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A Survey

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Radar Perception for Autonomous Unmanned Aerial Vehicles: a Survey

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ABSTRACT

The advent of consumer and industrial Unmanned Aerial Vehicles (UAVs), commonly referred to as drones, has opened business opportunities in many fields, including logistics, smart agriculture, inspection, surveillance, and construction. In addition, the autonomous operations of UAVs reduce risks by minimizing the time spent by human workers in harsh environments and lowering costs by automating tasks. For reliability and safety, the drones must sense and avoid potential obstacles and must be capable of safely navigating in unknown environments. UAVs' perception requires reliability in various settings, such as high dust levels, humidity, intense sun glare, dark, and fog that can severely obstruct many conventional sensing methods. Radar systems have unique strengths; they can reliably estimate how far an object is and measure its relative speed via the Doppler effect. In addition, because radars exploit radio waves to sense, they perform well in rain, fog, snow, or smoky environments. This stands in contrast to optical technologies, such as cameras or LIght Detection And Ranging (Lidars), which are more susceptible to the same challenges as the human eye. This survey paper aims to address the signal processing challenges for the exploitation of radar systems in unmanned aerial vehicles for advanced perception, considering recent integration trends and technology capabilities. The focus is on signal processing techniques for low-cost and power-efficient radar sensors, which operate onboard the UAVs in real-time to ensure their needs in terms of perception, situational awareness, and navigation. Additionally, we highlight the challenges that remain to be tackled and the opportunities that lie ahead in the search for a more efficient, safe, and autonomous way for UAVs to perceive and interact with the world.

CCS CONCEPTS

• **Computer systems organization** → **System on a chip**; **Embedded hardware**;

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KEYWORDS

radar sensing,radar odometry, drone sensory perception, micro-Doppler processing, deep learning

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1 INTRODUCTION

Modern UAVs offer easy maneuverability, stable flight, waypoint navigation, geofencing, and return to home abilities in autopilot mode. They take advantage of sensory fusion and exploit sensors such as inertial measurement units (IMUs) with integrated gyroscope and accelerometers, barometric sensors, ultrasonic sensors, and the Global Navigation Satellite Systems (GNNS). Some modern UAVs also exploit vision sensors (cameras) to detect and follow targets, mainly for kinematic applications. However, to obtain safe and autonomous mission execution, UAVs must be capable of reliably sensing the whole environment and must act autonomously. Target detection and collision avoidance are necessary to autonomously maneuver around obstacles that are not predictable in waypoint navigation scenarios, such as power lines, trees, birds, other UAVs, or other unexpected objects.

Up to now, visual perception is by far dominating in consumer and industrial drones. Computer vision-based navigation, pose estimation, tracking, obstacle detection, and avoidance are becoming exploited in tiny commercial UAV systems [3]. This is mainly driven by the large availability of cheap, small, and high-resolution cameras and by the advent of embedded deep learning models that meet the memory and power constraints of embedded computing platforms.

To ensure safe and reliable UAV systems, state-of-the-art perception systems for UAVs are based on a combination of infrared, ultrasonic, and vision-based sensors (monocular or stereo vision). In addition to these sensing modalities, especially when paired with machine learning algorithms, radar-based perception systems can be used to classify and identify several targets, for example, by analyzing their micro-Doppler signatures [7, 27]. Radar-based perception systems are also commonly used in remote sensing applications. For example, they can estimate water reserves, monitor crops, and can be used in agriculture applications [23].

Lidars and cameras are the main competing sensing technologies with radars to detect targets and measure their distances, motion directions, and speed. However, their main limitation compared with radar is the detrimental effect on their performance in bad weather and visibility conditions. Lidars are also still relatively heavy and costly. As a possible alternative, the use of ultrasonic technologies is, however, limited to very short ranges (<10m) for the detection of targets in the vicinity of vehicles in low-speed and urban scenarios (e.g., automotive parking assistant). In addition, ultrasound sensors are point-based and have difficulty in sensing soft or curved edges at large incidence angles [4]. Event-based cameras are also competitive sensors to traditional cameras in high-speed motion. They can solve the phenomenon called blur, which causes a loss of scene information [15]. Moreover, event-based cameras are popular in drone research as they enable high-speed control and a high-dynamic range. Nevertheless, these passive sensor technologies ultimately suffer from light conditions.

