



RaDro: Indoor Drone Tracking Using Millimeter Wave Radar

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Core to drone design is its ability to ascertain its location by utilizing onboard inertial sensors combined with GPS data. However, GPS is not always reachable, especially in challenging environments such as indoors. This paper proposes RaDro; a system that leverages millimeter-waves (mmWave) to precisely localize and track drones in indoor environments. Unlike commonly used alternative technologies, RaDro is cost-effective and can penetrate obstacles, a bonus in non-line-of-sight (NLoS) scenarios, which enhances its reliability for tracking objects in complex environments. It does this without the need for tags or anchors to be attached to the drone, achieving 3D tracking with just a single radar point, significantly streamlining the deployment process. Comprehensive experiments are conducted in different scenarios to evaluate RaDro's performance. These include employing different drone models with different sizes to execute a range of aerial manoeuvres across different flight arenas, each with its own settings and clutter, and encountering various LoS and NLoS scenarios in dynamic environments. The experiments aimed to assess the capabilities of the system to extract coarse-grained and fine-grained information for drone detection, motion recognition, and localization. The results showcase precise localization, achieving a 50% reduction in localization error compared to the conventional baseline. This localization accuracy remains resilient even when confronted with interference from other moving sources. The results also demonstrate the system's ability to accurately localize drones in NLoS scenarios where existing state-of-the-art optical technologies cannot work.

CCS Concepts: • **Human-centered computing** → **Ubiquitous and mobile computing systems and tools**.

Additional Key Words and Phrases: Drone, Localization, mmWave FMCW radar, micro-Doppler effect

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1 Introduction

Drones have various indoor and outdoor applications where they can navigate in locations that are difficult or even inaccessible for humans. These applications include search and rescue missions for locating victims, mining industry operations, traffic surveillance, agricultural monitoring and soil analysis, infrastructure health inspection, and warehouse operations [20, 53]. The increasing utilization of drones, especially in urban and densely populated areas such as workplaces, emphasizes the growing importance of safety and accuracy of

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drone localization and tracking. A search and rescue application [32] can be considered as an exemplar scenario where a drone acts as a scout for safety staff entering a partially collapsed building, through providing accurate location/mapping information in order to enable them to safely navigate around the space. Another illustrative scenario involves the support of mining operations [29], encompassing exploration, surveying, and mapping. Mining companies can use drones to gather data for topographical surveys and safety inspections, which supports operational optimization and safety enhancement. For such an application, drone accurate localization is essential for effective site navigation and data collection.

Localization is required for the drone's own navigation, that is, the autopilot typically relies on real-time tracking of its location during flight. GPS is the main tracking approach in outdoor settings where GPS coordinates are fused with the drone's onboard inertial sensor measurements [17]. However, GPS is rendered unusable if its signal is obscured by an object, this includes flying near tall buildings or moreover, when indoors.

Alternatives to GPS include optical motion capture systems, such as the VICON¹ camera-based tracking solution which is widely used in indoor environments providing accurate tracking over time. However, it is an expensive solution, requiring specialist camera hardware, and more importantly, it requires that the VICON system is pre-installed in the building, which may not always be viable (e.g. the aforementioned search and rescue mission). Camera-based systems, such as VICON, require specialist marker attachments to be added to the drone frame to help the camera identify the drone. The camera's ability to detect this marker is highly dependent on environmental conditions, such as well-lit surroundings and an unobstructed view, i.e., the drone is within line-of-sight (LoS) of the camera, which is not guaranteed in many scenarios. In search and rescue missions and mining operations scenarios, drones will navigate behind objects such as furniture, debris, safety workers, equipment, machinery, and structures, where camera-based localization will fail. Other localization approaches, such as Ultra-wideband (UWB)-based ranging [7, 40] are able to localize the drone in low-light or NLoS. They use transceivers on the drone's body to estimate pair-wise distances based on time-of-flight information. However, these approaches, like VICON cameras, also require careful placement of spatially separated UWB transceiver equipment where the drone will fly; (at least three) positioned around the operational tracking area for trilateration. This introduces significant complexity to their installation and calibration, which is not suitable for the unsafe conditions of our two scenarios. Eliminating the need for any modifications to the drone's body, *passive* localization systems based on acoustics have been introduced for drone tracking [10, 48]. However, they exhibit meter-scale inaccuracy and are sensitive to audio noise making them not suitable for precise indoor applications where such large errors can potentially result in poor navigation, drone collisions or crashes involving humans.

In this paper, we propose RaDro, a precise *passive* indoor drone localization and tracking system that utilizes a single-chip radar array without having to install multiple points in the operational area or requiring any additional hardware or software changes to the drone; significantly reducing the required effort to setup and deploy in a new environment. Radar-based drone detection has a longstanding history, particularly for military contexts in outdoor environments with extensive ranges (hundreds of meters) [9, 18], however they are restricted in resolution; their ability to determine a precise location. This limitation is due to the relatively long wavelengths of these radar technologies as they typically operate at lower frequencies, including S-band and X-band. Traditional radar systems tend to be larger in size due to the need for large antenna arrays (measuring in meters) which consume significant amounts of power. However, recent advancements in microchip manufacturing have resulted in the accessibility, cost-effectiveness, and reduced power consumption of mmWave radar antennas, operating at millimeter-wave frequencies (typically 30 GHz to 300 GHz). RaDro leverages the sensitivity of mmWaves to determine precise millimeter-level motion, thanks to its small wavelengths, to detect and track drones. It is also able to work in different levels of LoS and in NLoS scenarios, therefore tolerant to different environmental conditions where other common localization systems cannot work.

¹www.vicon.com

However, there are several challenges in using mmWave approaches to passively localize drones indoors that need to be addressed, which we introduce below.

