A Review of Automatic Classification of Drones Using Radar

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Automatic Classification of Drones Using Radar: Key Considerations, Performance Evaluation and Prospects

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***Abstract*—Automatic target classification is a critical capability for non-cooperative surveillance using radar in several defence and civilian applications. It is a well-established research field and numerous algorithms exist for recognising targets, including miniature unmanned air systems (i.e., small, mini, micro and nano platforms) or drones, from their radar signatures. They have notably benefited from advances in machine learning (e.g., deep neural networks) and are increasingly able to achieve remarkably high accuracy. Such classification results are often captured by standard, generic, object recognition metrics and originate from testing on simulated or real radar measurements of drones under high signal to noise ratios. Hence, it is difficult to assess and benchmark the performance of different classifiers under realistic operational conditions. In this paper, we first review the key challenges and considerations associated with the automatic classification of miniature drones from radar data. We then present a set of important performance measures, from an end-user perspective. These are relevant to typical drone surveillance system requirements and constraints. Selected examples from real radar observations are shown for illustrations. We also outline here various emerging approaches and future directions that can produce more robust drone classifiers for radar.**

***Index Terms*—radar, classification, deep learning, unmanned air traffic management, non-cooperative surveillance**

I. Introduction

OVER the last few years, there has been a significant surge in the use of Unmanned Air Systems (UASs) or Aerial Vehicles (UAVs), not only in military applications, but also in the civilian domain given the numerous benefits they bring such as to agriculture, e-commerce, filming, inspection-maintenance, to name a few. This is primarily driven by the wide availability of commercial off-the-shelf miniature UASs. They are relatively cheap, can be easily operated and are becoming more sophisticated, capitalising on advances in sensing systems, wireless communications, automation and Artificial Intelligence (AI). However, the potential security and safety threats UAVs pose, for example to manned aviation, privacy and sensitive infrastructure or assets, are widely recognised.

Therefore, there is a growing demand for reliable non-cooperative drone surveillance for either of the following:

1) *Counter UAS (C-UAS):* detect and mitigate the unauthorised use of drones by malicious or novice operators such as in exclusion zones around airports [1] or military bases.
2) *Unmanned Air Traffic Management (UTM):* harness the full potential of UAVs via enabling their safe, widespread, utilisation and integration into the airspace along with manned aviation, for instance the Single European Sky ATM Research SESAR programme 2004-2020 [2].

Non-cooperative C-UAS and UTM solutions often comprise of multiple sensors such as radar, electro-optical cameras, acoustic and radio frequency (direction finders) to deliver consistent situational awareness in complex and dynamically changing environments [3], [4], for example surrounding airports. Nevertheless, only radar offers 24 hour, all weather, surveillance at long ranges and for wide areas. In this paper, we consider (ground-based) radar which can be part of a multi-sensor system governed by a suitable Concept of Operations (CONOPS). For instance, radar cues a high-resolution camera to confirm the identify of a target of interest, such as a drone.

Here, we treat the specific problem of Automatic Target Classification (ATC) or Recognition (ATR) of UASs from radar data, in particular the proliferating sub-50kg Class I drones, see the NATO taxonomy in Table I. This encompasses improvised, commercial and military grade rotary or fixed wing drones. Spanning the "small" to "nano" categories, the sub-50kg platforms are thence referred to as miniature UAS (mUASs) or UAVs (mUAVs) for brevity. They pose unique challenges to radar as highlighted in Section II. Tactical and Medium/High Altitude Long Endurance (M/HALE) UAVs can be regarded to resemble traditional targets such as airplanes in terms of Radar Cross Section (RCS), speed and altitude.

Different classification tasks can be formulated depending on the sought target categories. For example, the objective might be to distinguish drone from non-drone targets, the UAS type (e.g., rotor or fixed wing), size (small, medium and

TABLE I: NATO drone platforms designations and taxonomy.

UAS Class	Maximum Take-off Weight (kg)	Label
I(a)	< 0.2	Nano
I(b)	$0.2 - 2$	Micro
I(c)	$2 - 20$	Mini
I(d)	$20 - 150$	Small
II	$150 - 600$	Tactical
III	> 600	M/HALE

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large), carrying a payload or not and others. In this paper and for simplicity, we predominantly focus on the radar ability to automatically discriminate between drone and non-drone objects. ATC enabler, considerations, performance metrics that are relevant to common operational requirements, and other related capabilities (e.g., ATR with drone sub-classes, global classifiers, detecting malicious intent, simulators, digital twins and others) are also discussed. Additionally, here we use real measurements from the Thales Gamekeeper radar for illustrations. It is an L-band staring, otherwise known as ubiquitous or holographic^{TM} [5], radar with 64-element receiver array designed for detecting, tracking in 3D and classifying mUASs within a 7.5km range, 90° azimuth coverage, and with an ≈ 0.27s update period in its current configuration.

The remainder of this paper is organised as follows. In Section II, we outline the key problems and considerations of classifying mUASs with radar. ATC performance indicators are introduced in Section III and example results are shown in Section IV. Opportunities to achieve enhanced (or more detailed) target recognition results are highlighted in Section V and conclusions are drawn in Section VI.

II. Drone Surveillance Radar and ATC

A. Why Are Drones Difficult Targets for Radar?

Class I (miniature) drones are particularly challenging targets to detect and track with radar because they can simultaneously have all (or most) of the following attributes:

- *Small (low observable)*: mUASs can have low RCSs, which can be $\ll 0.01\text{m}^2$ as with nano or micro drones, and discriminative features of their radar signatures (e.g., micro-Doppler components) are a further one to two orders lower [6]. This necessitates the sensor having a high sensitivity and thereby detecting a potentially large number of targets of similarly low RCSs such as birds.
- *Slow*: drones can have markedly low speeds, for example less than 10m/s which renders them virtually undetectable to conventional radar systems (e.g., primary airport radars); rotary-wing mUAVs can also hover. Consequently, their body return and/or any distinguishable features in their radar signatures (e.g., from their on-board rotors, if any) can be easily obfuscated by stationary or slow-moving clutter within the same resolution (e.g., range, azimuth and elevation) cell making them difficult to consistently detect and track.
- *Low*: mUASs can fly at low altitudes (e.g., between 30 to 150 meters above ground and remain not easily visible to the naked eye). At such heights, especially in urban-industrial environments, we can have: a) occlusions to the radar line-of-sight from terrain or buildings and electromagnetic RF interference; b) multipath effects, impacting targets height measurements; c) interference from ground targets (e.g., cars) and man-made equipment with moving or rotating parts such as air-conditioning units, generators or roof fans; and d) the potential presence of large number of birds of various types and sizes.
- *Agile:* whilst (semi-)autonomous mUAVs often follow optimised smooth paths (e.g., between pre-defined way-points), they can be highly maneuverable, and can undertake sharp maneuvers such as abrupt turns and accelerations. Manually operated drones, for example racing or first person view mUAVs, can fly erratically with frequent maneuvers. The radar Multi-Target Tracker (MTT) has to be able to handle a wide range of kinematic behaviours. This is generally constrained by the tracker employing motion models with fixed, fine-tuned, parameters for describing the expected level of variability in the targets movements. This encompasses models specifically developed for manoeuvring targets [7]. Alternative techniques, such as interacting multiple model [8] and adapted MTT [9], can be either hard to correctly configure or prohibitively computationally demanding when simultaneously tracking large number of objects, majority of which are non-drone targets such as cars, pedestrians, birds, etc.