This survey focuses on radar-based sensing technologies because they are less sensitive to weather conditions and provide excellent sensory information. Traditionally, radar sensors have been expensive, bulky, and power-hungry. Only recently, these factors have been overcome, and the production of cheap, lightweight radar sensors is becoming part of the modern mobile applications [20]. Current radar sensors come in the form of compact, millimeter-wave frequency-modulated continuous-wave (FMCW) radars. They can provide range and radial velocity in multi-target scenarios. In addition, the tremendous expansion of automotive radar technology has also produced compact MIMO (Multiple Input Multiple Output) radars capable of estimating the angular position of the targets beyond just range and velocity. Several lightweights demonstrate this tremendous progress in radar technologies, small and cheap radar systems that have entered the consumer market in Systems on Chip (SoC) solutions [16, 28, 31, 40, 43].

This paper provides an overview of radar technologies, focusing on their application onboard UAV systems for enhancing perception to enable high levels of autonomy and assisted/autonomous navigation. We will present a survey of radar sensing technologies, their working principles and advantages, and their challenges as novel onboard perception sensors for UAV systems. In section Principle of Operations of Radars and Signal Processing, we will discuss several methodologies commonly used to extract information from radar output and discuss some of the most widely used signal processing techniques for obtaining range, velocity estimations, and angle of arrival. In section Radar Perception onboard of UAV, we will review applications of UAVs from low-level to high-level autonomous tasks and some of the algorithms that have been recently proposed to attain safe, reliable, and autonomous control of UAVs. Finally, we will discuss opportunities for future research and open challenges, such as the development of advanced machine learning and deep neural networks for processing the information of radar systems.

2 PRINCIPLE OF OPERATIONS OF RADARS AND SIGNAL PROCESSING

2.0.1 Continuous Wave (CW) radar. Continuous Wave radars transmit a sinusoidal high-frequency signal continuously. The backscattered power from the environment is constantly received and processed. As CW-based radars transmit an unmodulated signal, they can only measure the speed of targets by using the Doppler effect. CW radars cannot measure the range, nor can they differentiate between two or more targets. When backscattered power (echo) is received, this carries only the information that there is an obstacle in the direction of propagation of the electromagnetic waves. To some extent, the properties of the obstacles may be inferred from certain properties of the backscattered power. For example, the size of the target can be estimated by the strength of the backscattered signal, but since this parameter, or more formally the Radar Cross Section (RCS), depends on many factors beyond the size of the target, this approach is usually not exploited in CW radar. The received signal can have its frequency shifted by the Doppler effect, depending on the radial velocity component of a reflecting target. CW radars are also called 'Doppler radars,' and they cannot determine distances or distinguish different targets in the same direction but can estimate radial velocity via the Doppler frequency, i.e., by measuring the phase difference of transmitted versus received signal. CW radars are not typically employed in advanced UAVs, as they cannot provide crucial multi-target range and speed information.

2.0.2 Frequency Modulated Continuous Wave (FMCW) radar. In multi targets scenarios, the most widely used radar in UAVs is the Frequency Modulated Continuous Wave radar with fast chirping [46]. FMCW radar emits continuous signals while changing its operational frequency during measurements, i.e., the transmission of power is modulated in frequency. The bandwidth of the radar is the frequency range of the signal, often referred to as 'chirp' or 'sweep', from $B = f_n - f_0$, being f_n the higher and f_0 the lower frequency. The most common modulation form for the emitted signal is a linear frequency ramp. Concretely, the instantaneous frequency f has a linear dependency with time t, as follows:

$$f(t) = f_0 + \frac{B}{T_c}(t - t_0) = f_0 + S(t - t_0) \tag{1}$$

in which T_c is the chirp duration or period, B is the bandwidth and f_0 is the starting frequency at time $t = t_0$. S denotes the rate of frequency change (i.e., the frequency slope, sometimes called 'chirp rate'). The time-domain function that describe the phase, ϕ, is obtained by integrating the angular frequency $\omega(t) = 2\pi f(t)$:

$$\phi(t) = \phi_0 + 2\pi \int_{t_0}^{t} f(t)dt = \phi_0 + 2\pi \left[f_0(t - t_0) + \frac{B}{2T_c}(t^2 - t_0^2) \right] \tag{2}$$