Reflections and Interference: In indoor environments, the presence of reflective surfaces and stationary/moving objects leads to complex multipath propagation of radar signals. The mmWave signal received at the sensor antenna is a combination of reflections from the target (flying drone) and signals bouncing off obstacles (causing multipath effects). Indeed, the structure of the drone itself results in multiple signal reflections from its rotating points (blades). These multipath effects, plus the interference caused by ambient RF noise in the environment, can make signal denoising difficult and localization identification error prone. To address this challenge, RaDro adopts several signal processing techniques, including wavelet denoising, false rate detectors, and clustering algorithms to filter out the noise and extract the important information reflected from the drone's body to locate it.

Target Detection: Identifying a particular drone and understanding the direction it is taking for tracking purposes is also more difficult for radar due to the lack of identifiers on the drone and the environment in which it is deployed. That is, direction detection is impeded by dynamic environments (e.g., the movement of workers and machinery in mining sites). For instance, camera-based detection relies on identifying reflectors on the drone body for tracking. However, from a radar view, the drone consists of multiple rotating points, which presents extra challenges for drone identification.

RaDro addresses this challenge by characterizing the drone's multiple rotating point (propeller) reflections and leveraging the unique micro-Doppler signature in the received signal. Leveraging this distinctive signature with autocorrelation analysis allows RaDro to effectively distinguish the flying drone from other moving objects, even when the drone is hovering.

mmWave Information Resolution: Resolution of measurement is another challenge. Typically angle measurements are used to localize the drone and this is prone to error. Therefore, instead of relying on angle measurements, we utilize the observation that the multiple rotating propellers of the drone result in dual channel reflections on the received signal, impacting the signal with distinct fundamental frequencies. These frequencies correspond to the propeller speeds that in turn denote the state of the drone. These rotation speeds are then fed into the drone's dynamic model, following the recognition of the drone motion type (i.e., hovering, vertical, horizontal, and yaw), and used in the tracking module to maintain robust tracking.

This paper's contributions can be summarized as follows:

- We propose RaDro; an mmWave radar-based system which enhances drone localization and tracking in indoor environments with minimal hardware requirements. Unlike other existing localization and tracking alternatives, RaDro utilizes a single-chip radar array with no need for multiple point installation in the working environment or any modification requirement to the drone hardware, which significantly reduces the effort required for setup and deployment in new environments. RaDro's capability to operate without additional hardware attachments further extends its application to intruder detection.
- We implement signal processing techniques to extract reliable information from received mmWave signals, including the unique micro-Doppler signature of drone propeller speeds, to distinguish the flying drone from moving objects or possible clutter in the working environment and recognize the drone's motion type. The signal processing techniques include wavelet denoising, discrete wavelet transformation (DWT), fast Fourier transform (FFT), 2D constant false-alarm rate detector (2D-CFAR), and autocorrelation analysis.
- We precisely measure the drone propeller speeds based on their sensed mmWave micro-Doppler shift for the first time in literature. The measured propeller speeds are incorporated into the drone's motion dynamic model to further promote RaDro's tracking accuracy.
- RaDro's performance is evaluated in flying arenas involving complex environments with moving humans and metallic obstacles using commercial drones and off-the-shelf mmWave radar through various operating

scenarios to verify its robustness. The experimental evaluation demonstrates RaDro's capability to accurately localize drones in NLoS scenarios where existing optical-based localization systems are ineffective. Moreover, it highlights the significant localization error reduction that RaDro can achieve compared to the baseline mmWave 3D point cloud localization method.

The rest of the paper is organized as follows. Section 2 provides an overview on related work. Sections 3 and 4 present basic concepts and technical details of the RaDro system, respectively. We evaluate the system in Section 5. Section 6 discusses directions for future work and, finally, we conclude the paper in Section 7.

2 Related Work

We provide a brief overview of previous research related to our system, organizing it into two categories: indoor drone tracking and mmWave-based passive sensing and localization systems.

2.1 Indoor Drone Localization and Tracking

Different methods have been proposed in the literature to enhance the localization and autonomous motion of drones. GPS is the widely used approach for outdoor applications, however, the challenge of the non-reachability in challenging areas makes it difficult to be used in indoor applications [15]. A current research trend improves the indoor drone's localization by either attaching markers or sensors to the drone's body or localizing drones in a totally passive way that relies only on sensors installed in the environment [4, 19]. The first category of indoor drone localization techniques includes vision-based [44, 52], optics-based [50], ultrasound-based [43], and RF-based [7, 12, 13, 38, 43] techniques. Common to these techniques, they require modifications to the drone in order to track it, which increases the installation and calibration complexity. Moreover, both vision- and optics-based techniques require LoS and are highly sensitive to the lighting conditions. Additionally, RF-based systems, which rely on the construction of an aerial mobile sensor network for indoor monitoring [12, 38], necessitate careful equipment placement and a large number of nodes/drones to ensure reliable navigation, which increases deployment costs and complexity. Additionally, these systems may experience a reduction in navigation accuracy over time.

Passive localization techniques are the other indoor drone localization category which does not require any change or addition to the drone's body, which greatly simplifies deployment. In addition to drone localization and tracking, such passive techniques are suitable for intruder detection and localization applications for security purposes. Light detection and ranging (LiDAR) [31] and laser detection and ranging (LADAR) [26] can detect drones passively but they remain sensitive to environmental conditions. Acoustic-based passive localization systems [10, 48] use audio sensor arrays for drone localization. However, their precision is in meter ranges and they are sensitive to ambient noise. Various types of radar systems [9, 18, 54] operating at lower frequencies, such as S-band, are commonly used for detecting and localizing drones, often in military contexts. However, these systems have limitations in terms of localization resolution, typically ranging from tens to hundreds of meters, which is not applicable to precise indoor localization applications. Additionally, they tend to be bulky and costly which can range from tens of thousands to several millions of dollars based on the application. Recent progress in microchip manufacturing has led to the availability of cost-effective (~ \$300) wideband mmWave radar transceivers operating at millimeter-level wavelengths. These transceivers have been effectively utilized across a range of applications, as discussed in Section 2.2. In this work, we use a single-chip mmWave radar to passively and precisely detect and localize drones indoors, which can work independently of the lighting conditions and in NLoS scenarios, achieving an average localization error of less than 0.8m in an area covering up to 8m where existing optical-based systems are ineffective.

