An Artificial Intelligence Application for a Network of LPI-FMCW Mini-radar to Recognize Killer-drones

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Abstract: The foundation of Internet Information Systems has been initially inspired by military applications. Means of air attack are pervasive in all modern armed conflicts or terrorist actions. Thus, building web-enabled, real-time, rapid and intelligent distributed decision-making systems is of immense importance. We present the intermediate results of the NATO-SPS project "Anti-Drones" that aims to fuse data from low-probability-of-intercept mini radars and a network of optical sensors communicating with web interfaces. The main focus of this paper is describing the architecture of the system and the low-cost miniradar sensor exploiting micro-Doppler effect to detect, track and recognize threats. The recognition of the target via an artificial intelligence system is the pillar to assess these threats in a reliable way.

1 INTRODUCTION

Killer drones represent a real threat, today we cannot not mention them as a surprisingly lethal weapon, e.g., in the Russian invasion in Ukraine, so far. Unmanned Aerial system (UAS), which carry lightweight, laser-guided bombs, normally excel in low-tech conflicts, have carried out unexpectedly successful attacks in the early stages of Ukraine's conflict, before the Russians were able to set up their air defenses in the battlefield. Commercial-derived, self-built as a hobby, UAS have long been used for terrorist attacks on civilians and institutions or used for other crimes such as weapons infiltration into prisons.

To facilitate the countering of killer-drones and minimize the risk for people and assets, a NATO SPS Anti-Drones project 1 has been focalized on the development of a new concept of a Threat Evaluation Subsystem (TE) of an anti-drone system able to detect, recognize and track killer-drones. The project scope is to progress the state of the art applying mini-radar technology and signal processing, web data processing and fusion, for improving real-time intelligence of the TE subsystem and dramatically reducing the environmental impact (e.g., ECM pollution) in an urban environment. The core of the system architecture is a network of LPI (Low-probability-of-intercept) mini-radar with FMCW or noise-like waveform, web-interfaced with on-demand, fully digital, optical camera-integrated imaging capability, capable of working in all weather conditions, to be deployed and appropriately placed on the ground in the area of the asset to be protected. Detection, tracking and recognition of UAS with mini-radar using micro-Doppler features is becoming more and more popular in last few years as noted in Guo et al. (2019), Harman (2016) and Huizing et al. (2019).

The optical part is essential to support correct classification and tracking of the threat and thus to minimize false alarms. However, this paper mostly focuses on the proposed system from the radar point of view.

Next, the paper is organized as follows. The system conceptual design is described in Section 2. System requirements are described in Section 3. Section 4 describes the developed radar devices. System implementation detailed design takes part in Section 5. After the citation of the requirements needed, some results obtained during a preliminary measurement campaign are shown and discussed in Section 6. Section 7 describes the implemented

[1] https://antidrones-project.org/, last access 22.08.2022

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features extraction process. Finally, the paper concludes with ending notes.

2 THE CONCEPTUAL MODEL

The solution proposed in Anti-Drones project is based on the following subsystems:

- A network of LPI polarimeter mini-radar with wave shape FMCW or noise-like, with low environmental impact and capability of camera imaging on-demand, fully digital, easy reconfigurable and high level of flexibility and versatility, able to work in all weather conditions, to be deployed and opportunely positioned (on ground) in the zone of asset to be protected.
- A data processing and fusion subsystem able to generate the situational awareness and to enable the fast detection, recognition and tracking of the threats within the max time to activate the neutralization action.

A high-level representation of the system is given in Figure 1. As can be seen, the sensing layer is responsible for gathering the information from the operational environment and it includes all the sensors involved in the proposed solution. Such information is passed to the Information Layer that is responsible to process and transform it in order to get a global situational awareness of the observed scene. More specific, such layer include the detection process and the tracking and classification one. The algorithm that will be used to fulfil these tasks are out of the scope of the paper and will be not described here. The architecture includes also a communication layer responsible for communicating the gathered data to the processing unit through Internet protocols. Well-defined APIs and web services will be used for each sensor module to support data fusion in the Information Layer.

