Fusion of RADAR and acoustic arrays for drone detection in restricted air-space

Fusion of RADAR and Acoustic Arrays for Drone Detection in Restricted Air-Space

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***Abstract*—During the past decade, the popularity and availability of drones have increased drastically. This is a concern for airports worldwide as unauthorized drone traffic is also increasing. Because of this, there is a need for robust and accurate drone detection systems. Multiple drone detection techniques already exist in literature, each with their respective shortcomings. In this paper, we implement a proof-of-concept in which the accuracy of a RADAR system is expanded with an acoustic array that can differentiate between objects based on their ultrasonic emissions. This approach allows for a robust active sensing system with a decreased number of false positives (e.g., birds). Outdoor tests have been carried out with off-the-shelf components against multiple variants of drones. Both the strengths and weaknesses of this approach are identified and discussed, along with potential improvements that can aid the practical implementation of this concept.**

***Index Terms*—RADAR, Acoustics, arrays, signal processing, drone detection**

I. Introduction

Low prices and ease of use have increased the popularity and availability of multi-rotor drones in recent years. The total market size for personal use was valued at 3.6 billion dollars in 2021 and is expected to grow at a compound annual growth rate of 20.8% from 2022 to 2028 [1]. This is a concern for many airports worldwide as unauthorized traffic in restricted zones is also increasing. In a report by the UK Civil Aviation Authority, which investigates aerial near-miss incidents, they state that there is a 10% year-on-year rise of unmanned aerial vehicle near-miss incidents in 2021 [2]. In the following years, drones will become even more prevalent as they can be used for applications in surveillance, disaster relief, agriculture, health care, or emergency response. However, they do not come without risks and dangers, such as the possible usage in terrorist attacks, illegal spoofing, collision hazard or surveillance of security-sensitive areas.

Due to increasing concern of the involved industries, this is an active area of research. At the moment, there are multiple techniques that can be used to detect drones: RADAR, radio-frequencies (RF), and cameras being the most common [3]. As every technique has advantages and limitations, sensor fusion can combine the strengths of multiple techniques for a more robust and accurate system. In literature, there are already many of these multi-technique drone detection systems present [4]. However, the exclusive combination between RADAR and passive acoustic arrays has not yet been explored at the time of writing.

The reasoning behind the fusion of RADAR and acoustic arrays is based on two characteristics that are inherent to these multi-rotors. First, RADAR's short wavelength allows for the detection of small objects but it is not able to distinguish between e.g., a drone or a bird. The acoustic array will allow the system to focus on that second inherent characteristic, sound. Multi-rotors are well known for emitting a high pitched whining noise, which is an aspect that will be investigated in this paper. The combination of these two sensors will then make up a system capable of detecting and identifying a drone on its own, without relying on external signals such as RF communication.

The rest of this paper is structured as follows: In section II drone detection techniques existing in literature are described to give an overview of what is possible, along with the advantages and limitations. Section III will dive deeper into the system architecture used for the measurements in this paper. In section IV the results are given and discussed. Finally, a conclusion is given along with possible future work in section V.

II. Current Drone Detection Techniques

1) Vision Based: A popular and intuitive way to detect drones is by using RGB cameras. Using machine learning techniques for object detection, objects in the sky can be detected, and through analyzing consecutive frames, the motion features can be determined and the object identified [5], [6]. This relies on having clear frames, which is influenced by the weather, the distance between the drone and the camera, and available lighting. The latter requires vision-based methods to be combined with other methods if night-time operation is needed.

2) Radio Frequency Based: The ubiquity of RF-signals used for wireless communication makes them the go-to option for companies in the field. These signals can also be exploited to achieve localization, both in an active or passive sensing approach. An example of using active RF can be found in [7], where drone detection is achieved using WiFi signals emitted by the localization system that are reflected by the drone's propellers. For passive sensing, both drones and controllers communicate multiple times per second using RF. As most drones use the 2.4 GHz and 5 GHz frequency channels, these channels can be captured and further processed to detect the presence of drones. This can be done using Machine Learning (ML) [8] or Deep Learning (DL) [9]. Both approaches require training data. An attempt for a large open-source database was made by [10]. Although, in the same way as an acoustic database [11], it is impossible to capture all different drone and background RF signals. Furthermore, if a drone uses a frequency that is not in the trained frequency range, it cannot be detected. These RF-based methods do have a blind spot. When the drone is flying autonomously, there are no RF signals, and thus, the drone cannot be detected.