2.2 mmWave-based Passive Sensing and Localization Systems

This section provides a literature overview on mmWave-based passive sensing applications to highlight its capabilities, with a specific focus on mmWave-based localization systems. Compared to other technologies, such as WiFi [1, 3] and acoustic [48] signals, mmWave is highly sensitive to tiny mm-level displacements due to its small wavelengths, making it suitable for recognizing and tracking the movement of people or objects [2, 46, 51]. mmWave sensing has been utilized across various applications, including activity recognition [24, 30], vital sign monitoring [58], voice recognition [59], and vibration measurement [16, 23].

Several research works have proposed methods for indoor object localization and tracking using mmWaves [11, 14, 35, 55–57]. These systems typically extract range, Doppler, and angle measurements from mmWave radar received signals and then apply tracking algorithms, including the Kalman filter (KF) [25] and the joint probabilistic data association filter (JPDAF) [5], to estimate the object's trajectory. For instance, a human tracking system [61] uses mmWave radar measurements and adopts the Hungarian algorithm [28] for data association and KF to correct sensor noise for people tracking. To enhance the precision of human detection and tracking, other systems [14, 57] rely on a multi-radar setup, which increases the installation cost. Alternative methods [36, 37] rely on extracting the target's position and speed from the mmWave range-angle and range-Doppler profiles using neural networks. However, these approaches necessitate extensive data collection for model training, which can be costly and limit their generalizability across different environments. Another system [11] enhances human detection by developing a geometric model to characterise and eliminate multipath of interfering objects from mmWave range-angle profile. However, these localization systems are tailored for tracking objects such as humans and cannot be extended for drone localization due to their different structures. Drones are rigid bodies with multiple rotating points, leading to multiple reflections from these rotating points. Former mentioned mmWave localization systems might interpret these multiple reflections as indicative of distinct objects, potentially failing to specifically detect drones, especially at close ranges from the radar. In contrast, RaDro extracts these multiple reflection signatures to identify drones, effectively distinguishing flying drones from other moving objects. Furthermore, it uniquely correlates these signatures with the drone's propeller speeds, enhancing tracking accuracy by integrating these speeds into the drone's dynamic model.

Recently, few systems have emerged adopting the mmWave technology for detecting and localizing flying drones [41, 60]. Proposed systems leverage neural network and regression methods along with mmWave measurements to discriminate drones from other objects [6, 47].

In outdoor environments, systems have been proposed to detect drones at long distances [21, 33]. The system presented in [33] uses the constant false alarm rate detector on the Range-Doppler spectrum to detect drones in outdoor environments at ranges reaching 40m, while the system in [21] extends the detection range by adopting a neural network with Doppler spectrum. However, the working principle of these systems is to detect the altitude (one dimension) of the drone in outdoor environments which typically have fewer obstacles compared to indoor environments. Additionally, they are designed for relatively heavy drones, typically measuring in the range of 8 ~ 10 kg drones, that are suitable for outdoor environments. These drones are significantly large compared to the target of RaDro which can detect and localize a 27g drone indoors (more than 300 times smaller compared to [21, 33]). RaDro is a system proposed for detecting and localizing drones indoors in 3D space, which is a more complex problem than only detecting the height in one dimension.

In indoor environments, a passive localization technique proposed in [60] was to track a drone in a small area of 2.5×2.5 m using frequency modulated continuous wave (FMCW) mmWave radar. This technique involved the extraction of range and angle information from the mmWave signal, with a restricted localization area due to a lack of angle resolution. It also relied on a deep-learning approach, requiring additional time for extensive training that needs to be re-established for new environments. Our work leverages mmWave signals to localize drones passively, without requiring any reflectors or any training prior to deployment. It expands the operational tracking

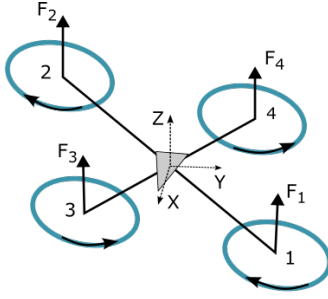


Fig. 1. Quadrotor model

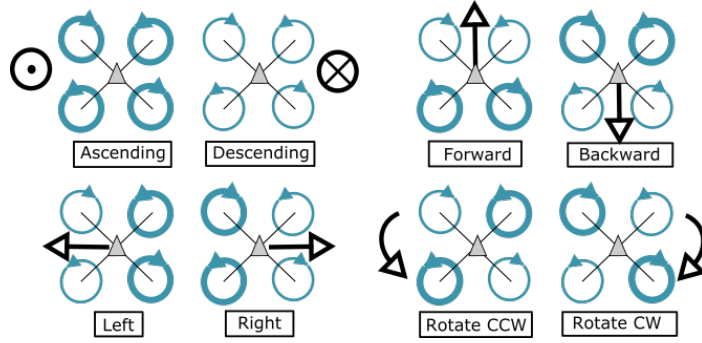


Fig. 2. Relation between quadcopter different motion types and propellers spinning direction (line thickness denotes high/low propeller speed)

area covering up to 8m (more than four times the area compared to [60]) through leveraging micro-Doppler information which is mapped to the propellers' speeds, and integrates the drone's dynamic model in the tracking process. Compared to existing mmWave indoor drone 3D localization approaches, RaDro achieves the same precision error of less than 10cm at a range of 3m, while uniquely extending the working area to 8m with a slight increase in the error to 50cm.