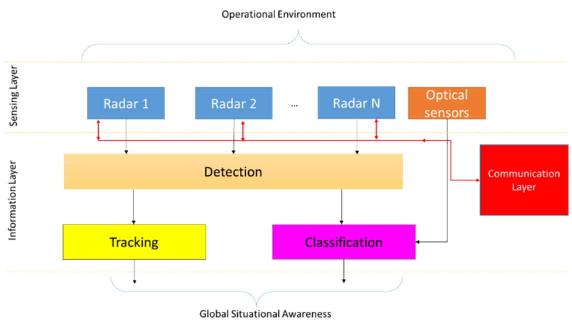


Figure 1: Anti-Drones high-level architecture.

3 AIM, REQUIREMENTS AND OUTLINE

The solution proposed in Anti-Drones project is based on the following subsystems: Air surveillance is divided into four phases:

1) Detection
2) Recognition
3) Identification
4) Tracking.

As much for airspace surveillance in general as for UAS' detection specifically, the radar surveillance means remain the primary sources of information in the predictable future. The significance of optical, acoustic and laser sensors is anyway rising quickly – according to technology development. Their mutual interconnection, interoperability and modularity should lead to synergic effects reside at minimum in detection probability rise and false alarms reduction, as cited in Krátký & Fuxa (2015).

With this project, we foresee a cooperation of sensors, aiming to a better evaluation of potential threats.

Several requirements can be assessed in term of the range needed

- General requirements (in clutter free environment and for hovering drones);

  Detection of the drones: 3km; Recognition: 2.5km

- The range requirements will be subject to the constraints of the selected scenario that can limit the radar visibility range. In this case, the following requirements will be considered the proper trade-off between the desired ones and the concept demonstration (in clutter free environment and for hovering drones);

  Detection of the drones: 1.5km; Recognition: 1km

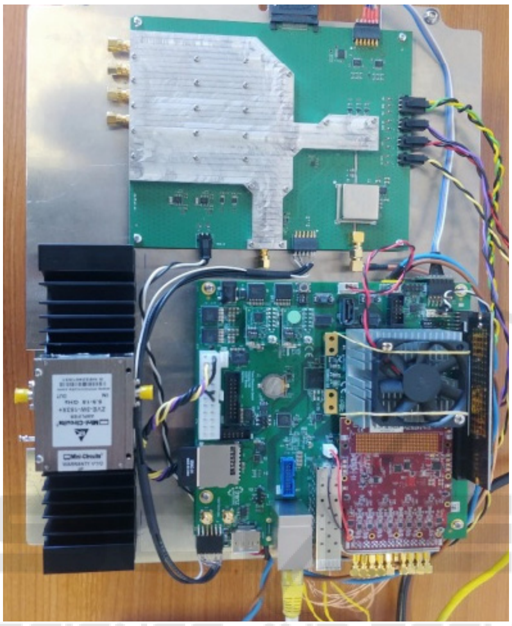
- In the case of moving drones, the following requirements will be considered the proper trade-off between the desired ones and the concept demonstration;

  Detection of the drones: between 500m and 1km, according to the flight trajectory, type of drones and speed; Recognition: 300m.

4 SENSOR PROTOTYPES

4.1 Radar

The radar sensor developed within this project in collaboration with Italian company Echoes S.r.l., shown in Figure 2, is a multichannel linear frequency modulated continuous wave (FMCW) radar system for the detection and recognition of moving targets.



(a)

(b)

Figure 2: (a) radar structure. (b) case with antenna connectors.

The architecture of this radar consists of one transmitting and three receiving channels. A fourth receiving channels can be installed if needed during further research. The ability to use a fourth channel allows the use of this hardware to be extended and also reduce costs to future follow-ons of the ANTI-DRONES project currently under review by NATO-SPS offices for the three-year period 2023-2025. The antennas are external to the main cabinet to allow different acquisition geometries to be created. In fact, this configuration allows different radar processing techniques to be applied. For example, by assuming that the antennas are correctly positioned, three-dimensional interferometric inverse synthetic aperture radar (3D InISAR) algorithms or monopulse processing can be applied. In addition, several radar fusion techniques can be exploited in order to increase the detection and recognition capabilities of the system. The sensor works at X-Band at 9.6GHz, with a selectable bandwidth from 300 to 500MHz. Transmit power is up to 33dBm, with a Noise Figure of 6dB.