A linear chirp has a corresponding time-domain function, as indicated in [24]

$$y_{tx}(t) = A_c sin\left(\phi_0 + 2\pi f_0 t + \pi \frac{B}{T_c}(t - mT_c)^2\right) \tag{3}$$

Where A_c represents the chirp's amplitude, m refers to the m^{th} chirp in a sequence of many chirps and $t_0 = 0$, with the assumption that chirps are continuously transmitted. The carrier frequency is defined as $f_c = f_0 + B/2$, and it is the central frequency for the spectrum band.

Contemporary FMCW radars can be fully integrated into a system on a chip solution, consisting of single or multiple transmitters (TX) and single or multiple receivers (RX) antennas and processing chains. Figure 1A shows a simplified block diagram for a system-on-a-chip FMCW radar. First, a synthesizer generates an appropriate chirp signal, modulated with a modulation scheme involving a phase-locked loop (PLL) and an oscillator. Then, the signal is sent to a power amplifier (PA) that amplifies the sweep, which is later transmitted by the transmitting antenna. The backscattered power from the environment and the targets are captured by the receiving antenna that sends the signal through a low-noise amplifier (LNA). Before the analog baseband block in figure 1, a downconversion frequency mixer multiplies the RX and TX signals to generate an intermediate frequency (IF) signal at the output. This IF signal is often referred to as 'beat frequency' and contains useful information about the possible targets. The beat signal is low-pass filtered in the analog baseband block and sampled by analog to digital converters.

2.0.3 FMCW Range processing. For a single static target, the beat frequency signal, f_{beat}, has a constant frequency proportional to the reflected signal's round-trip delay, which can be easily found by spectral analysis (e.g., Fast Fourier Transform).

$$f_{beat} = \frac{2r}{c}S = \frac{2B}{cT_c}r \tag{4}$$

where r is the target-radar distance, c is the speed of light, and S is the slope coefficient. Therefore, in a situation with multiple targets at different locations, there will be several beat frequencies at the RX antenna, each directly proportional to the target-radar distance of each of the objects. Figure1B shows a cartoon of an SoC radar receiving backscattered power with distinct beat frequencies f_{b1}, f_{b2}, indicating the presence of the two targets at respective distances $r1$ and $r2$, with the assumption of the distance between the two targets higher than the range resolution.

2.0.4 FMCW Doppler processing. In the case of moving targets, the beat frequencies of the round-trip delays will be affected by the Doppler shift. This can be estimated in the frequency domain by applying two successive Fourier Transformations (FT) over multiple chirps. FMCW radars with fast chirps assume that the duration of the transmitted waveform is longer than the round-trip time delay related to the desired range to measure. Because of the rapid chirps, the velocity influence on the first FT can be, in normal situations, neglected while obtaining the range information [46]. Velocity estimation is obtained with a second FT over multiple chirps at the resulting range of the target. The second FT extracts motion-induced phase changes from chirp to chirp, and such motion is proportional to the velocity of the targets [38]. Figure 1C shows the typical signal processing pipeline for radar frames. A radar frame is a commonly used format in radar signal processing. It comprises a number of digital samples per chirp over a set of multiple chirps. Typical radar frames have small dimensions (8x64,64x128,256x256) and are compatibles with Micro Controller Boards (MCUs) (as in figure 1A). By storing 2D radar frames, a first Fast Fourier Transform (FFT) on the data estimates the range information. A second FFT obtains the Doppler shifts proportional to the velocities of the targets.