3 mmWave Drone Interference

This section presents the key features of FMCW mmWave and the impact of drone motion on the mmWave signal.

3.1 FMCW mmWave Parameters

FMCW is a modulation technique used in mmWave radar for measuring the range, velocity and angle of the target object. FMCW radar emits electromagnetic wave chirps whose carrier frequency increases linearly with time. The reflected waves from the target are received by the radar system (Rx) and mixed with the original transmitted signal (Tx) to produce an intermediate frequency (IF) signal containing information about the frequency shift caused by the target object's distance and velocity. The object's distance is estimated by extracting the peak frequency components of the IF signal caused by the frequency change corresponding to the round-trip time taken by the signal for back and forth traveling to the object. The Rx chirp, being a time-delayed rendition of the Tx chirp, yields a consistent frequency component f_0 in the IF signal, which is expressed as:

$$f_0 = S \tau = S \frac{2d}{c} \quad (1)$$

where S is the chirp slop, τ is the time delay between the Tx and Rx chirps. τ can be further derived in terms of the distance to the detected object d and the speed of light c . Therefore, the distance to the detected object is:

$$d = \frac{f_0 c}{2 S} \quad (2)$$

As the radar emits chirps continuously, the velocity of the target can be determined by analyzing the rate of chirp phase change at a particular frequency in the IF signal. The initial phase of the IF signal Φ_0 can be expressed as

follows:

$$\Phi_0 = 2\pi f_c \tau = \frac{4\pi d}{\lambda} \quad (3)$$

where f_c is the chirp start frequency and λ is the wavelength (corresponds to the start frequency for simplicity). By utilizing the observed phase change $\Delta\Phi$ associated with an object's motion of vT_c , the Doppler velocity of the object can be derived as follows:

$$v = \frac{\lambda \Delta\Phi}{4\pi T_c} \quad (4)$$

mmWave radar systems usually employ multiple-input multiple-output (MIMO) antenna arrays, that is important for the target object's angle measurement estimation. With multiple spatially separated MIMO antennas, the angle-of-arrival (AoA) can be estimated by observing the differential distance from the object to each of the antennas, which also results in a phase change in the IF frequency peak. The AoA between two antennas separated by a distance l can be determined by analyzing the phase difference $\Delta\Phi_{ant}$ of the signals received by the two antennas as:

$$\theta = \sin^{-1} \left(\frac{\lambda \Delta\Phi_{ant}}{2\pi l} \right) \quad (5)$$

The received data can be arranged into a 3-D tensor of complex numbers, a radar data cube, that contains all the information provided by the radar device for a given time frame. For one frame that contains M chirps where each chirp contains N samples and received by K antennas, the radar data cube dimensions are chirp data sample $1..N$ (denoted as fast time samples), chirp number $1..M$ (denoted as slow time samples), and antenna number $1..K$ (denoted as spatial dimension).

3D point cloud spatial information of the target object, captured using mmWave radar, includes range, velocity, and angle data, can be used to track drones [60]. However, conventional point cloud drone tracking is not stable due to the noisy captured frames. The source of the noise is caused by the instability of the radar information accuracy, such as the dependency of AoA estimation accuracy on angle value – i.e., the larger the angle between the radar and the target (reference to the norm of the antenna plane), the lower the accuracy of estimation [22]. Such AoA accuracy restrictions impact the localization coverage area to obtain reliable angle measurements, particularly for moving targets such as drones. For instance, the system proposed in [60] relies on the range and AoA measurements to localize the drone within a limited area of 2.5×2.5 m. To overcome this challenge, RaDro depends on more reliable measurements of micro-Doppler information.

The moving drone introduces a frequency shift in the radar received signal corresponding to the platform movement due to the Doppler effect. However, the structure of the drone's body consists of multiple rotating blades rather than a single point. These small-scale rotations of drone blades produce additional Doppler shifts, referred to as micro-Doppler effects, which cause a phase change in the reflected signal. The micro-Doppler shifts work independently of the relative position of the target and radar. Consequently, their signatures are commonly utilized for object identification [35]. The sensitivity of the micro-Doppler effect increases with smaller wavelengths of mmWaves. We leverage this micro-Doppler information to detect the drone and to sense its propeller speeds which indicate the drone state by integrating the drone's dynamic model for more robust tracking.

3.2 Drone Motion

Drones are mounted with propellers which provide lift and drag forces while spinning. In this work, a quadcopter, a popular type of drone (Figure 1), is considered. Quadcopters have four vertically oriented propellers placed symmetrically around the center of the vehicle. The four propellers produce four thrust forces $F_{1..4}$ that pull it upward. F_i is related to the i^{th} propeller spinning speed as $F_i = k \omega_i^2$, where ω_i is the spinning speed of the i^{th} propeller and k is the thrust coefficient constant which depends on various factors including the propeller

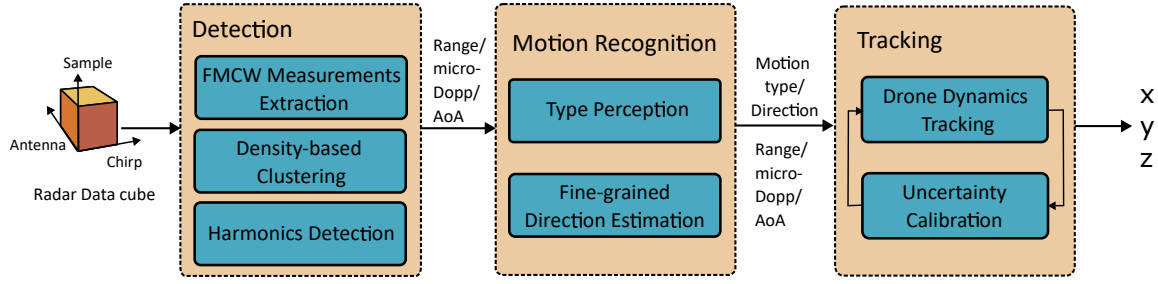


Fig. 3. Structural overview of RaDro

motor specifications and aerodynamic properties. By varying the rotation speed and direction of these propellers, quadcopters can perform different types of movements. The primary quadcopter movements are (Figure 2):