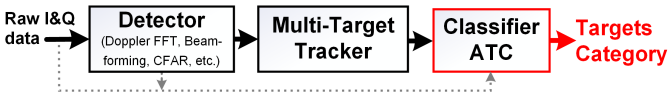


Fig. 1: Standard processing chain of a drone surveillance radar.

A drone surveillance radar processing chain normally consists of the standard three sequential operations for: 1) detection, 2) tracking and 3) classification of targets within the field of coverage. Each is carried out within a separate software-firmware module which can share information. An example block diagram is shown in Figure 1. Merging two or more of these tasks is known to substantially improve the radar performance against mUASs, for instance track-before-detect [10], joint tracking-classification [11] and even recognise-before-detect. The latter however regularly refer to a rule-based filtering of detections to prevent overloading the multi-target tracker or the operator. Next, we focus on ATC.

B. Automatic Discrimination: Drone versus Confuser Targets

Several radar systems, including in multi-static configurations, have emerged to address the formidable challenges presented by mUASs [3], [5], [12]. Within a relatively large field of coverage (e.g., spanning a few kilometers in range), they have to contend with a large number of potential "*confuser*" targets, such as birds, which co-habit the same aerospace and exhibit similar characteristics to mUASs, for instance their RCSs, altitude and speeds. A reliable automatic target classifier is thus fundamentally important in drone surveillance radars to distinguish between mUASs, which are usually rare, and confuser targets (e.g., birds), which can be abundant in (semi-) rural or urban environments. The surveillance system resources (e.g., secondary optical sensors) and/or operator attention should be dedicated to scrutinising targets that can pose a threat (e.g., mUAVs). Otherwise, they can be overwhelmed by the large number of tracked targets. ATC is also crucial for automation to reduce the overall C-UAS/UTM system operating cost by circumventing human-intensive CONOPS.

To demonstrate the sheer number of targets drone surveillance radars often handle, in Table II we list the average numbers of trajectories formed on targets per hour by the Thales Gamekeeper sensor within a range of 7.5km; 90°

TABLE II: Average number of tracks per hour from a staring radar, within 7.5 km range and 90° azimuth at different sites.

Site	Description	Average number of tracks (/hr)
A	Dense urban environment with the radar overlooking a major UK city	6803.2
B	Mixed semi-urban and semi-rural environments with small-medium villages/towns distributed in coverage	9204.5
C	Semi-rural environment with major roads in coverage	9863.3
D	National airport within a semi-rural environment and surrounded by small-medium villages/towns	6532.3
E	International airport with mixture of dense urban and industrial areas within coverage	9394.4
F	Mixed urban and semi-rural environment with major roads and villages/towns within coverage	11183.9

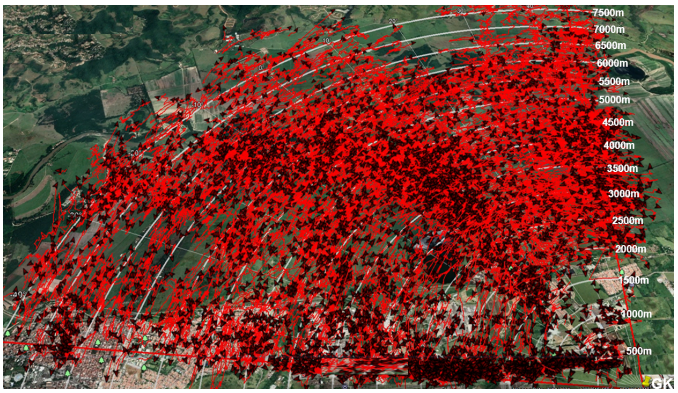


Fig. 2: Trajectories of tracked targets within a range of 7.5km at Site B during a typical 30 minute radar recording.

azimuth coverage. They are attained from 24 hour continuous recordings at various sites in the UK and France. From the table, it can be seen that several thousands tracks per hours are processed on average by the radar; this can exceed 15,000 per hour at certain times in mixed urban and semi-rural areas. On average several hundred tracks can be considered at any point in time. Figure 2 displays all the trajectories reported by the radar MTT during a 30 minutes period at semi-urban/rural environment (Site B). Although no ground-truth is available for all targets within the radar coverage, analysis of the characteristics of the tracks in Table II and Figure 2 (e.g., height, location, speed, etc.) confirm that they are not spurious. Accordingly, ATC module has to correctly classify the vast majority of tracks as non-drone and avoid triggering False Alarms (FAs) whose prominence is emphasised in Section III.

C. Classification Algorithms and Enablers

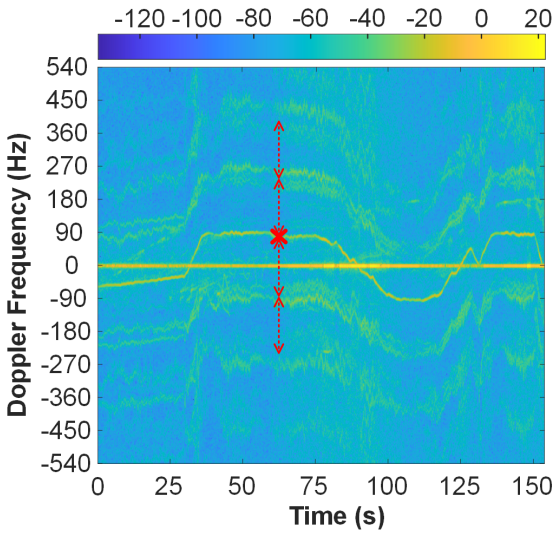
Automatic classification or recognition of non-cooperative targets with radar, including UASs, is a well-established research field with a plethora of existing techniques [13]. Conventional approaches are commonly based on hand-crafted rules applied to selected target features (e.g., RCS, height, velocity, etc.) and/or employ classical spectral analysis tools (e.g., cepstrum). Recent ATC algorithms on the other hand are increasingly data-driven and leverage advances in Machine Learning (ML), such as Deep Neural Networks (DNNs), to achieve impressive classification performance, see [14]–[21].

Whilst progress is being made to better understand the behaviour of DNNs [22], the main difficulty in developing generalisable machine learnt classifiers, usually within a supervised learning framework, is the availability of extensive and sufficiently representative labelled training datasets. This is due to the great diversity of potential targets to be recognised relative to the available real radar measurements. For example, the wide range of possible mUAS sizes, designs, speeds, heights, trajectory profiles-maneuvers, rolls-pitch-yaw angles with respect to the radar (i.e., incident angles), rotor speeds which may depend on the ambient wind, clutter characteristics, etc. Obtaining ground-truth of bird targets can involve further complications, for example due to the difficulties and cost of conducting controlled trials with birds instrumented with transceivers or employing a specialised targets labelling solution with electro-optical cameras, secondary radars, etc. Using synthetic data (e.g., to complement the available real sensor data, see Section V-C), can be critical to mitigate over-fitting effects and ensure that data-driven classifiers deliver robust performance when applied under real operational conditions (e.g., low SNR and previously unseen drone data).