2.0.5 Direction of Arrival (DoA) Estimation in FMCW radar. To obtain angular information at high resolution, it is required to have a radar with a large aperture (i.e., with multiple antennas). Because modern high-frequency (60-140 GHz) radar can be integrated into an SoC and their antennas have dimensions of a few millimeters, multiple-input, multiple-output (MIMO) radars can be used onboard UAVs. MIMO radars are capable of generating large virtual apertures with a limited number of transmitters and receivers. Most of the time, for example, in [8, 42], a time-division multiplexing (TDM) technique is employed to switch transmitters on and off consecutively. The actual direction of arrival estimation can be calculated using several techniques such as MUltiple SIgnal Classification (MUSIC) [37], Maximum likelihood methods [41], and single snapshot DOA estimation [17, 33], amongst others. One limitation of TDM techniques is the presence of phase errors when the targets and/or the radar is in motion between the switching among the transmitters. This phase error may lead to inaccuracies in the angular estimation. For this reason, one possible solution is to use virtual apertures with overlapping elements where the phase offset between the active transmitters can be readily measured and corrected [2].

A simple way of resolving the direction of arrival of the targets can be employed when the radar platform has multiple receiving antennas. DoA estimation can be carried out by looking at the phase difference of the range maps from the several receiving antennas. Once the location of a target has been identified in the range-Doppler map (see figure 2A), a phase difference among the signals from the two antennas can be estimated. Given a fixed wavelength λ, the one corresponding to the carrier frequency of the radar, and given a d spacing between the antennas, the phase signal relates to the DoA by means of the physical relation shown in figure 2A.

2.0.6 Synthetic Aperture Radar. Synthetic-Aperture Radar (SAR) is traditionally used in remote sensing applications and through cloud sensing when traditional optical sensors would fail [39]. In SAR radar systems, a sequence of acquisitions from a smaller antenna are combined to simulate a much larger virtual antenna aperture, as in figure 2B. This synthetic larger aperture provides higher resolution cross-range data, as the resolution is inversely proportional to the antenna aperture. SAR processing and its applications are particularly interesting for radars placed on UAVs, as they provide a cheaper platform than larger aircraft to construct the synthetic aperture for ground observations.

3 RADAR PERCEPTION ONBOARD OF UAV

While there is a significant body of literature on UAVs signatures seen by ground-based radars [7, 27, 32], radar perception onboard of UAVs and the related algorithms are still relatively unexplored. This section summarises some of the notable contributions in state-of-the-art.

3.1 Radar Odometry

Radar odometry (RO) is a technique to estimate the relative motion of the UAV with respect to the environment by analyzing scans obtained by the onboard radar sensor [25]. Radar odometry can be viewed as a two-step process. First, there is the need to detect essential features from the radar scans. Second, there is the need to track the scattered points in radar data that directly relates to the target objects over time.