3) RADAR: Also using radio frequency signals, but now only for detection and ranging, RADAR is often used for applications just like this one. With a long standing reputation in aviation and maritime applications, they are capable of recognizing small objects at long ranges [12]. Detection of drones, however, poses significant challenges as small drones typically have very low Radar Cross Sections (RCS), i.e., the measure of how detectable an object is by RADAR [12]. Researchers in [13] show that mini-drones are hard to detect if they are more than 3000 m away. While this range might already be sufficient for applications like this one, a more powerful RADAR unit might be needed. The main limitation of RADAR is that it cannot differentiate objects of roughly the same size. Accordingly, as drones and birds are roughly the same size, they cannot be differentiated. For this reason, the RADAR used in this paper will only be used for object detection.

4) Sound Based: Drones are known for producing a typical high-pitched whining sound. This acoustic signal generated by the propellers, motor, and mechanical vibrations of the drone is sufficiently unique to be recognized by humans. In ideal conditions, people can pick up drone sounds from up to 500 m away [13]. This makes it interesting to see whether microphone arrays are a useful tool for tracking down these systems. Instead of using the original audio signal being picked up by microphones, the focus is placed on the signal's acoustic features in the frequency domain, which is more reliable for tasks such as this. In [14], researchers have already proven to be able to distinguish between different types of drones based on these features. However, in this context, binary classification (drone or no drone) is sufficient from a security standpoint. The main limitation of a system based solely on sound is limited range, as sound attenuation in air is poor [15] and sensitive to noise. Therefore, it also makes sense to combine the acoustic method with one that performs better at longer range.

III. Proposed System Architecture

A. RADAR

The RADAR part of the system is implemented using the Texas Instruments AWR1843 Boost module, chosen because of its availability in the lab. This module uses Frequency Modulated Continuous Wave (FMCW), which sends a frequency-modulated signal continuously in order to measure range, angle, and velocity. The AWR1843 operates at 76-81 GHz, which corresponds to a wavelength of about 4 mm, and thus should have the ability to detect objects that are as small as a millimeter [16]. However, due to the high frequency, the path loss will be higher, limiting the effective range of the unit. Another limitation to keep in mind is the RCS of the drones used, influenced by the material and size of the drone as well as the wavelength, incident, and reflected angle of the RADAR signal [12]. In our experiments, we have used the DJI Tello and the Parrot Bepop 2 drones. We assume that the RCS values of these drones are in line with the results of Semkin et al. [17]. These results were interpolated, leading to an RCS of 0.01 m^2 and 0.1 m^2 for the DJI Tello and Parrot Bepop 2 drones, respectively.

B. Microphone Array

The microphone array used for this proof-of-concept is taken from an embedded real-time imaging SONAR, the eRTIS from Cosys-Lab [18]. The module features a 32 element pseudo-random MEMS microphone array with a sampling frequency of 450 kHz, which allows us to measure well into the ultrasonic range. As the RADAR module is responsible for object detection, the eRTIS' emitter will not be used. A band-pass filter between 20 kHz and 100 kHz is also applied to filter any low and high frequency noise and keep the focus of the algorithm in the ultrasound region. The advantage of using a microphone array is the ability to implement beamforming algorithms that will allow for optimized Signal to Noise Ratios (SNR) in predetermined directions. As the range of sound is limited, enhancing the SNR is crucial to increase the distance at which drones can be detected. In this paper a Delay-and-Sum (DAS) beamformer is used. The directions in which the array will be steered are determined by the points detected by the RADAR, limiting the number of calculations that would other wise be necessary when scanning in every direction.

C. Classification Algorithm

Following an approach similar to [19], we also assume that drones emit a significant amount of ultrasonic frequencies. Figure 1 shows the results of measurements made using the eRTIS microphone array, which confirm this hypothesis. Figure 1a shows that when the drone is present, the frequency band between 20 to 45 kHz contains a significant amount of energy which is absent when no drone is flying nearby as seen in figure 1b. Additional peaks can be seen around 50 kHz and 100 kHz, which is system noise found in all measurements. In this paper, the energy between 20 to 45 kHz will be used as the discerning factor to define the presence of a drone. However, in order to be able to use the system at places