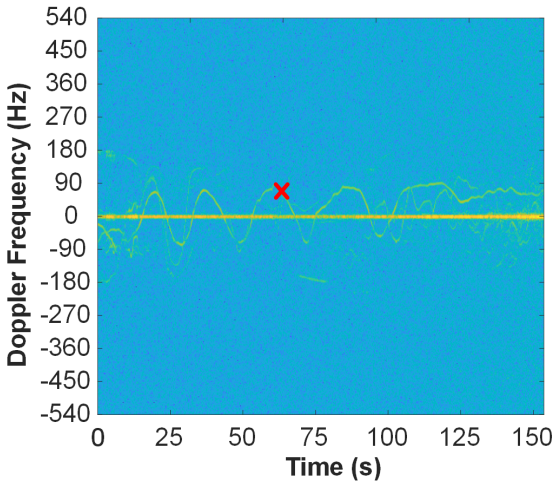
Given the drastic measures that might need to be taken when an unauthorised or malicious mUAS is declared (e.g., closure of the airspace near civilian airports that can severely disrupt the aviation traffic), it can be highly desired for the radar ATR module to report the certainty level in its classifications/predictions such as confidence scores for all considered target categories. For instance, a DNN micro-Doppler classifier can have a *softmax* output layer to produce these confidence scores, in lieu of the target final label [14], [18]–[20]. This permits the multi-sensor counter UAS or UTM system to not only adopt different risk management strategies for different targets, but also a more informed data fusion and CONOPS.

Drone classification often relies on target discriminative features that can be grouped into three categories: micro-Doppler, kinematics, and long-term behaviour. They are described next along with their limitations.

1) Micro-Doppler Signatures: The motion of rotors or propellers on-board a mUAS produce spectral lines in the radar Doppler spectrum, with approximate harmonic structure around the target body Doppler frequency. These are dubbed micro-Doppler components and their characteristics depend on the number of blades, blade length, frequency of rotation, radar wavelength and respective incident angle [23]. Example Doppler spectrograms from a bird and DJI Inspire 2 quadcopter drone are depicted in Figure 3, where both targets are approximately $1.5 - 2$km from the L-band Gamekeeper radar. Unlike the bird, the mUAV Doppler spectrogram in Figure 3a has visible micro-Doppler components symmetrically distributed around the target body. Nevertheless, bird wings motion can result in intricate micro-Doppler-type spectral features for appropriately short radar wavelengths [24]; they are notably distinctive from those originating from mUAS blades



(a) DJI Inspire 2 UAS (diameter ≈ 0.5m, weight ≈ 3.5kg).



(b) Bird target.

Fig. 3: Doppler spectrograms from real radar data of a quadcopter drone (a) and bird (b) at ranges $\approx 1.5 - 2$km. Red crosses mark the target body Doppler frequency at one time step; arrows indicate the UAS micro-Doppler returns.

rotating up to several thousand times a minute (i.e., drone's propellers move at a very different speed to a bird's wings). On detecting micro-Doppler signatures for ATC, convolutional Neural Networks (CNNs) have shown great promise [14]–[16], [18], [19], [21]. Their input can be Doppler spectrograms from multiple radar frames/scans (e.g. magnitude spectrogram as in Figure 3), complex time series data or covariance matrices. The former can be treated as an image and micro-Doppler harmonic structure becomes the sought pattern. Popular and specialised CNN architectures such as GoogLeNet, AlexNet , CRNet, SPDNet or an aggregation of various models can be utilised. Recurrent neural networks and other hybrid DNNs have also proven effective for micro-Doppler-based drone recognition [14]. Whilst micro-Doppler is a strong classification cue, especially against prevalent confuser targets such as birds, rotors radar signatures can be -15dB to -20dB lower than that of the mUAS body. The corresponding Signal to Noise (SNR) ratios decay rapidly with range and can be reduced further due to the blades characteristics (e.g., small size, fairing and constructions from a low reflective material such as carbon or plastic) as well as deliberate concealment (e.g., with blade guards). Consequently, the dectectability of micro-Doppler from drone propellers can be restricted to specific scenarios such as mUASs at short ranges and/or with certain rotor blades physical properties. Furthermore, there are several (false positive) micro-Doppler sources in industrial/urban settings such as air-conditioning units, generators or roof fans, etc.

2) Target Body Kinematics and Characteristics: Features extracted from the kinematic movements and characteristics of the target main body can facilitate distinguishing between drone and non-drone targets, for instance velocity, acceleration, jerk, height above ground, 2D/3D trajectory curvature, torsion, body Doppler stability and spread over time, RCS and others [16], [17]. They are typically derived from the multi-target tracker output or even associated detections/plots; hence their quality is dependant on the detection-tracking accuracy. The classifier employs a statistical measure of each kinematic feature (e.g., mean, L-moments, median, standard deviation, smoothness metric, quantiles, etc.) computed from the time series of its consecutive instantaneous values for a given trajectory. Contrary to micro-Doppler signature, the range of possible values of the kinematic features for the mUAS and bird targets can largely overlap. Thereby, relying on them alone can lead to a relatively low classification performance.

3) Long-term Behaviour and Patterns of Life: Drones can follow distinctive trajectory shapes dictated by a mission planning software to optimise use of resources (e.g., time the platform is airborne under limited battery life) such as waypoints-driven paths, hippodromes, hexagon and others [25]. These are generally not characteristic of birds behaviour. Conversely, frequent swooping maneuvers are more likely to be displayed by birds. Revealing such distinctive long-term kinematic patterns can allow identifying mUASs targets. They are however not always present and demand a persistent tracking of low observable and agile targets over extended durations, which is difficult to maintain at long ranges and in high clutter-noise environments (see Section II-A). Additionally, a substantial delay is incurred before a distinguishable motion pattern (if any) materialises and this degrades the ATC timeliness which we discuss in Section III-D. For some target types (e.g., cars or birds), revealing high activity areas and times (e.g., on major roads) can be salient pattern-of-life information that can be exploited by the classifier; this can be viewed as contextual data as in Section V-E.

Subsequently, it is imperative that combining micro-Doppler, kinematic and long-term behaviour features (if available) can boost the ATC overall performance [16], [17].

D. Summary of ATC Considerations

Linked to the challenges of detecting/tracking mUASs in Section II-A, in summary the major considerations for formulating drone surveillance radar ATC approaches are:

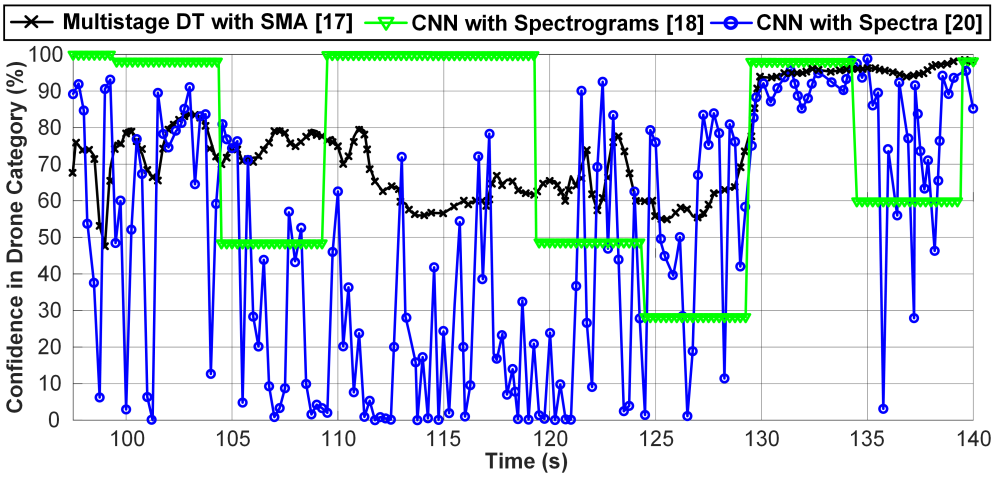


Fig. 4: Confidence scores in UAS category from three classifiers for the quadcopter whose spectrogram is shown in Figure 3a; decision tree (DT), simple moving average (SMA) and convolutional neural network (CNN).