Table 1 shows the maximum range for each RCS value. In our case, we should have a RCS between -20 and -10dBm^2

Table 1: Maximum range vs. RCS with 20dBi antenna gain and 0.5s integration time.

RCS Values	Max Range [m]
-30 dBm^2	890.89
-20 dBm^2	1591.59
-10 dBm^2	2822.82
-5 dBm^2	3763.76

4.2 Camera

Optical-based detection, recognition and tracking is based on real-time optical camera images and sequences. This process is implemented with deep learning (DL) methods, providing the target class, the corresponding bounding box and accuracy rate, as described in Jajaga et al. (2022). Namely, the camera detection and recognition components are implemented with the popular DL framework YOLOv4 as explained in Bochkovskiy et al. (2020). The model is trained following a fine-grained methodological approach for refining the dataset based on a number of open drone datasets.

5 IMPLEMENTATION

This section describes in more detail the processing chain of the TE system. The flowchart shown in Figure 3 emphasizes the dual path needed for a reliable detection and recognition. In general, optical and radar systems will operate together in order to increase the probability of success in the recognition chain. Moreover, an information fusion system will recommend the end user with a proposed decision to be taken as the final operative decision.

The processing flow is the following:

1) Noise mitigation with 2D Wiener Filter
2) Moving Target Indicator (MTI) filtering to remove clutter and radar artefacts
3) Detection of the body of the drone via CFAR filtering
4) Kalman Filter Tracking (useful only if multiple tracks are present), made on subsequent data batches
5) Recognition via feature extraction (number of blades, micro-Doppler spectrum shift)

The camera module will use the detection details from the radar module to initiate the recognition and tracking process of the target. Namely, for each radar-detected target, the camera will accurately and quickly the position in the direction of the moving target. Radar data to support camera recognition and tracking include the following: the target angle, the height where it is located and the speed. The two branches will work separately achieving their objective.

However, the success of a single system is not given for granted. It must be noted that the system performance gets affected on several operating environment circumstances, such as: day vs night, rain vs sun, distance of the target, colour of the target, intrinsic resolution of the sensor, etc. Given these issues, we need a final step where we fuse the decision achieved from the two sensors, together with the confidence level and the possible knowledge of false alarms.

Typically, this step is needed for confirming sinergically the decisions of either branch, or to overcome shortcomings of one of the two, when particularly adverse conditions for a specific sensor arise. Thus, in our approach the data fusion module will be performed in heterogeneous and homogeneous manners.

Namely, the system must fuse together heterogeneous radar and camera data, while also supporting fusing of homogeneous data from the corresponding data source. Specifically, our solution will fuse the following target attributes based on two sensor sources:

1) Radar data: Direction of arrival, range, angular coordinates elevation and radar cross section.
2) Optical camera data: photo and video images.

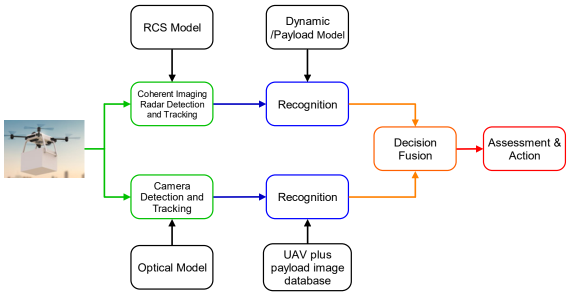


Figure 3: Processing Flowchart.

Data Assurance techniques for maximum confidence in data quality are also ensured. Data from the sensors are saved in a RAW format so phenomena of bit-rot (the decay of electromagnetic charge in a computer's storage) or bit-flip could alter present or future analyses on the data collected during the trials. For this reason, a highly resilient long-term storage solution was chosen to avoid any impediment to the pace of research. Such a solution inspires the so-called next-generation "black boxes" (i.e., EVENT DATA RECORDER) and is based on cryptographic filesystems and Merkle trees as cited in Cantelli-Forti & Colajanni (2019). The proposed solution has periodic and on-the-fly self-diagnosis and self-healing capabilities. The maximum throughput currently achieved is 2 GB/s and ready for the next stages of SPS-AntiDrones research.