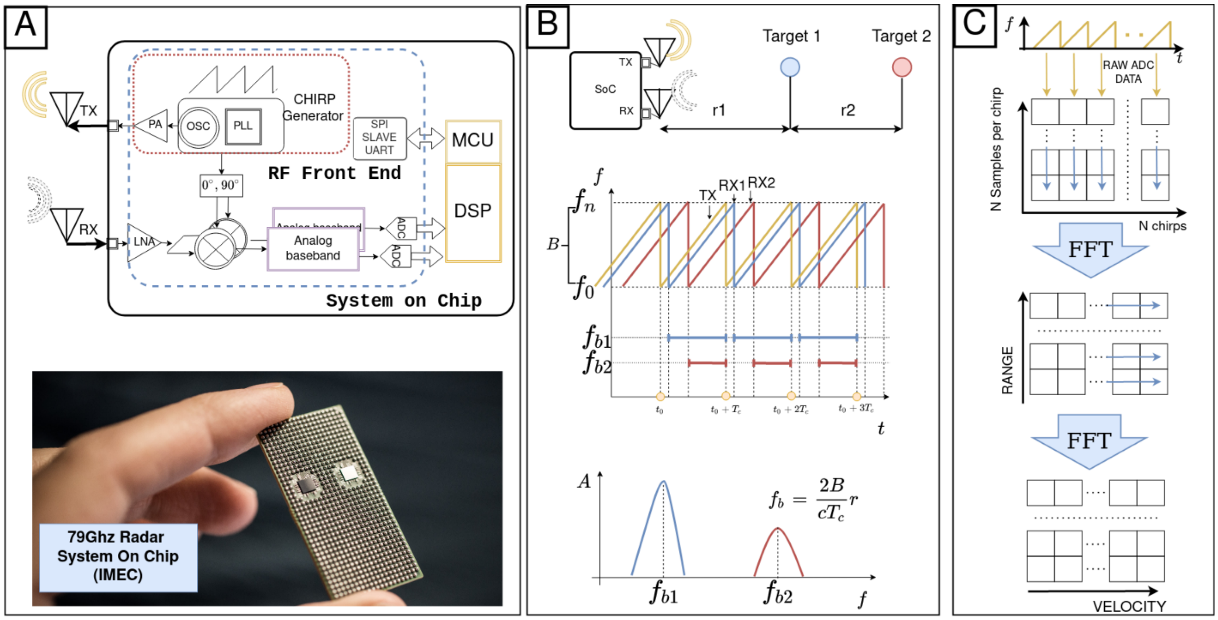

Figure 1: FMCW radar and signal processing. A) Simplified block diagram for a system-on-a-chip FMCW radar with single TX and single RX antenna and a picture of a modern mm-wave radar [16]. B) Static multi-target detection using beat frequencies measurements. C) Range and Velocity estimation via double FFT (first across the digital samples per chirp, then across multiple chirps).

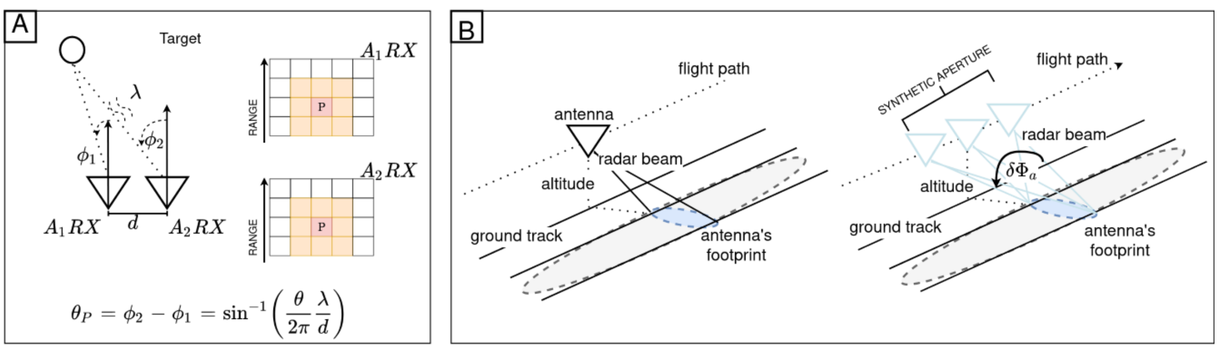

Figure 2: A DoA estimation with two receiving antennas. B Synthetic aperture radar concept.

The first step can be accomplished by accumulating a grid map from the radar scan and transforming it into a grayscale image. Interesting points can then be detected using features extraction techniques, e.g., Scale-Invariant Feature Transform [5]. An example of estimating motion from a fixed-wing drone using only radar odometry can be found in [29]. In [29] the authors exploited a range-compressed image together with a Hough transform to detect strong scatters by searching for hyperbolas in the range-compressed image. They demonstrated that radar odometry for motion estimation of lightweight UAVs is feasible and offers an interesting alternative to visual odometry systems. In [30], an extension of this work proposes the use of a threshold for better performance in natural and cluttered environments. More recently, in [35], they proposed an end-to-end multiple-target tracking strategy that exploits both range and bearing measurements provided by radar onboard a lightweight UAV. Their method detect strong and stable scatters in two steps by employing a range-bearing estimation and Constant False Alarm Rate (CFAR) detection. The bearing angle was estimated using a range-compressed signal generated by two channels by subtracting their phase components. To enhance the detection, remove clutter, and therefore reduce the computational cost, the ordered static CFAR algorithm was applied.

In the second step, i.e., for tracking the scattered points, several methods have been used. In [30] a recursive-RANSAC method was employed to track effectiveness scatters from the radar range-compressed images. In [44] a matching method was proposed to track features over several radar scans. The extracted features are aligned, and a cost function is minimized using matching algorithms, such as iterative closest point. The drawback of these algorithms is their inability to rely on poor initial estimates. For this reason, the authors in [34] proposed an outlier rejection scheme for use onboard UAVs for radar odometry.