– *Large number of confuser targets* that can potentially trigger false alarms; this can render stringent FA specifications (e.g., a maximum of one false alarm every 24 hours or even every several days in urban-rural settings) unachievable in practice with radar alone.
– *Fleeting discriminative target features*, such as micro-Doppler from a drone's rotors, that are intermittently observed due diversity in target type, flight profiles, behaviours, clutter, multipath, respective incident angle, etc. This can lead to fluctuations in the classification results over time. For illustration, an example of confidence scores in the UAS class from three ML classifiers are depicted in Figure 4. This is from real Gamekeeper radar data of the DJI Inspire 2 drone, whose Doppler spectrogram is shown in Figure 3a. The ATC methods are: **i)** multistage with machine-learnt Decision Tree (DT) [17] trained on real sensor data and using micro-Doppler as well as kinematic features at each radar frame with a Simple Moving Average (SMA) at its output, **ii)** AlexNet-based CNN in [18] with nonoverlapping Doppler spectrograms of length ≈ 5.5s (updates every ≈ 5.5s) and trained on real radar data, **iii)** low-latency simple CNN model [20], trained exclusively on synthetic data to use as its input the Doppler spectrum from one update/timestep. Both multistage and low-latency CNN classifiers update every ≈ 0.27s. The noticeable changes in the classification results over time is visible in Figure 4 for the three classifiers which all perform reasonably well in terms of declaring this tracked target a UAV (e.g., with a 50% decision threshold). This variability in their outputs can be attributed to changes in the radar measurements quality over time (see spectrogram in Figure 3a).
– *Limited available data and generalisability of the classifier*, especially for data-driven (machine-learnt) ATC algorithms expected to tackle previously unseen drone types or targets whose data is not in the training datasets.
– *Capturing classification certainty* to enable multi-sensor C-UAS or UTM solutions to apply effective CONOPS at the Command and Control (C2) system level.
– *Computational efficiency and swarms*, to process large number of targets with a track-level classifier. An initial coarse plot-level classification is sometimes used by radars for pruning detections fed to the tracker. This can be exacerbated by drones ability to fly in swarms where 3281 is the Guinness world record for most unmanned aerial vehicles airborne simultaneously [26]. With large number of confuser targets, a much smaller swarm could risk overwhelming the radar sensor processing chain.

III. Classification Performance Evaluation

There are widely used detection and multi-target tracking Key Performance Indicators (KPIs) for non-cooperative surveillance systems, for example the Single Integrated Air Picture (SIAP) [27]. On the other hand, radar automatic target classification efficacy is often assessed in terms of standard object recognition metrics from the machine learning field, such as accuracy, True Positive (TP) and False Positive (FP) rates, confusion matrix, F_1 Score, and Receiver Operating Characteristic (ROC), if relevant. Whilst these are informative, especially for developing and refining the classification algorithm, in this section we revisit the definitions of some of the traditional KPIs and propose additional metrics that are important to the end-users in various C-UAS/UTM applications.

A. Evaluation Framework

For simplicity, we note that the classification KPIs are presented here for a binary discrimination problem, namely miniature drone/truth versus non-drone/truth (i.e., birds, cars, pedestrians, etc.) targets. This also considers a framework underlined by the following essential stipulations from the ATC considerations outlined in Section II-D:

- *ATC specific metrics are exclusively studied*; they are disentangled from issues that arise from the detection and tracking steps which have own KPIs (e.g., SIAP). For instance, true positive classifications are obtained from time steps where a track is formed and associated

with the truth/drone target. This permits a more objective examination of the classifier behaviour and benchmarking its performance. This is despite the dependence of the ATC on the detection-tracking results.

- *Classification confidence and hard positives/negatives are reported*. The former, whose values can range from 0 to 1 (or 0 to 100%), is the certainty level in the classifier predictions for each of the nominal target categories. A decision rule is then applied to determine the target category, for instance the most probable class, i.e. Maximum *a Posteriori* (MAP), or the confidence score in the UAS class exceeding a threshold value. Thus, the notion of "*Hard*" TP (HTP) and FP (HFP) is introduced to signify their post-decision nature. Confidence scores can be attained from a time average (e.g., SMA) or other method for combining the classifier results over time.
- *All metrics are calculated per radar recording/dataset* (e.g., during a live drone trial) and combined measures, such as average, across multiple ones can be obtained. An example is the 30 minutes recording in Figure 2. This ensures that a poor performance at a specific site or time (e.g., due to high number of confuser targets) is not overlooked, especially in relation to false alarms, see Table II for the variability between locations. Even at one site, the surveyed scene characteristics can substantially change with time. Conversely, *traditional* ATC performance assessments (e.g., with accuracy and confusion matrix) are usually computed from all of the available test data (i.e., from the aggregate of all datasets).
- *FPs from individual non-truth tracks in a recording are first calculated and subsequently combined* (e.g., via average, standard deviation, etc.) to represent FP metrics. This facilitates defining KPIs such as timeliness and false alarms. Truth information is regularly unavailable for non-drone targets such as birds. This is unlike TP metrics pertaining to cooperative UAS targets during flight trials (e.g., from on-board GPS). True positive KPIs are attained from data of all tracks associated with the truth, within the corresponding radar recording.

For context, consider a fixed site protection scenario where a C-UAS radar at a civilian airport is tasked with reporting the presence of mUASs in the vicinity of (or within) the restricted flying zone covering the protected aerodrome [1]. Notation of the discussed metrics are listed in Table III. We make one further assumption here to streamline the notation. At any k^{th} time step (i.e., radar frame or update at time instant t_k), only one track can associate with the j^{th} truth/drone target. This can be easily generalised to multiple associations at t_k by appropriately defining the set $\mathbb{A}_j$ in Table III.

TABLE III: Notation for the proposed key performance metrics.

