Radar-Based Drone Detection Technologies

Subjects: Engineering, Electrical & Electronic

Contributor: Ulzhalgas Seidaliyeva , Lyazzat Ilipbayeva , Kyrmyzy Taissariyeva , Nurzhigit Smailov , Eric T. Matson

The fast development of unmanned aerial vehicles (UAVs), commonly known as drones, has brought a unique set of opportunities and challenges to both the civilian and military sectors. While drones have proven useful in sectors such as delivery, agriculture, and surveillance, their potential for abuse in illegal airspace invasions, privacy breaches, and security risks has increased the demand for improved detection and classification systems. *Principles of radar-based detection:* Radar, which stands for “Radio Detection and Ranging”, is generally considered one of the most trustworthy sensing devices that comes to mind when addressing UAV detection since it has traditionally been utilized for aircraft detection in both military and civilian purposes (such as aviation). Radar is an electromagnetic technology that employs radio waves to detect and locate nearby objects. Any radar system works on the basis of echo-based measurements and consists of a radar transmitter that sends out short electromagnetic waves in the radio or microwave band, transmitting and receiving antennas, a radar receiver that receives the reflected signals from the target, and a processor that identifies the objects’ attributes. Therefore, radar can calculate important object characteristics, including distance, velocity, azimuth, and elevation.

unmanned aerial vehicles (UAVs) UAV detection drone detection detection technologies radar

1. Introduction

In recent years, as a result of the ongoing development of technology, micro unmanned aerial vehicles (UAVs), more often referred to as drones, have seen improvements in their technical capabilities and an expansion in their range of applications. Due to their ability to fly long-range distances and their compact size, mobility, and payload options, the potential applications for drones have expanded from personal to military usage. Drones play a significant role in modern life as a result of their low cost and ease of usage in many sectors of daily life, from official government work like border security and wildfire surveillance to civilian private sector work such as first aid, disaster management, monitoring of crowded places, farming, delivery services, internet communications, and general filmmaking [1]. Therefore, drone technology’s democratization has resulted in broad acceptance, making the sky more accessible than ever before. Along with the benefits, the increased use of drones has created substantial issues in ensuring the security, privacy, and safety of both airborne and ground-based organizations. Effective drone detection and classification systems have become a key concern for regulatory agencies, security services, and aviation authorities all over the world.

2. Drone Detection Technologies

In recent years, many research works have been published to address UAV detection, tracking, and classification problems. The main drone detection technologies are: radar sensors [2][3][4][5][6][7][8][9][10][11][12][13][14], RF sensors [15][16][17][18][19][20][21][22][23][24][25], audio sensors [26][27][28][29][30][31][32][33][34][35][36][37][38], and camera sensors using visual UAV characteristics [39][40][41][42][43][44][45][46][47][48][49]. Based on the above-mentioned sources, the advantages and disadvantages of each drone detection technology are compared in **Table 1**. In addition, the academic and industrial communities have begun to pay attention to bimodal and multi-modal sensor fusion methods; however, these methodologies are still in the early stages of development and implementation.

Table 1. Comparison of different drone detection technologies.

Detection Technique	Principle of Operation	Advantages	Disadvantages
Radar-based	employs radio waves to detect and locate nearby objects	long range; all-weather performance; ability to recognize micro-Doppler signatures (MDS); speed and direction measurement	limited detection capability due to low radar cross section (RCS); limited performance due to low altitudes and speeds; high cost and complexity of deployment
RF-based	captures wireless signals to detect the radio frequency signals from drones	long-range detection and identification; resistance to all weather conditions; ability to capture signals and communication spectra from the UAV and its operator; ability to distinguish different types of UAVs	unable to identify autonomous drones; interference with other RF sources; vulnerable to hackers
Acoustic-based	detects drones by their unique sound signatures	cost effective; no line-of-sight (LoS) required; quick deployment	background noise; limited detection range; vulnerability to wind conditions
Vision-based	captures drone visual data using camera sensors	visual confirmation; non-intrusive; cost-effective	limited detection range and requires LoS; weather and lighting dependence

3. Radar-Based Drone Detection Technologies

Principles of radar-based detection: Radar, which stands for “Radio Detection and Ranging”, is generally considered one of the most trustworthy sensing devices that comes to mind when addressing UAV detection since it has traditionally been utilized for aircraft detection in both military and civilian purposes (such as aviation) [50]. Radar is an electromagnetic technology that employs radio waves to detect and locate nearby objects. Any radar system works on the basis of echo-based measurements and consists of a radar transmitter that sends out short electromagnetic waves in the radio or microwave band, transmitting and receiving antennas, a radar receiver that receives the reflected signals from the target, and a processor that identifies the objects’ attributes. Therefore, radar can calculate important object characteristics, including distance, velocity, azimuth, and elevation [2].

