li, Xianrong Wan, Andrew Chadwick and Stephen Harman, for the kind reuse of their figures for this review.

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