T	Duration (in hours) of the processed radar recording
J	Total number of detected-tracked drone/truth targets
N_T	Total number of formed tracks with unique IDs in the radar recording
$\mathbb{A}_j$	Set of time steps (i.e., radar updates/frames) where there is a track-plot associated with the j^{th} truth/drone target
N_j^+	Total number of time steps in set $\mathbb{A}_j$ and $N_j^+ = \lvert\mathbb{A}_j\rvert$
$\mathbb{T}_{j,i}$	Set of time steps where the i^{th} track is associated with a UAS
$c_{j,k}^+$	Confidence $c_{j,k}^+ \in [0,1]$ in the truth/UAS class at the k^{th} step (at time instant t_k) when a track is associated with the j^{th} drone target
$C_{j,k}^+$	Hard true positive, $C_{j,k}^+ \in \{0,1\}$, that the target is a UAS/truth when a track plot at t_k is associated with the j^{th} UAS/truth target
γ	Threshold value of a hard TP, $C_{j,k}^+ = 1$ if $c_{j,k}^+ > \gamma$ and 0 otherwise
$\mathbb{H}_j^+$	Set of tracks (of unique IDs) that are associated with the j^{th} drone/truth with $C_{j,k}^+ = 1$ for at least one time step
$t_{j,i}^0$	Time instant (in seconds) of the start of the i^{th} track which associates with the j^{th} truth/drone target for at least one time step
$\tau_{j,i}^+$	Time instant (in seconds) of the first/earliest HTP declared for the i^{th} track associated with the j^{th} drone/truth target
I	Total number of tracks (with unique IDs) not associated with any drone/truth target
$c_{i,k}^-$	Confidence $c_{i,k}^- \in [0,1]$ in the UAS/truth category for the i^{th} track plot at t_k not associated with the drone/truth target
$C_{i,k}^-$	Hard false positive, $C_{i,k}^- \in \{0,1\}$, that the target is a UAS/truth at t_k for the i^{th} track plot not associated with the drone/truth target
$\hat{\gamma}$	Threshold value for a hard FP, $C_{i,k}^- = 1$ if $c_{i,k}^- > \hat{\gamma}$ and 0 otherwise
$\mathbb{B}_i$	Set of time steps (i.e., radar update intervals) where i^{th} track is not associated with any of the truth/drone targets
N_i^-	Total number of time steps in set $\mathbb{B}_i$ and $N_i^- = \lvert\mathbb{B}_i\rvert$
M_u	Number of successive hard FP for a track not associated with a drone/truth track that produces a unique false alarm as per eq. (9)

B. TP Confidence, Deviations and Hard True Positives

The confidence $c_{j,k}^+$ estimated by the classifier is the one for the UAS/truth category when a track plot at time instant t_k (i.e., k^{th} radar frame or update interval) is associated with the j^{th} drone/truth target. Its values can range from 0 to 1 (or 0 to 100%) and represent the ATC certainty level in the target being a UAV. A decision on the target class can then be taken leading to the Hard TP (HTP) $C_{j,k}^+ \in \{0,1\}$ at t_k. This can be based on $c_{j,k}^+$ being larger than the value for all other target classes, or its own value exceeding a certain threshold γ, for instance at $C_{j,k}^+ = 1$ if $c_{j,k}^+ > \gamma = 0.9$ and zero otherwise.

The mean TP Confidence (TPC) for the j^{th} UAS/truth is

$$\text{TPC}_j = \frac{\sum_{k\in\mathbb{A}_j} c_{j,k}^+}{N_j^+}. \tag{1}$$

from the set $\mathbb{A}_j$ of all time steps where a track-plot is associated with the j^{th} truth and $N_j^+ = \lvert\mathbb{A}_j\rvert$. The average across all J drone targets in the radar recording (e.g., during a live drone trial) is given by: $\text{TPC} = \sum_j \text{TPC}_j/J$. An increase in TPC implies a better ability to recognize drone targets and with higher confidence. A related metric that can measure the consistency of the TP confidences is the standard deviation

$$\text{DevTPC}_j = \sqrt{\sum_{k\in\mathbb{A}_j} \left(c_{j,k}^+ - \text{TPC}_j\right)^2 / N_j^+}, \tag{2}$$

with average $\text{DevTPC} = \sum_j \text{DevTPC}_j/J$. A decrease in its value signifies an improvement in the ability of the classifier to recognise drones over a period of time.

Another metric to capture the variability in the TPC can be explored. Hard True Positive Classification Probability (HTPCP) for the $j = 1, 2, ..., J$ drone/truth targets is

$$\begin{aligned} \text{HTPCP}_j &= \sum_{k\in\mathbb{A}_j} C_{j,k}^+ / N_j, \\ \text{HTPCP} &= \sum_j \text{HTPCP}_j / J, \end{aligned} \tag{3}$$

where HTPCP is the *traditional* true positive or recall KPI.

C. UAS Declaration Probability (UDP)

The likelihood that the j^{th} UAS/truth target is correctly classified as a drone for at least one time step . This is termed UAS target Declaration Probability (UDP) and is given by

$$\text{UDP}_j = \begin{cases} 1 & \text{if } C^+_{j,k} = 1 \text{ for any } k \in \mathbb{A}_j \\ 0 & \text{otherwise} \end{cases} \tag{4}$$

and $\text{UDP} = \sum_j \text{UDP}_j / J$ for $j = 1, 2, \ldots J$. In other words, if a drone is within the radar system field of view and it has been detected-tracked, this is the likelihood of it being identified as a UAS. Higher UDP indicates a higher ATC reliability; it should be considered with the timeliness metric detailed next. A more demanding UDP rule can be adopted such as HTPs are required to be maintained for a fixed duration.

D. Timeliness: Classification Time Delay (CTD)

This conveys the delay incurred prior to successfully declaring, for the first time, a detected-tracked UAS/truth target as a drone. This is an ATC timeliness measure. For the i^{th} track which starts at time instant $t^0_{j,i}$ and associates with the j^{th} drone/truth target, its classification time delay (in seconds) is

$$\text{CTD}_{j,i} = \tau^+_{j,i} - t^0_{j,i}, \tag{5}$$

where $\tau^+_{j,i} = min\{t_k : C^+_{j,k} = 1, k \in \mathbb{T}_{j,i}\}$ is the first time step this track is declared as a drone target. A demonstration is shown in Figure 5 where we have a track break due to a temporary loss of the target (e.g. due to a target manoeuvre, loss of detections of the low observable target, high clutter region, etc.). Time instants $t^0_{j,i}$ and $\tau^+_{j,i}$ for the two tracks formed on the drone are marked by arrows. Track 1 and 2 last for five and four time steps (or updates), respectively. In this case and for a radar update period of 0.27s, $\text{CTD}_{j,1} = 0.27$s and $\text{CTD}_{j,2} = 0.54$s; $\text{HTPCP} = 5/9$ and $\text{UDP} = 1$.

The average and minimum CTD from all tracks (with unique IDs) that are associated with the j^{th} UAS/truth target and each have at least one HTP, i.e. set $\mathbb{H}^+_j$, are

$$\begin{aligned} \text{CTD}_j &= \sum_{i \in \mathbb{H}^+_j} \text{CTD}_{j,i} / |\mathbb{H}^+_j|, \\ \text{CTD}_{j,\text{min}} &= min\{\text{CTD}_{j,i}, i \in \mathbb{H}^+_j\}. \end{aligned} \tag{6}$$

Averages can be computed for all J targets as per $\text{CTD} = \sum_j \text{CTD}_j / J$ and $\text{CTD}_{\text{min}} = \sum_j \text{CTD}_{j,\text{min}} / J$. If one continuous track is formed on the UAS, i.e. no breaks, then $|\mathbb{H}^+_j| = 1$.

ATC timeliness can be critical where a minimal CTD is often sought. Early recognition of the mUAS provides C-UAS system operators with sufficient time to take necessary action to address any threat the drone might present, for example Air Traffic Management (ATM) can divert flights. If a new trajectory with a unique ID is created by the MTT for the same drone target (e.g., following a track break), it will be treated as a new track that may require scrutiny/interrogation by the surveillance system. Consequently, the average CTD can be a more suitable timeliness metric with a radar multi-target tracker that has a high rate of track number changes (R) and/or low longest track segment (both are SIAP measures of MTT continuity). CTD can be in reference to the time instant $tD0_j$ the mUAS was detectable in principle in lieu of $t^0_{j,i}$ in (5). This mixes detection and classification metrics and it is difficult to specify $tD0_j$ in complex environments.