- **Hovering:** This maintains a stable position for the drone in the air by rotating the propellers at the same speeds (assuming absence of external environmental forces which need compensation). Thus, the relation between the four propeller speeds is: $\omega_1 = \omega_2 = \omega_3 = \omega_4$.
- **Vertical movement:** The drone can move vertically by increasing or decreasing the overall thrust produced with the four propellers. To rise vertically, the rotation speeds of the four propellers are equally and simultaneously increased to generate more lift force. Similarly, equally decreasing the four rotation speeds gradually implements a descend/landing motion. Therefore, the propeller speeds relation is $\omega_1 = \omega_2 = \omega_3 = \omega_4$.
- **Horizontal movement:** This refers to the forward, backward, rightward or leftward tilt of the quadcopter while maintaining vertical stability. To achieve that, the propellers operate in pairs where each pair rotates at the same frequency. For forward/backward tilt, the rotation speeds are as follows $\omega_1 = \omega_3$ and $\omega_2 = \omega_4$ which achieve a pitch movement. The same is applied for the rightward and leftward to achieve roll movement.
- **Yaw:** The speeds of each set of diagonal propellers are adjusted to $\omega_1 = \omega_2$ and $\omega_3 = \omega_4$, that achieve yaw movement around the drone's vertical axis. The speed mismatch between the two sets of diagonal propellers generates a torque imbalance steering the drone in the desired direction.

Interestingly, we found various drone movements affect the mmWave signal differently as the pattern of propeller angular motion changes. The speed of the propeller is highly correlated with the micro-Doppler frequency f_{Dopp} which, in combination with the other mmWave range and angle information, can identify and localize the drone's movement. As the propeller has a number of blades n , two blades in our case, we observe that the micro-Doppler frequency represents the blade crossing frequency, thus, $f_{Dopp_i} = n \omega_i$.

It is challenging to differentiate the exact locations of different propellers in the drone's body due to the lack of AoA resolution accuracy. Instead, RaDro leverages the mmWave FMCW ability to differentiate between objects within close range as they move at different speeds. Each object exhibits a distinct chirp phase change rate, extracted using the Doppler-FFT. Thus, the mmWave radar can differentiate micro-Doppler signatures resulting from individual propeller rotations at varying speeds. The extracted rotation speeds are then assigned to different propellers based on the motion type recognition and calibration steps, as discussed next.

4 Tracking Pipeline

Our approach for drone localization includes three parts. Firstly, the radar cube data is preprocessed to extract range, AoA, and micro-Doppler mmWave radar information. Secondly, the extracted mmWave information is

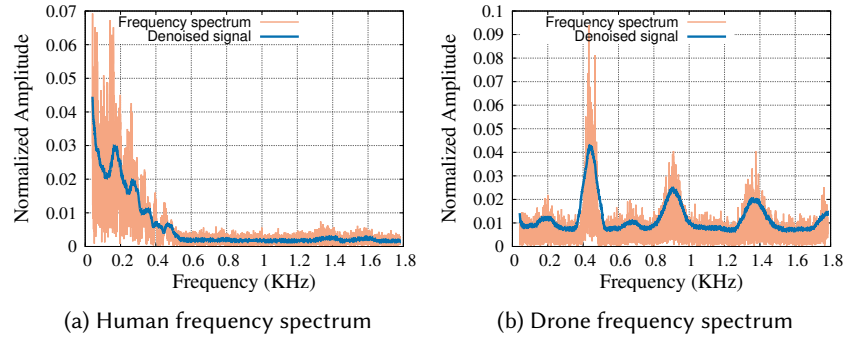


Fig. 4. The different effect of human and drone on the frequency spectrum

used to detect and recognize the motion type of the drone, and finally, the mmWave extracted information with the recognized motion type are combined with the drone's dynamics to achieve accurate drone tracking. Figure 3 shows the pipeline of the proposed approach.

4.1 Drone Detection

4.1.1 Unveiling FMCW Radar Information. The input raw radar data is the radar cube of the 3D signal that is produced at each time frame with dimensions of chirp data sample (fast time samples), chirp number (slow time samples), and antenna number (spatial dimension), as discussed in Section 3.1. The radar cube input data is used to build a range-Doppler-angle (RDA) map. This is achieved by first applying FFT along the fast time dimension, followed by Doppler-FFT along the slow time dimension to construct the range-Doppler map. This map is then fed into a 2D-CFAR algorithm to extract dominant points, i.e., removing background clutter and reducing noise, making it less dependent on the environment's characteristics. The angle of each dominant point is then estimated by observing the phase change between different antennas, achieved by applying an additional FFT on the antenna spatial dimension.

4.1.2 Moving Drone Detection. Then, the detection process distinguishes the target drone from other moving objects in the environment through the following steps:

Density-based Clustering. A density-based spatial clustering of applications with noise (DBScan) algorithm is applied on the RDA map to separate different clusters, which correspond to potential objects in the operational area. DBScan operates by sequentially scanning all the data points and expanding a cluster until a certain density condition is no longer satisfied.