Types of radar: Radars come in two varieties: active radars and passive radars. Active radar transmits a signal and then receives the reflected signal to detect objects. Therefore, if the radar sensor illuminates objects, it is defined as active [3]. In contrast, passive radar does not emit any kind of signal; instead, it relies on external signal sources such as natural sources of energy (the Sun and stars) as well as other signal sources, including cellular signals, frequency modulation (FM) radio, etc. Active radars are frequently referred to simply as radars in the literature. If there is a difference between the transmitting and receiving antennas, active radar is said to be bistatic; otherwise, it is referred to as monostatic. An (active) radar transmits either trains of electromagnetic energy pulses or a continuous wave; in the first case, these are known as continuous wave (CW) radars, such as stepped frequency continuous wave (SFCW) radar; in the second case, these are known as pulse radars. Pulse-Doppler radar is an alternative form of radar that combines the characteristics of the two radar systems mentioned above. Depending on operating frequency band designations, radar sensors have several classifications. Radar frequency bands in accordance with Institute of Electrical and Electronics Engineers (IEEE) standards and their typical applications are presented in [3].

Several common varieties of radar are briefly explained below:

(1) Surveillance radar: The typical application for this kind of radar is long-range surveillance and detection. It has extensive coverage and can detect UAVs up to a few kilometers away. Radars used for surveillance often operate in the X-band or S-band frequencies and feature an elevated platform to increase the detection range. In [4], the authors proposed a reliable bird and drone target classification method using motion characteristics and a random forest model. Different flight patterns and motion characteristics of birds and drones, such as velocity, direction, and acceleration, extracted from the surveillance radar data were used as the primary features for the classification system.

(2) Millimeter-wave (mmWave) radar: The use of mmWave technology in radar systems can be an effective tool for UAV detection due to its abilities to penetrate various weather conditions, improve resolution, and assist in the detection of tiny drones. A mmWave radar uses radio waves with wavelengths ranging from 1 to 10 mm and can detect the presence of drones by measuring the radio waves reflected off their surfaces. In [51], the authors presented a novel drone classification approach using deep learning techniques and radar cross section (RCS) signatures extracted from millimeter-wave (mmWave) radar. The majority of drone classification techniques typically convert RCS signatures into images before doing classification using a convolutional neural network (CNN). Due to the added computational complexity caused by converting every signature into an image, CNN-based drone classification shows low classification accuracy concerning the dynamic characteristics of a drone. Thus, by adding a weight optimization model that can minimize computing cost by preventing the gradient from flowing through hidden states of the long short-term memory (LSTM) model, the authors presented an enhanced LSTM. Experimental results showed that the accuracy of the long short-term memory adaptive-learning-rate-optimizing (LSTM-ALRO)-based drone classification model is much greater than the accuracy of the CNN- and Google-based models.

(3) Pulse-Doppler radar: This type of radar emits short radio wave pulses and detects the frequency shift brought on by the motion of an unmanned aerial vehicle (UAV) even in the presence of background noise or interference [5].

(4) Continuous wave (CW) radar: This type of radar detects unmanned aerial vehicles (UAVs) by continuously transmitting radio waves and analyzing the frequency shift in the reflected signal [6].

(5) Frequency-modulated continuous wave (FMCW) radar: FMCW radar continually transmits an electromagnetic signal with a fluctuating frequency over time and uses the difference in frequencies between emitted and reflected signals to determine the range and velocity of objects [50]. These signals, often known as chirps, vary from CW in that the operational frequency is not changed throughout the transmission [7]. Due to their constant pulsing, inexpensive cost of hardware components, and superior performance, FMCW and CW radars are recommended for use in UAV detection and identification [8].