3.2 Radar-Inertial Odometry

Radar-Inertial Odometry refers to the fusion of radar data with IMU measurements to increase the robustness and precision of the motion estimation. The fusion of radar and IMU data was performed with an extended Kalman filter (EKF) to estimate the state of small aircraft already in [29, 30]. In [11] there is an implementation of radar inertial odometry directly on board a lightweight drone. They extended a filter-based approach to 3D Radar Inertial Odometry with yaw aiding for indoor environments. Their system enabled instantaneous yaw aiding using only a single radar scan from an FMCW 60GHz radar in 3Tx and 4Rx configuration running at 10Hz and mounted on a lightweight quad-copter. To overcome the limitation of inconsistent features matching between consecutive radar frames, the detrimental effect of multipath and other environmental scattering phenomena, and the low RCS of some targets, radar sensors are also combined with sensing modalities such as cameras and lidar. For example, in [26] a localization system to accurately estimate the forward velocity was proposed by fusing information from the five primary sensors of a UAV (i.e., radar, camera, IMU, barometer, and magnetometer). All the sensors were fused in a loosely-coupled fashion via an extended Kalman filter, yielding improved performances compared to using radar and IMU only.

3.3 Obstacle Detection and Tracking

Algorithms for radar-based detection and tracking of multiple objects in the air or on the ground exist, providing relatively low computational complexity and fast implementation on cheap MCUs. However, the ability to distinguish different target categories, such as people, other UAVs, walls, or trees, without resorting to SAR processing requires more advanced processing for classification, for instance, based on micro-Doppler signatures. As this analysis is data-intensive and typically requires the execution of power-hungry deep learning models, to the best of our knowledge, there is little evidence of these functionalities implemented onboard small, lightweight drones in the open literature. Nevertheless, this functionality is well explored in automotive settings. For example, in [10], a deep convolutional neural network model (U-Net) was weakly trained on radar cubes data. The radar cube is a 3D data structure containing range-azimuth-Doppler maps. The authors experimentally evaluated the performance of the CNN model, achieving detection performance compared to classical techniques when identifying vulnerable road users (pedestrians and cyclists) in an automotive setting. Bringing these functionalities into small UAVs will require solving the challenge of executing memory and compute-intensive CNN models at fast micro-Doppler frame rates. The lack of examples of drones' onboard radar-based classification using deep neural network models with high-resolution radar can be partially due to the lack of labeled radar data and the significant power required to run deep neural networks on embedded systems.

In [45] a commercial FMCW 24GHz radar was used in an indoor environment to perform detection and avoidance of fixed obstacles. The radar had 1TX and 2RX with a bandwidth of 200MHz. Experiments demonstrated the ability of a Micro Aerial Vehicle (MAV) to resolve objects 0.75m apart in range, with an accuracy of about 15cm and an angular accuracy of 2° from $0-20^\circ$, and up to about 8° from $20-65^\circ$. The radar board weighed about 12g and was mounted on a lightweight drone of less than 0.5 kg of Mass at Take Off (MOT). In [12] an active drone detection system exploiting an mm-wave radar was mounted on a drone with the objective of detecting, tracking, and pursuing target drones. The work offers a solution for each component, including detection, search, and actively pursuing. However, their approach has the limitation that the intruding drone was the only airborne object.

3.4 Swarm in flight formation

In [42], a MIMO 77GHz automotive radar with 4TX and 16RX was integrated into a custom-designed 15x15 cm board and mounted on a commercial UAV of about 4kg MOT. The use of this radar demonstrated the capabilities of the perception system to perform three-dimensional sensing in UAV formation flight and obstacle avoidance.

3.5 Environmental Monitoring and Remote Sensing

In remote sensing applications, SAR is commonly used to enhance the aperture for high-angular resolution. SAR imaging radars are still heavy, and they can fit in larger drones, such as the example of the 85Kg drone equipped with a 94GHz SAR with a bandwidth of 1GHz [13]. SAR radar has the potential of sensing small-scale features. The integration of SAR radar technology in smaller commercial drones with a MOT of less than 5 kg is currently possible, as it was demonstrated in [14, 19, 22] where 3.1 GHz and 5.3 GHz SAR imaging radars were used for surface and subsurface imaging. Recently [9] demonstrated the possibility of achieving a lightweight, 250g, multi-frequency radar module (0.5 to 3 GHz) to detect buried mines. Interestingly, they offered a novel approach based on multi-static observations directly onboard the UAV to create nearly arbitrary azimuth sampling trajectories. The system and methodology used have identified the mines thanks to their spatial radar-cross section distribution in the SAR images.