Harmonics Detection. For each cluster, the micro-Doppler information that contains the propellers' motion signature is extracted by applying the short-time Fourier transform (STFT) on the slow-time dimension after integrating along the extracted cluster range bin index. The spinning propeller causes fundamental frequency component that represents the propeller spinning speed and harmonics which are integer multiples of the fundamental frequency. The other slow moving objects, relative to drone propeller spinning speed, in the environment (such as human movements) result in low-frequency variations in the received signal. As a result, harmonics of these low frequencies are also in the low-frequency range. Figure 4 demonstrates the difference between human movements and a hovering drone effect on the received mmWave signal spectrum. The distance between the mmWave radar and the drone is set to 2m, with the person standing 1m away along the line perpendicular to the line connecting the radar and the drone. During the experiment, the drone takes off, hovers,

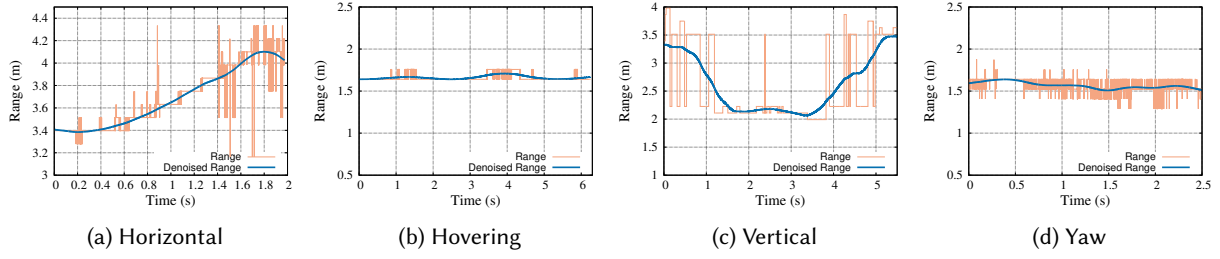


Fig. 5. Range pattern of the drone while performing different motions

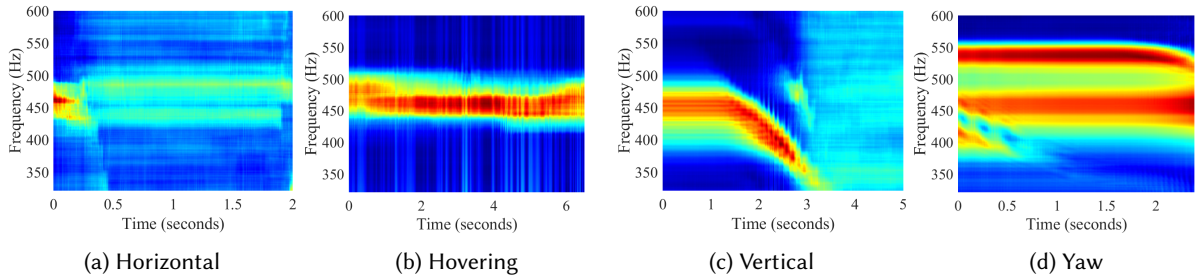


Fig. 6. Micro-Doppler spectrogram of the drone's different motions

and then lands, while the person engages in in-location activities at a normal speed, such as taking out a phone from her pocket, returning it, waving hands, and rotating her body. The experiment lasts for approximately 1 minute. Referring to Figure 4, it can be shown that hovering drones produce distinct frequency harmonics which are integer multiples of the fundamental frequency. In contrast, human movements do not generate significant harmonics in the received waves, with both the fundamental and harmonic frequencies concentrated at low frequencies. By calculating the autocorrelation of each cluster's micro-Doppler spectrum, the cluster that represents the drone is extracted where its autocorrelation coefficients are much higher than that for spectrums corresponding to other slow moving objects. The drone cluster range and angle information are used to represent the range and angle of the drone. The unveiled information of range, micro-Doppler and AoA are used to recognize and track the drone as explained next.

4.2 Motion Recognition

FMCW radar information is used to recognize the four main movements discussed in Section 3.2 along with further estimated fine-grained motion parameters to distinguish the ambiguity of motion direction.

4.2.1 Coarse-grained Motion Recognition. Different drone motions impact the mmWave signal differently; therefore, the extracted range, AoA, and micro-Doppler patterns are distinct. Figures 5 and 6 show the range and corresponding micro-Doppler spectrograms of the drone while performing different motions. The drone moves in front of the radar at distances ranging from 1 to 4 meters, executing horizontal, hovering, vertical, and yawing movements, each lasting for a few seconds. During hovering motion, the drone maintains a constant distance from the radar while having a single fundamental frequency band. In vertical motion, the distance from

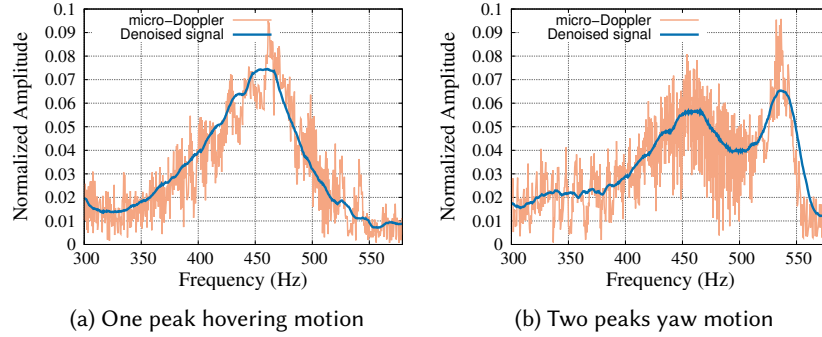


Fig. 7. Wavelet denoising impact on micro-Doppler spectrum

the radar changes while having one frequency peak at a time. Figure 6c illustrates a landing vertical motion of the drone, in which the single frequency band decreases with time. In contrast, the frequency band is split when performing horizontal or yaw motions as shown in Figures 6a and 6d. During horizontal motion, the drone's distance from the radar changes, while in yaw motion, the distance remains stable. Thus, the combination of range and micro-Doppler provides the necessary information to distinguish between different drone movements.