Micro-Doppler effect in radar: Compared to conventional measurements like radar cross section (RCS) and speed, micro-Dopplers created by moving blades can be used as more efficient signatures for detecting radar signals from UAVs. Recent years have seen a significant increase in the importance of the detection and classification of UAVs using the radar micro-Doppler effect [6]. Due to the rotating blades of drones modulating incident radar waves, it is known that drones cause micro-Doppler shifts in radar echoes. Specific parts of an object that move separately from the rest provide a micro-Doppler signature. These signatures may be produced by drones simply by rotating their propeller blades [9]. As well, the drone's moving components, such as rotors or wings, produce distinctive radar echoes known as micro-Doppler signatures. By examining these signatures, the authors of [10] proposed a novel approach that focuses on developing some patterns and characteristics to identify various small drones based on blade types. The presence or absence of these micro-Doppler shifts, which are produced in the spectra of drones, helps to separate drone signals from background noise like birds or humans. Distinctions between drone types were made using the variations in the micro-Doppler parameters developed by the authors, such as the Doppler frequency difference (DFD) and the Doppler magnitude ratio (DMR). X-band pulse-Doppler radar was used to analyze radar signatures of different small drone types such as multi-rotor drones with only lifting blades, fixed-wing drones with only puller blades, and hybrid vertical take-off and landing (VTOL) drones with both lifting and puller blades. Experimental results demonstrated that for all three types of drones, lifting blades produced greater micro-Doppler signals than puller blades.

Even when using very sensitive radar systems, it is not possible to differentiate between multi-copters and birds with sufficient accuracy using either the physical size or the radar cross section (RCS). Investigations of multi-copters for their micro-Doppler signatures and comparison with those of birds have shown excellent findings in related studies [11][14]. In [11], the authors presented the characteristic radar micro-Doppler properties of three different drone models and four bird species of different sizes obtained by processing a phase-coherent radar system at K-band (24 GHz) and W-band (94 GHz) frequencies. The experimental outcomes clearly showed that there are considerable differences between the micro-Doppler signatures of birds and proved that a K-band or millimeter-wave radar system is capable of detecting drones with excellent fidelity. The findings demonstrated that micro-Doppler signatures such as bird wing beat signatures, helicopter rotor modulation (HERM) lines, micro-Doppler dispersion across the Doppler axis, and rotor blade flash might all be employed as classification features for accurate target recognition. Thus, target classification may be accomplished using the micro-Doppler effect based on the feature “micro-Doppler signatures”. Flying multi-copters can be detected using the radar micro-

Doppler signatures produced by the micro-movements of rotating propellers. In the case of multi-copters, rotating rotor blades are the primary source of micro-Doppler signatures, while the wing beats of birds provide these signatures. The authors of [11] demonstrated that drones and birds may be consistently distinguished by analyzing the radar return, including the micro-Doppler characteristic. Further, the work [9] addresses the problem of classifying various drone types such as DJI and Parrot using radar signals at X- and W-band frequencies, Convolutional neural networks (CNNs) were used to analyze the short-time Fourier transform (STFT) spectrograms of the simulated radar signals emitted by the drones. The experimental results demonstrated that a neural network that was trained using data from an X-band radar with a 2 kHz pulse repetition frequency outperformed a CNN trained using the aforementioned W-band radar. In [12], the authors proposed a deep-learning-based technique for the detection and classification of radar micro-Doppler signatures of multi-copters. Radar micro-Doppler signature images of rotating-wing-copters and various other non-rotating objects were collected using continuous wave (CW) radar, and then the micro-Doppler images were labeled and fed to a trained CNN model. Experimental measurements showed 99.4% recognition accuracy with various short-range radar sensors. In [13], the authors examined micro-Doppler data obtained from a custom-built 10 GHz continuous wave (CW) radar system that was specifically designed for use with a range of targets, including UAVs and birds, in various scenarios. Support vector machines (SVMs) were used for performing different classification types, such as drone size classification, drone and bird binary classification, as well as multi-class-specific classification among the five classes. The main shortcoming of the research is the limited conditions for data collection, and the authors hope to address this limitation in their future work.

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