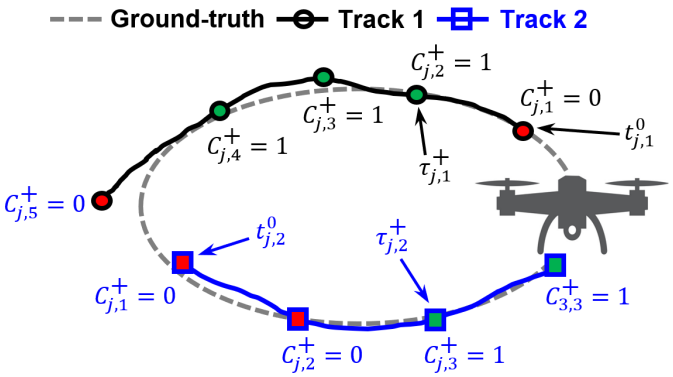


Fig. 5: Example of a UAS trajectory with two formed tracks on a mUAS due to a temporary loss of the target (i.e. a track break/death, for instance due to the target going through zero-Doppler and/or undertaking a sharp maneuver). Hard TPs are displayed (green is for 1 and red for 0). Time instants of tracks start and first HTP are indicated by arrows.

E. FP Confidence, Deviations and Hard FP

For the i^{th} track, which is not associated with a drone/truth target during the time steps in set $\mathbb{B}_i$ and $N^-_i = |\mathbb{B}_i|$,

$$\text{FPC}_i = \frac{\sum_{k \in \mathbb{B}_i} c^-_{i,k}}{N^-_i}, \quad \text{DevFPC}_i = \sqrt{\frac{\sum_{k \in \mathbb{B}_i} \left(c^-_{i,k} - \text{FPC}_i \right)^2}{N^-_i}}, \tag{7}$$

are the mean False Positive Confidence (FPC) and its deviations, respectively. Hard False Positive (HFP) follows from a decision scheme with $C^-_{i,k} \in \{0, 1\}$ at t_k, for instance $C^-_{i,k} = 1$ if $c^-_{i,k} > \hat{\gamma}$ and 0 otherwise. Whilst average from all non-truth trajectories can be obtained, reporting the L (e.g., $L = 10$) tracks with the highest mean FPC can be highly beneficial to understanding the ATC false positive behaviour.

A decrease in the mean false positive confidence implies an improvement in the ability to classify a non-drone as a non-drone, hence potentially reducing hard FPs and false alarms (see Section III-F). Lower DevFPC (for selected tracks or average across all non-drone tracks) suggests a more consistent classification of non-drone targets. The *traditional* (hard) false positive metric, referred to here by False Positive Classification Probability (HFPCP), within the studied radar recording is

$$\text{HFPCP} = \sum_i \sum_{k \in \mathbb{B}_i} C^-_{i,k} / N^-_i. \tag{8}$$

F. False Alarm Rate

This is the number of tracks that trigger a false alarm and can require the operator and/or secondary sensor attention (e.g., camera to confirm the target class). We measure this as a

rate, per hour and/or per R_{Track} tracks. False alarms are based on hard false positives, i.e. post deciding the target class (e.g., with a thresholding or MAP criterion). The i^{th} track triggers a Unique False Alarm (UFA), i.e. $\text{UFA}_i = 1$, if the ATC makes a M_U successive hard false classifications for this non-drone trajectory, at least in one occasion such that $M_U \geq 1$ is an integer. We can formulate this for the i^{th} track not associated with the UAS target at the $k \in \mathbb{B}_i$ time steps as follows

$$\text{UFA}_{i,k} = \begin{cases} 1 & \text{if } k \in \mathbb{B}_i \text{ and } \sum_{min(k,k-M_U+1)}^{k} C_{i,k}^{-} \geq M_U \\ 0 & \text{otherwise} \end{cases},$$

$$\text{UFA}_i = \begin{cases} 1 & \text{if } \sum_k \text{UFA}_{i,k} > 0 \\ 0 & \text{otherwise} \end{cases}. \tag{9}$$

It is thus unique since one track can cause one false alarm.

The False Alarm Rate (FAR) per hour is

$$\text{FAR} = \sum_{i=1}^{I} \text{UFA}_i / T, \tag{10}$$

and FAR Ratio (FARR) per R_{Track} tracks (e.g., $R_{\text{Track}} = 100$),

$$\text{FARR} = R_{\text{Track}} \sum_{i=1}^{I} \text{UFA}_i / N_T. \tag{11}$$

These two performance metric determine: a) the user confidence in the radar classifications since false alarms can be extremely distracting for operators; b) the load on the C-UAS solution secondary sensors (e.g., cameras, RF direction finders, etc.); and c) potential for automation to reduce human-intensive CONOPS. Minimising the false alarm rate is amongst the main challenges for long-range drone surveillance radars [14], [17], [20]. It is noted that less strict UFA_i scheme can be employed in (9), e.g. M_U nonsuccessive hard FPS.

G. Standard Metrics and Others

As well as the standard recall (i.e., HTPCP) in (3) and FP (i.e., HFPCP) in (8), other standard metrics such as accuracy, F_1 score, confusion matrix and ROC (e.g., for any of the TP versus FP measures to ascertain a suitable decision threshold) are well-understood and can be utilised to evaluate the ATC performance. The mUAS classification problem is however markedly unbalanced, with typically far more non-drone data compared to drone due to confuser targets (e.g., birds). It can be more reasonable to apply different weights to HTPs and HFPs when calculating any measure that mixes them, thereby "*weighted*" accuracy, F_1 score, etc. Otherwise, the true negative and FP data points can dominate the outcome. For this reason, we introduced in this paper additional metrics.

Examining ATC results with accuracy and/or F_1 scores alone can hide a high false alarm problem. This is because only if a small "percent" (e.g., 0.1%) of the large number of non-drone tracks (e.g., 8,000 per hour, see Table II) can lead to an excessive FAR (per hour) that can deluge the C-UAS system and/or operators. This can occur even if the accuracy and F_1 scores are satisfactory high (e.g., exceeding 95%).

We explored SIAP inspired ATC metrics [28] such as classification spuriousness (i.e., ratio of extant HFPs to all hard positive classifications), continuity (i.e., maintaining correct UAS identification over time) and ambiguity (i.e., over reporting drone presence). They were viewed to rank lower in terms of relevance to requirements of non-cooperative drone surveillance systems compared with those detailed above.

H. Sensitivity to Signal to Noise Ratio

Classifiers efficacy is generally sensitive to the SNR pertaining to the drone target, especially in terms of the detectability of its micro-Doppler signatures [14], [19], [21]. For example, CNNs' impressive classification accuracy drastically degrades as SNR decreases [21]. A lower SNR can be due to one or more of the following reasons: 1) longer target range, 2) smaller UAS platform (i.e., RCS), and 3) complex environment with higher background noise from clutter and interference.