6 EXPERIMENT DISCUSSION

The aim of the campaign was primarily to assess the possibility of recognition of small drones and medium-sized drones. The second objective is to assess the possibility of tracking such UAS in a noisy environment, and finally, to assess the possibility of recognition among different types of UAS.

Figure 4: Photos of the hexacopter (left) and quadcopter (right).

The observation campaign was performed in a mostly building and tree free area, where the main source of clutter came from short grass, mainly from the sidelobes of the radar, whose orientation was slightly toward the sky.

Two UASs, a hexacopter and a quadcopter were used as a test target as shown in Figure 4.

As an example, on a generic UAS, first step deals with noise reduction. A 7x7 Wiener filtering was performed. The drawback of this procedure is that there is a little loss in resolution, so if the target is very small, is probable that only a single point can be detected, and this can be detrimental for recognition.

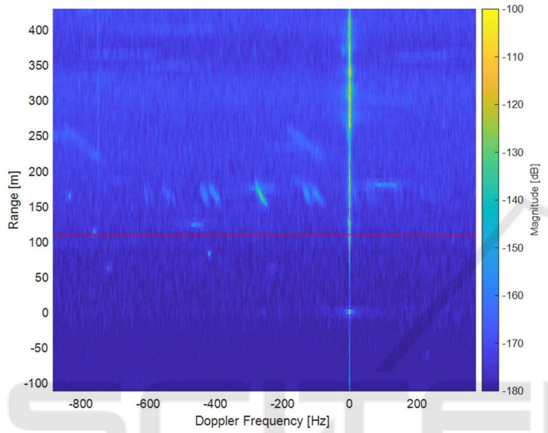


Figure 5: Range-Doppler map after smoothing.

Figure 5 shows the result of the smoothing operation, while several artefacts and the clutter are still visible. Figure 6 shows the result of MTI filtering, which enhances the target and the blades (moving parts) while cutting clutter and artefacts. Red lines represent minimum and maximum limits for correct detection.

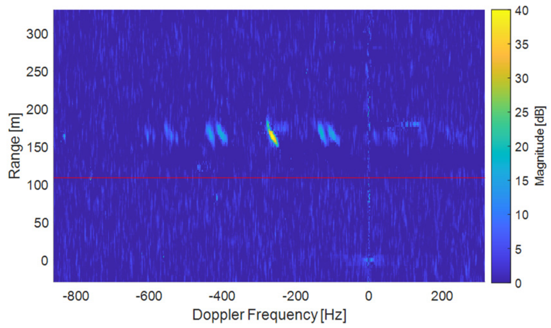


Figure 6: Detail of Range Doppler map after MTI.

Figure 7 shows the results for the hexacopter. It is interesting to observe, as shown in Figure 7, the contribution for recognition given by the blades. A total of six contributes from the six blades are visible, three to the left and three to the right (highlighted in red boxes). Usually, for a helicopter drone, for symmetry reasons half of the rotors are in front of the body (the signatures at the left) and half are on the back (signatures on the right) with respect to the line of sight. The image lacks more detail for further identifications, but with the next images, ulterior details will be more visible. The Doppler distance between blades signature is about 50Hz.

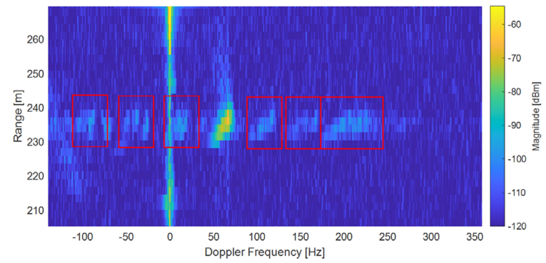


Figure 7: Detail of drone body and blades for the hexacopter.

Being it a quadcopter, we have four blade signatures, as can be seen in Figure 8. It is interesting to see that each of the signature of the blades has two separate contributes. This happens because the rotating movement of a blade makes that a part of it moves away from the radar, and one moves toward the radar, inducing two different micro-modulation effects.