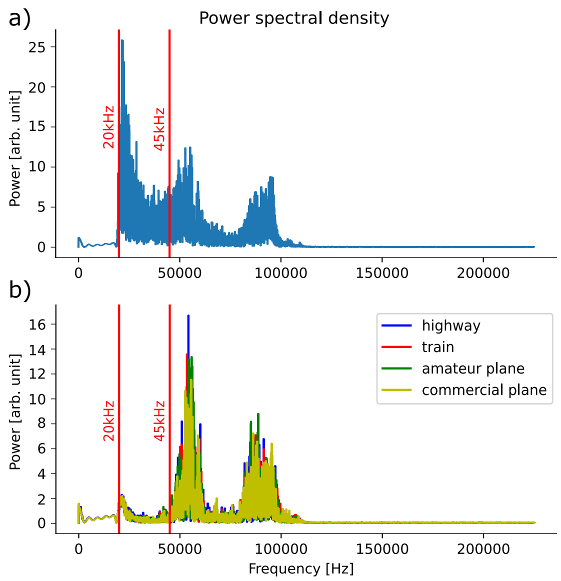

Fig. 1. a) Power spectral density plot of a sound recording made at a parking lot with a drone flying at 1 m distance. b) Power spectral density plots of the highway, planes and the train.

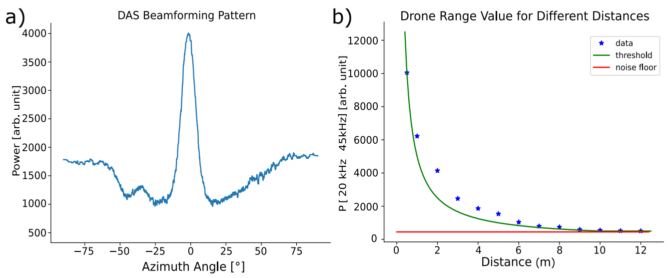

Fig. 2. a) DAS Beam Pattern when beamforming from -90° to 90° on the azimuth and a drone is present at 2 m. b) Total energy in the 20 kHz to 45 kHz range for a drone flying at different distances.

where more ambient noise is present, we need to investigate if this frequency range is not contaminated by other sound sources. Ambient measurements were made of amateur planes, commercial planes, trains, and the highway around the city of Antwerp (Belgium). All the measurements contained an equal amount of energy in the 20 to 45 kHz range. The spectra can be seen in figure 1b. The next step is finding a threshold that can reliably indicate whether a drone is present. In doing this, it is important to remember the DAS beamformer is not ideal and that, besides the main lobe, it also has sidelobes. In figure 2a, the energy across the 20 and 45 kHz range at different beamforming angles is plotted when a drone is flying at 2 m. It is important to have a setting for the threshold that accounts for these sidelobes so as to reduce chances of detecting 'ghost' drones that are not actually present at those angles. For the current setup, the following method is used to define an adaptive treshold:

$$\text{threshold}(d) = \begin{cases} \frac{n \cdot 10}{d}, & \text{if } 0 < d \leq 10 \\ n + 50, & \text{otherwise} \end{cases} \tag{1}$$

Where n is the noise floor obtained during the calibration of the system. In figure 2b, this sits at around 450 au. $n + 50$ has experimentally proven to be a safe offset above the noise floor.

IV. Results & Discussion

As mentioned in the previous section, the low RCS poses problems for the detection of drones using the AWR1843 RADAR. When hovering at less than 1 m distance to the sensor, the drone is detected around 80% of the time. When this distance is increased, the drone is only detected during its movement. This is likely because the tilt of the system during movement results in less specular reflections, increasing the effective RCS and increasing the detectable range to 8 m. This indicates that for drone detection, automotive FMCW RADAR units are not suitable to capture small drones at large distances and researchers should focus on more powerful systems that are better at detecting objects with an RCS below 0.1 m^2. In figure 2, the acoustic energy in the frequency-band between 20 kHz to 45 kHz for a drone flying at increasing distances is shown. The detections between 0.5 m and 10 m lie above the calculated threshold value and thus will be detected correctly. For larger distances, the SNR prevents the current system to identify sounds originating from the multirotor drone. As a result, the maximum range at which the current proof-of-concept can detect and identify a drone is 10 m. This can be improved using a larger beamforming array, a more complex beamforming algorithm, and other methods for increasing SNR.

V. Conclusion & Future Work

This paper started with an overview of the strengths and weaknesses of the current most common drone detection techniques. Then a system making use of the Texas Instruments AWR1843 mmWave RADAR and an acoustic array was constructed. The RADAR will detect objects and then feed the coordinates to the microphone array. The system will then use beamforming methods to increase the SNR in the objects' directions located by the RADAR, searching for the typical high frequency noise being emitted by multi-rotor drones. This allows for a robust system that can localize objects and differentiate between drones and other suspects, such as birds, which are not seen as a threat. Tests were conducted, where we identified the RADAR module for automotive applications to be the main limitation, limiting the practical range to 8 m when the drone is moving. This is due to the low RCS of drones and can be solved by using a RADAR module capable of reliably detecting objects with an RCS below 0.1 m^2. Another bottleneck using the current setup is the range at which drone ultrasound can be differentiated from noise, being 10 m. While sufficient for proving this concept, steps must be taken before any practical implementation can be made. The authors encourage future work to include using a more powerful RADAR module. Also, more advanced beamforming algorithms and larger microphone arrays would further increase the SNR and range of the system.