To reduce noise and better extract frequency peaks, a wavelet denoising filtering scheme [45] is used. Wavelet denoising is effective in reducing noise while preserving the important features of the signal. Additionally, it does not make any particular assumptions about the nature of the signal and permits discontinuities in the signal, which makes it compatible in different scenarios. Figure 7 shows the impact of applying wavelet denoising on a frequency spectrum of a time frame captured during hovering and yaw motions. The DWT analysis [49] is further used to extract these frequency peaks. Additionally, we employ the AoA as supplementary information to boost recognition accuracy. The AoA remains stable during hovering and varies across horizontal, vertical, and yaw motions.

4.2.2 Fine-grained Motion Recognition. The various potential assignments of the micro-Doppler peaks to propellers can cause ambiguity in determining the direction of motion. To reduce this ambiguity, after recognizing the drone's basic motion, further processing is applied to recognize the direction of the movement. For yaw motion, the AoA changing pattern over time is processed to distinguish between clockwise (CW) and counterclockwise (CCW) motion. The dominant estimated AoA is the angle of the highest speed propeller facing the radar while yawing. Figure 8 shows the angle of the highest speed during full drone rotation (i.e., 360 yawing) in CCW and CW directions. As shown in the figure, the captured AoA decreases over time for CCW yaw motion and, in contrast, increases for CW yaw motion.

In horizontal motions, the drone motion closer to or farther from the radar is estimated using the range signal. Crucially, we note the estimated range increases with time when the drone moves far away from the radar, as shown in Figure 5a, and decreases when moving closer. The fine-grained information is extracted for horizontal motion using the AoA measurements. For example, consider a scenario where the drone is positioned in front of the radar with its front propellers facing the radar, and the detected coarse-grained motion is horizontal. If the range decreases, indicating forward horizontal motion. If the range increases, there are three potential directions. If the AoA is stable, the horizontal motion is in the backward direction. If the AoA decreases, the horizontal motion is to the left, while increasing AoA indicates motion to the right. Due to the susceptibility of AoA's estimation to noise, a weight inversely proportional to the smoothed signal variance is incorporated into the tracking module to represent the confidence level of yaw and horizontal directions estimation, which is used in the uncertainty calibration module as explained in Section 4.3.2.

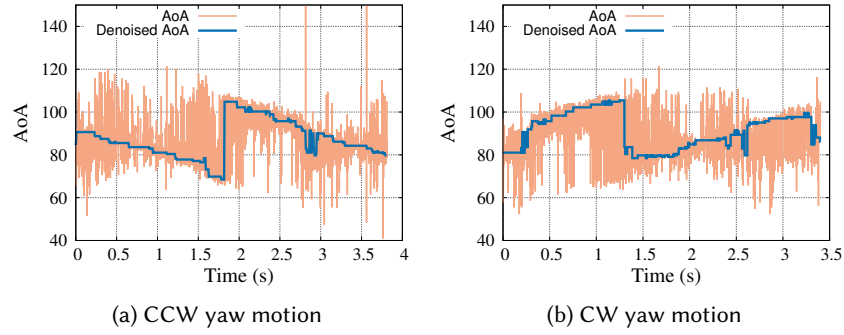


Fig. 8. Yaw motion direction

For vertical motion, the direction of descending (landing) or ascending (take-off) motion is recognized using the micro-Doppler frequency band. The frequency band increases with time during ascending movement. On the other hand, when descending, the frequency band decreases with time (Figure 6c).

Such fine-grained information reinforces the estimated location and reduces the motion direction ambiguity. Upon identification of the motion and its corresponding direction, these findings are subsequently fed into the dynamic model of the quadcopter.

4.3 Drone Tracking

This section illustrates the integration of the mmWave information with the drone's dynamics, leading to simplified motion equations to attain precise tracking.

4.3.1 Drone Tracking Model. The dynamic model of the quadcopter is initially derived from its movement, which is subsequently used for tracking. If the recognized motion of the drone is hovering, there will be no change in the drone's state. For the remaining motion types, the following motion equations are applied:

- **Vertical:** The rotation speeds $\omega_{1...4}$ are equal and increase or decrease slightly and simultaneously to produce a vertical force to counteract gravity and downward resistance $b^v (v_t^v)^2$ during ascending or descending movements, where b^v is a drag coefficient constant and v_t^v is the vertical velocity at time t . Based on Newton's second law, the vertical acceleration a^v at time t is captured using the following equation:

$$k \sum_{i=1}^N \omega_{i_t}^2 - mg - b^v (v_t^v)^2 = m a_t^v \quad (6)$$

Where ω_i is the angular frequency of propeller i corresponding to the single peak extracted from the micro-Doppler profile.

- **Yaw:** By increasing the speed of one set of diagonally opposite propellers while decreasing the speed of the other set, a torque imbalance is created as $|F_1 + F_2 - F_3 - F_4|$, causing the quadcopter to rotate around its vertical axis. The rotation angular acceleration $\dot{\Omega}$ is acquired using the following equation:

$$k \left| \sum_{i=1}^{N/2} \omega_{2i-1_t}^2 - \sum_{i=1}^{N/2} \omega_{2i_t}^2 \right| = I \dot{\Omega}_t \quad (7)$$

Where I is the moment of inertia constant, while ω_i corresponds to the two extracted peaks from the micro-Doppler spectrum. The direction of orientation is determined from the angle changing pattern as explained in Section 4.2.2.