Therefore, it is paramount to quantify the ATC sensitivity to SNR. This can be achieved by plotting the true-positives-related classification metrics (e.g., HTPCP, TPC, accuracy and F_1 score) versus the estimated SNR from real radar data (see next section) and/or from synthetically injected noise as in [21]. This ensures a better assessment of the radar "classification range" against different mUAS types/sizes and resilience to environmental factors. Maximising ranges at which miniature drones can be recognised is vital to implementing effective system level CONOPS and threat mitigation protocols. For instance, a mUAS moving at a speed of 15m/s towards the airport glide slope and classifying it at 1.8km away from this prohibited region gives ATM operators 2 minutes to warn civilian airplanes landing and taking off; this can be increased to 4 minutes if the ATC range is extended to 3.6km.

IV. Example Results[1] from Real Data

To demonstrate the ATC metrics in Section III, here we use real measurements from the Gamekeeper staring radar. They were collected during 25 live drone trials (i.e., radar recordings) at various sites, including those in Table II. Each recording is of a duration of 5 to 16 minutes and can have up to 6300 target tracks with unique IDs. It has one UAS target (i.e. $J = 1$), whose ground truth information from onboard GPS is available. The overall test data is ≈ 4 hours of radar measurements in total and comprises of over $55,000$ trajectories to be classified (drone versus non-drone). It contains observations from numerous mUASs such as the DJI Phantom 2 (diameter $\approx$ 0.4m and weight $\approx$ 1.38kg), DJI Inspire 2 as in Figure 3, DJI Matrice 200 (diameter $\approx$ 0.9m and weight $\approx$ 5.5kg), DJI Mavic 2 ($\approx 0.35m$ and weight $\approx$ 0.9kg), fixed-wing BlueBear Blackstart (diameter $\approx$ 1.5m and weight $\approx$ 4kg), Alta X (diameter $\approx$ 1.4m and weight $\approx$ 10kg) and Octocopter (diameter $\approx 0.9m$ and weight $\approx$ 4.5kg) at ranges up to 7.5km; over 50% of drone flights were at ranges exceeding 3km. This is a diverse and challenging data with a wide range of SNRs (mean 35.14dB and standard deviation 7.42dB).

The machine-learnt ATC algorithm [17] with an SMA as in Figure 4 is utilised with a MAP decision criterion for the hard

[1]Results here are from experimental algorithms and should *not* be considered in anyway to represent the performance of the Thales Gamekeeper radar, which uses proprietary processing chain inclusive of the ATC.

TABLE IV: Average ATC performance from real radar data.

Metric	Value	Optimal Value
Accuracy	0.97	1
F_1 Score	0.85	1
Hard TP Classification Probability (HTPCP)†	0.83	1
TP confidence (TPC)	0.76	1
TPC Deviation (DevTPC)	0.17	0
Hard FP Classification Probability (HFPCP)†	0.02	0
False Alarm Rate FAR (per hour)	3.4	0
FAR Ratio FARR (/100 tracks); $R_{\text{Track}} = 100$	0.03	0
Classification Time Delay CTD (seconds)	9.15	0
UAS Declaration Probability (UDP)	0.98	1

†They correspond to the traditional (hard) TP and FP metrics definitions.

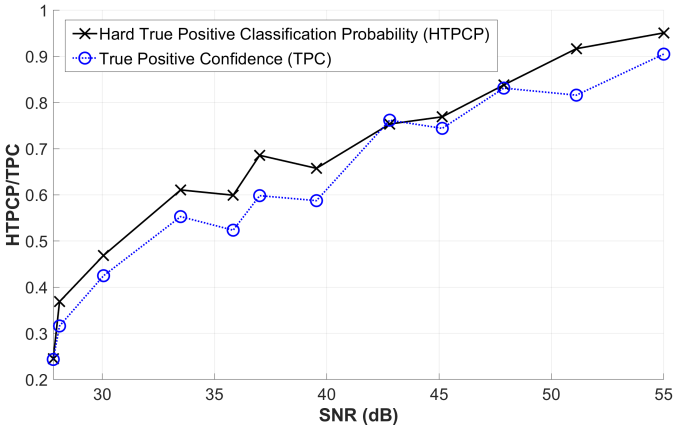


Fig. 6: Hard true positives and TP confidence for the test dataset versus the estimated SNR for the truth (drone) targets.

true and false positives. Table IV lists the averages of selected ATC metrics from all of the 25 radar recordings. One hard FP per track produces a FA with $M_U = 1$ in (9). It can been noticed that the high accuracy and low hard FP (HTPCP) does not give any insights on the potential false alarm rate, where 3.4/hour on average can be regarded as high in some C-UAS scenarios if only a radar sensor is employed.

The average true positive confidence and hard true positive classification probability versus SNR from the real data is depicted in Figure 6. The substantial decay in TPC and HTPCP is visible as SNR declines. Finally, Figure 7 shows the ROC plot of the average HTPCP (recall) versus FAR (per hour) from all of the testing datasets; this is for a wide range of possible decision thresholds (i.e., rather than choosing the target category with the highest confidence score as with the MAP decision criterion as in Table IV). It exhibits the usual compromise between the classifier's TP and FP performance.

V. Additional Capabilities and Prospects

We now discuss a few opportunities and technologies that can aid improving the ATC functionality in drone surveillance radars, for example to keep pace with the continuously evolving drone platforms. This goes beyond general system-level resilience, coverage and data quality issues [3], [5], [29], for instance utilising distributed, multi-static, sensing-processing concepts and state-of-the-art hardware (e.g., quantum oscillators, antenna designs, GPU-TPU-CPU, etc).

A. Target Recognition Beyond Drone versus Non-drone

Estimating the drone physical parameters such as the number of rotors and their rotation/flash rates, from the radar micro-Doppler signatures has a long history. It can offer indicators of the mUAS type (e.g. fixed or rotary wing), specific platform and any payload [12], [30]–[32]. For example, the number of blades and their rotation speeds can be referenced against a database to establish the drone model. Similarly, the heavier the weight a drone needs to carry, the faster its rotors typically need to spin to provide sufficient lift. An abrupt change in the rotation rates can pertain to the drone releasing a payload. This information can aid ATC, where classical spectral analysis tools (e.g., cepstrum) or neural networks can be utilised for estimating the UAS physical parameters [30].

The ML classifier can be explicitly trained to recognise particular drone types or models [14], [18], [33]. This necessitates the availability of datasets per target label, thus higher training data requirements and/or applying a well-defined pipeline for refining a learnt ATC algorithm, for instance with transfer learning [14]. An alternative approach is to label the training data with parent (abstract) classes that the ATR then treats, for example small fixed-wing, large rotary wing and small rotary wing for a CNN micro-Doppler classifier as in [18].

B. Cognitive Radar and Sensing Networks

The availability of low-cost electronic antennas, high performing, easily programmable, signal/data processing hardware and high-quality digital waveform generators are amongst those technology advancements that enable embedding intelligence or cognition within modern radar systems. These sensors can in principle be proactive and tailor their resources to multiple mission, for example to increase performance against certain low observable targets such as drones whose salient radar signatures (e.g., micro-Doppler from rotors) can be otherwise undetectable due to the background noise-clutter [34], [35]. The radar can suitably adjust its transmission, beam-forming, and other parameters. It can specifically adapt its data acquisition (dwell-time) and processing (e.g., complexity of applied tracking and ATC algorithms) in a given target resolution cell in order to increase the SNR and maximise chance of detecting any micro-Doppler signature(s).