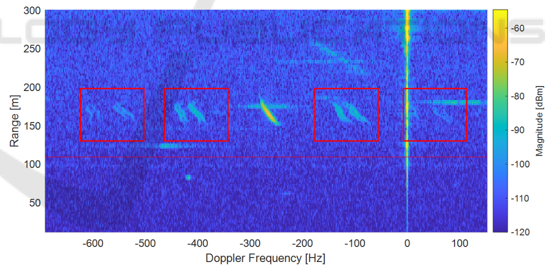


Figure 8: Detail of drone body and blades for the quadcopter.

Moreover, two blades compose each blade group, so it is possible to see that for each blade signature group there are four lines, divided into two couples, by accounting for the movement of each half of a blade itself. The Doppler spacing is about 150Hz.

7 FEATURE EXTRACTION WITH AI

The micro-Doppler signature of the blades of a UAS (which travel at high speeds) provides an effective mechanism, which can discriminate targets from objects from nature with similar characteristics, such as birds, and differentiating between UASs.

Spectrogram is the most popular technique for micro-Doppler analysis, as it is simple and able to reveal the time-frequency variation of spectral content. The spectrogram is the squared magnitude of short-time Fourier transform (STFT), where the STFT is done by segmenting the raw data into a series of overlapping time frame and performing FFT on each time frame

The clustering is performed with the spectrogram. For each cluster, the sum of within-cluster matrix $\mathbf{S_w}$ and between-class matrix $\mathbf{S_b}$ is calculated and the Fischer Discriminant Analysis is conducted again (further subspace reliability analysis). The application of between-class matrix can greatly improve the discriminability of different classes. Finally, the Mahalanobis distances of all training samples to the centre of each cluster of two class are calculated, which then undergo a min-max normalization and are taken as the training features feeding to the classier for model training. Here, the Support Vector Machine (SVM) is used as the classifier

The extracted features from the data are:

- Base velocity or body radial velocity.
- Total BW (Bandwidth) of Doppler signal.
- Offset of total Doppler.
- BW without micro-Doppler.
- Normalized standard deviation Doppler sig. strength
- Cadence/cycle frequency.

The SVM is able to correctly classify most of the target and false alarms are higher only when comparing, as expected, quadcopter and hexacopter, as shown in the Confusion matrix in Figure 9.

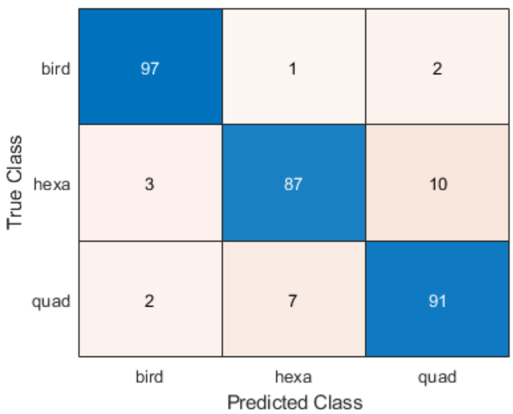


Figure 9: Confusion matrix from SVM.

At the project status, a thorough comparative evaluation with the optical system is still running, but the final aim of the project itself is the merging of the two system in order to overcome each shortcoming. Also, a more extensive database is needed to train better the classification system to be more efficient for different non-cooperative scenarios.

8 CONCLUSIONS

In this paper, a solution to monitor a scenario where potential threats posed by armed drones is proposed by combining a network of low-power low-cost FMCW radar and optical sensors. In this work, it was analysed principally the radar solution, and after an overview of the system, the results of a preliminary measurement campaign showing the feasibility of the solution. It has been shown how it is possible to detect even low RCS target, given a reasonable range, and how from the data acquired is even possible to detect different features of different drones exploiting micro-Doppler effects, giving also information on rotor numbers, number of blades and rotation speed.

Future work should demonstrate how the performance of the TE subsystem could be improved by the development of an AI-framework (i.e. algorithms, methodologies and techniques) on sensor signal processing, such as radar signals and EO/IR images, and target trajectories to enable the multi-targets' detection, classification and tracking.

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