REFERENCES

[1] Yogesh Jane. Global consumer drones market research report — industry. 06 2022.

[2] Analysis of airprox in uk airspace. Available at https://www.airproxboard.org.uk/media/lisbn3ze/book-37-ukab-annual-report-2021.pdf, 2021. Accessed on 27/10/2022.

[3] Ismail Guvenc, Farshad Koohifar, Simran Singh, Mihail L. Sichitiu, and David Matolak. Detection, tracking, and interdiction for amateur drones. *IEEE Communications Magazine*, 56:75–81, 4 2018.

[4] Xiufang Shi, Chaoqun Yang, Weige Xie, Chao Liang, Zhiguo Shi, and Jiming Chen. Anti-drone system with multiple surveillance technologies: Architecture, implementation, and challenges. *IEEE Communications Magazine*, 56:68–74, 4 2018.

[5] Abdel Gafoor Haddad, Muhammad Ahmed Humais, Naoufel Werghi, and Abdulhadi Shoufan. Long-range visual uav detection and tracking system with threat level assessment. volume 2020-October, pages 638–643. IEEE Computer Society, 10 2020.

[6] Halil Utku Unlu, Phillip Stefan Niehaus, Daniel Chirita, Nikolaos Evangeliou, and Anthony Tzes. Deep learning-based visual tracking of uavs using a ptz camera system. pages 638–644, 2019.

[7] Phuc Nguyen, Mahesh Ravindranathan, Anh Nguyen, Richard Han, and Tam Vu. Investigating cost-effective rf-based detection of drones. pages 17–22. Association for Computing Machinery, Inc, 6 2016.

[8] Yongxu Zhang. Rf-based drone detection using machine learning. pages 425–428. Institute of Electrical and Electronics Engineers Inc., 1 2021.

[9] David Shorten, Ashley Williamson, Saket Srivastava, and John C. Murray. Localisation of drone controllers from rf signals using a deep learning approach. In *Proceedings of the International Conference on Pattern Recognition and Artificial Intelligence*, PRAI 2018, page 89–97, New York, NY, USA, 2018. Association for Computing Machinery.

[10] Mohammad F. Al-Sa'd, Abdulla Al-Ali, Amr Mohamed, Tamer Khattab, and Aiman Erbad. Rf-based drone detection and identification using deep learning approaches: An initiative towards a large open source drone database. *Future Generation Computer Systems*, 100:86–97, 11 2019.

[11] Sara Al-Emadi, Abdulla Al-Ali, Amr Mohammad, and Abdulaziz Al-Ali. Audio based drone detection and identification using deep learning. In *2019 15th International Wireless Communications & Mobile Computing Conference (IWCMC)*, pages 459–464, 2019.

[12] Mark A. Richards, James A. Scheer, and William A. Holm. *Principles of modern radar: Basic principles*. Institution of Engineering and Technology, jan 2010.

[13] Jan Farlik, Miroslav Kratky, Josef Casar, and Vadim Stary. Radar cross section and detection of small unmanned aerial vehicles; radar cross section and detection of small unmanned aerial vehicles, 2016.

[14] Harini Kolamunna, Junye Li, Thilini Dahanayaka, Suranga Seneviratne, Kanchana Thilakaratne, Albert Y. Zomaya, and Aruna Seneviratne. Acousticprint: Acoustic signature based open set drone identification. pages 349–350. Association for Computing Machinery, 7 2020.

[15] Allan D. Pierce. *Acoustics: An Introduction to Its Physical Principles and Applications*. Number 3. Springer, 6 2019.

[16] Merrill I. (Merrill Ivan) Skolnik. *Introduction to radar systems*. McGraw-Hill, 1980.

[17] Vasilii Semkin, Jaakko Haarla, Thomas Pairon, Christopher Slezak, Sundeep Rangan, Ville Viikari, and Claude Oestges. Analyzing radar cross section signatures of diverse drone models at mmwave frequencies. *IEEE Access*, 8:48958–48969, 2020.

[18] Jan Steckel. "Embedded Real Time Imaging Sonar" https://www.3Dsonar.eu, 2019.

[19] Maksim Balakin, Anton Dvorak, and Daniil Kurylev. Real-time drone detection and recognition by acoustic fingerprint. pages 44–45. Institute of Electrical and Electronics Engineers Inc., 2021.