3.6 Above Ground Level (AGL) measurements

Radar-based sensing of altitude or Above Ground Level (AGL) with a 24GHz FMCW radar fused with an accelerometer was first validated with a motion caption system [21]. Recently, these systems have become commercially available as long-range radar altimeters for autonomous landing and AGL measurements [1]. With a power consumption of about 11W and 250MHz bandwidth, these sensors weigh only 300g and can measure altitude values from 1.4m up to 500m with a precision of less than 1m. To reduce hardware complexity and costs, [36] proposed a pulse-correlation radar for AGL measurements. The radar is based on a 26GHz system with an update rate of up to 40Hz. A particle filter tracks the AGL altitude. Compared to a low-cost lidar and Real-Time Kinematic Positioning (RTK) based on GNNS, the radar system outperformed the lidar that was measuring the distance to vegetation instead of the AGL altitude.

4 DISCUSSION AND OUTLOOK

Looking at the state-of-the-art, improved onboard capabilities for detecting, tracking, and classifying multiple objects are needed to unlock fully autonomous operations of small UAVs and their safer integration in the airspace. For this, radar systems and related algorithms require novel solutions to fit the constraints of small UAVs' onboard operations in terms of size, weight, power, and cost. This affects both the hardware, i.e., how the radar and processing units are implemented, and the software, i.e., how radar signal processing is executed, unlike in ground-based radar systems.

System in package radar solutions have made notable progress in 1) packaging antenna-array design; 2) integration of multi-channel radio-frequency transceivers in system-on-chip (SoC) endowed with high-performance Analog To Digital converters; and 3) signal processing algorithms embedded in real-time, low-power computing platforms and in deep learning accelerators (e.g., neural processing hardware units).

The first two points are critical enablers for a compact and light radar that small UAVs can physically carry, even if the precise specifications depend on the speeds envelope of the UAVs system and its intended use (e.g., functionality for DOA, AGL, or others). At the same time, this hardware progress enables improving general performances in terms of waveform quality (e.g., bandwidth and SNR) and the number of MIMO channels for better angular resolution. The latter point is fundamental to operating the required signal processing for perception and situation awareness while meeting the latency, computational complexity, memory, and power requirements. It is unlikely that conventional radar processing pipelines of feature extraction and classification and related deep learning models can be directly used onboard UAVs. Therefore, reformulating such algorithms is needed by limiting the amount of accumulated data for processing (e.g., the classic 'radar cube' or multiple shots for estimation of covariance matrices) in favor of techniques that can exploit the natural intra-frame sparsity and the inter-frame temporal correlations.

Because scaling up on-device intelligence by scaling sensor resolution, model size, and computing needs is not a viable solution on edge devices, much research is devoted to developing devices capable of accelerating the inference of deep learning workloads [6]. In addition, dynamically-reconfigurable computing approaches offer the possibility of accelerating several workloads with the same hardware, which is appealing to accelerate distinct workloads for the different phases of autonomous UAVs' missions [18]. The field of neuromorphic sensing and computing addresses the challenges of scaling up on-device intelligence using a more bio-inspired approach. For example, in machine vision, neuromorphic sensing has already brought significant contributions with the advent of event-based cameras [15]. The same principles can be applied to mm-wave radar sensors using sparse event-based sampling directly at the radar front-end. This could potentially reduce computations by exploiting on-demand approaches while exploring the natural temporal relations in the world. Thus, a new approach to radar sensing should include both sensing and computing strategies. Only then, at the system level, many opportunities and challenges can be tackled, e.g., by performing closed-loop front-end adaption based on high-level representations of the scene. For these reasons, neuromorphic sensing and bio-inspired computing can drive innovation in the next generation of cognitive radar systems for drones.

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