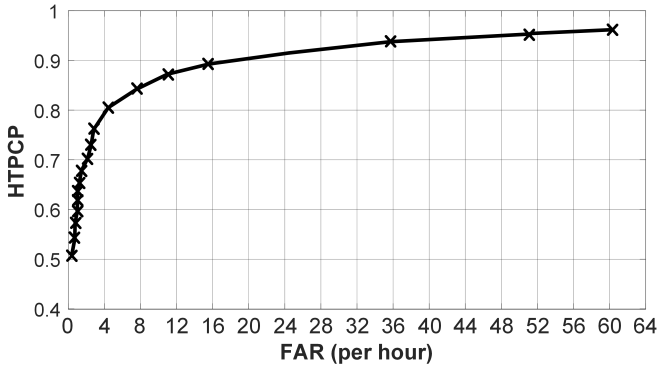


Fig. 7: Hard true positive classification probability versus false alarm rate per hour from radar measurements.

Given the prevalence of occlusions to the radar line of sight and persistent clutter in dense urban or other environments with large structures such as wind turbine, a networked or multi-static radar system with multiple spatially distributed transmitters and/or receivers might be required to maintain situational awareness over wide monitored regions. Such solutions have additional system-level challenges to overcome such as synchronisation, data fusion, networking topology, etc. This is an active research area, see [3], [12], [29], [31], [36].

C. Simulators and Digital Twins

The main limitation for training generalisable ML classifiers is the availability of extensive radar datasets for all targets of interest. This is compounded by the relatively high cost of conducting controlled drone trials to collect real measurements; more so for birds instrumented with sensors (e.g., GPS tags) to provide ground truth information or utilising a sophisticated automated labelling system (e.g., using cameras). Hence, there is a pressing need to generate representative synthetic radar data, including to augment the limited available real radar measurements. Conventional full electromagnetic physics-based radar simulators are generally prohibitively complex and time consuming to construct as well as difficult to validate. On the other hand, generative AI technology, such as transformers, generative adversarial networks, variational autoencoders, can expedite the process of simulating realistic radar signatures of various targets for training ATR algorithms. Easy and cheap access to representative simulated radar data can be revolutionary to the drone surveillance radar functionalities in the era of AI and data centric engineering. For example, it can permit adopting advanced fully or model-driven ML/AI for target detection [19] and track-before-detect methods [10] to enhance the radar ability to detect micro-Doppler and track low observable UAS targets (including when hovering).

Leveraging fully digitised and easily programmable processing chain as well as access to elaborate data simulators, digital twins can promote the rapid development, verification-validation and integration of new ATR algorithms [35]. For example, the Thales Gamekeeper radar has a full digital twin of its processing chain, and the raw I&Q data from each receiver element can be recorded and re-processed. Refinements to the detection, MTT and ATC modules can then be rapidly validated and deployed on radars in the field.

D. Global Classification Architectures

Different classifiers can rely on distinct underlying salient characteristics in the target radar signatures (e.g., micro-Doppler components or kinematic behaviour) and over different time-scales as in Figure 4. Simultaneously employing disparate classifiers that can be potentially asynchronous (i.e., update at different rates) and heterogeneous (i.e., have different target categories) can deliver more robust automatic target classification, such as the global classification architecture with classifiers dedicated to kinematic-features-based discrimination and others to micro-Doppler detection in [16]. Applying different versions of a classifier (e.g., several realisations of the same deep neural network, each configured following a particular initialisation of its weights) and combine their results is common in supervised learning; see [37]. This can be extended to utilising asynchronous and heterogeneous recognition algorithms with the associated fusion mechanism.

E. Exploiting Contextual and Pattern-of-life Information

Given the complexity and diversity of the large surveyed areas with radar, available contextual (e.g., terrain type) or pattern-of-life (e.g. bird migration times) information can be highly effective at improving ATC and addressing the high false alarm challenge at the sensor level. These can bias/influence the classifier results and the associated decision criteria on the target category. For example, false alarms originating from objects near major roads or dense urban areas, where high density vehicle traffic is expected (or even dynamically detected) at selected times can be suppressed or have a higher decision threshold. Similar schemes can be applied for detected large flocks of birds or even the occasional presence of bird species that can trigger FAs such as large gliding birds (e.g., from ornithologist studies or observations).

Therefore, a data fusion approach (e.g., within a Bayesian framework) would be required to capitalise on additional information about the monitored scene or present targets at the radar sensor or even at the C2 system level for a more robust ATC. This nonetheless carries the risk that inaccurate priors can undermine the radar ATC effectiveness and adversaries can exploit them. It is noted that contextual or pattern-of-life data can also be learnt from historical radar data as with discriminative long-term behaviour features in Section II.

F. Meta-level Information Inference and Malicious Intent

As drones use is set to proliferate further, it will be critical for surveillance systems to be able to infer "*meta-level*" information on the detected-tracked-classified UAVs, namely their intent (e.g., final destination and future trajectory to unveil, as early as possible, malicious activities) and group interactions-hierarchies in drone swarms (e.g., reveal coordinated mUASs groups and, if relevant, their leaders which can have more on-board capabilities). This can circumvent the system or operator being overwhelmed by swamping tactics. It facilitates timely decision making, automation and prioritisation of potential threats as well as selective deployment of countermeasures (if relevant), thereby minimising potential collateral damage.

Bayesian meta-level tracking offers a generic framework, for instance to determine, early, if a drone intends to reach a prohibited zone [38] or reveal a swarm hierarchy [39]. This can incorporate the ATC results as priors. For example, if the ATC indicates that a drone is carrying a payload, then this is strong indicator of malicious intent. Some of these functionalities can be employed at the C2 level, rather than by the radar sensor.

VI. Conclusions

Robust automatic target classification is fundamentally important for drone surveillance radar, especially given the large number of potential confuser targets (e.g. birds) and complex monitored environments. Although mUASs are formidably difficult targets to detect, track and classify with radar, several

sensors (including in multi-static configurations) have emerged over the last few years. They increasingly exploit recent advances in data processing and machine learning (e.g., deep neural networks) to deliver a strong ATC performance.

It is however crucial to: a) understand the unique challenges mUAVs pose to radar sensors and ATC enablers, especially that drone platforms are expected to continuously evolve and adapt as adversaries strive to make them harder to detect; b) consider relevant classification metrics when evaluating the efficacy of the classification approach; and c) highlight opportunities for future radar solutions. These aspects are discussed in this paper. The objective is to promote a better appreciation of what is achievable in practice now and in the future, i.e. articulate the relationship between the art of the possible and operational effectiveness of automatic classification of drones with radar. An example is the common stringent ATC false alarm rates requirement on a C-UAS solution (e.g., one FA every several days or weeks). This is currently unrealistic to meet with a radar sensor alone whilst maintaining the ability to detect-track-classify miniature (e.g., micro and nano) drones in complex urban/semi-rural environments. Whilst this can be fulfilled by a multi-sensor system within which radar is a critical component, the full potential of the C-UAS/UTM radar technology is yet to be realised.

Although we predominately focused here on ground surface radar and performance evaluation for a binary classification task (i.e. miniature drone versus non-drone), several of the presented arguments seamlessly apply to maritime and airborne radars. Metrics can also be easily extended to multi-class ATC scenarios and other targets (e.g., larger UAVs).

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