- **Horizontal:** The rotation speed of two propellers on one side increases while decreasing the rotation speed of the other side, where two frequency peaks can be extracted from the micro-Doppler spectrum. Thus, the quadcopter tilts with angle θ , with respect to the vertical axis of the drone, and the drag force allows the drone to move horizontally. The net force caused by the propeller rotation speeds can be decomposed into two components: vertical and horizontal forces. The vertical force works against the gravity as follows:

$$k \sum_{i=1}^N \omega_{i_t}^2 \cos(\theta_t) = mg \quad (8)$$

With the information of the drone's mass m and gravity acceleration g , the tilt angle θ can be obtained. The horizontal force works against the resistance force $b^h(v_t^h)^2$ to make the drone move horizontally with an acceleration of a_t^h , where b^h is a drag coefficient constant and v_t^h is horizontal velocity. Based on Newton's law, the motion equation can be represented as follows:

$$k \sum_{i=1}^N \omega_{i_t}^2 \sin(\theta_t) - b^h (v_t^h)^2 = m a_t^h \quad (9)$$

The angular and linear accelerations and velocities for different motions are used to track the drone using the equations of motion in discrete time [39]. To avoid error drift over time, the estimated coordinates of the drone are calibrated as discussed next.

4.3.2 Uncertainty Calibration. An extended Kalman filter (EKF) [42] is used to calibrate tracking inaccuracies over time in the estimation of the yaw and horizontal motion direction and in the absolute drone localization. The drone's state vector represents the position and velocity, denoted as $S_t = [x_t, y_t, z_t, \psi_t, x'_t, y'_t, z'_t, \psi'_t]$ where x_t , y_t , and z_t are the drone position coordinates at time t and ψ_t is the drone yaw orientation angle relative to the radar. The algorithm is outlined through the following steps:

- The state vector is initialized and a prediction step is applied to estimate the a priori state estimate $\hat{S}_t$.
- mmWave parameters are calculated and the drone's motion type with weighted direction estimation is recognized. Then, the drone's location and yaw angle are estimated through the dynamic motion equations.
- The estimated state $\hat{S}_t$ is then corrected with the estimated position of dynamic equations and mmWave range parameters to output the optimal a posteriori state estimate.
- All weighted potential trajectories are traced until reliable AoA measurements are obtained. If the variance of the AoA estimations falls below a certain threshold, any ambiguity is resolved by updating the current coordinates through the incorporation of AoA and range information. Consequently, the weights of potential trajectories are updated, taking into account their distance from the current coordinate. The potential trajectories with low weights are then filtered out.

5 Evaluation

In this section, we proceed to implement RaDro and conduct experiments across diverse scenarios. These include varying LoS and NLoS conditions within dynamic environments, different flight arenas characterized by varying settings and clutter levels, a range of aerial maneuvers, and the utilization of drones of different sizes and models. The experiments are conducted to evaluate the performance of RaDro's modules: coarse- and fine-grained identification of drone movement types, measurement of propeller rotational speeds, and detection and tracking of drones.

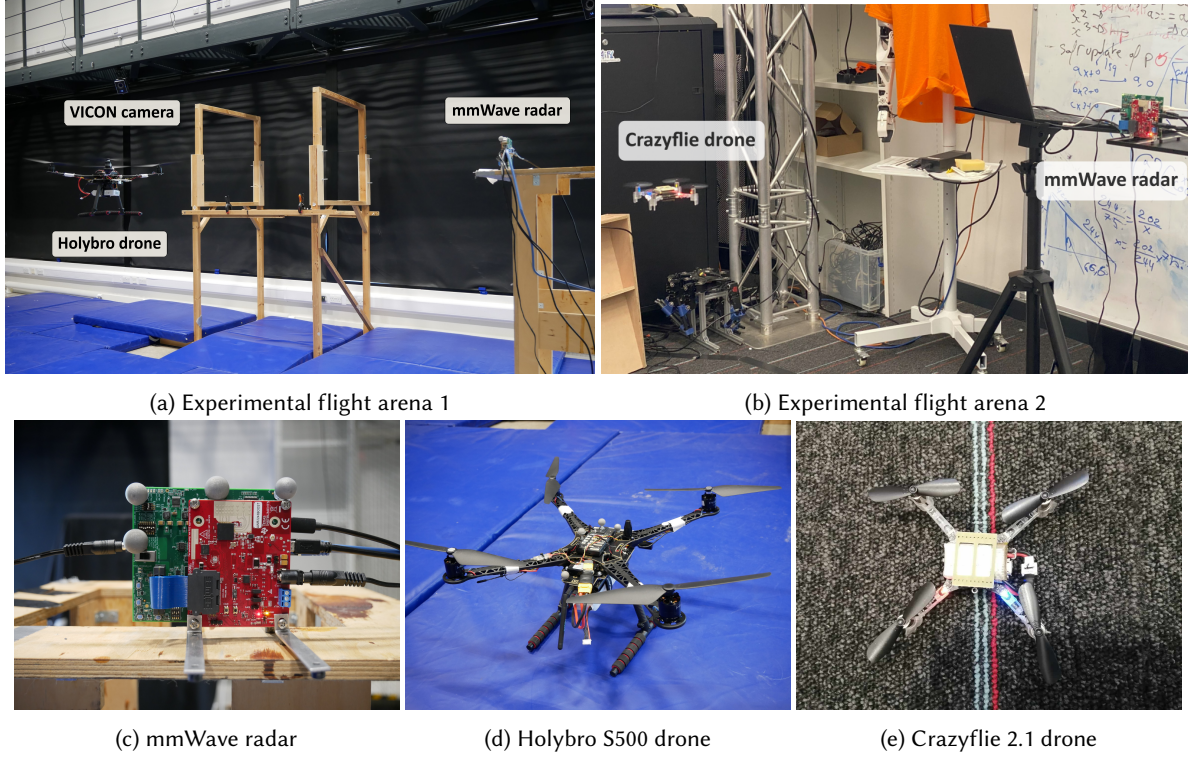


Fig. 9. Experiment setup of RaDro

5.1 Implementation and Settings

5.1.1 Hardware. We implemented and evaluated RaDro using a standard commercial mmWave radar board and drones. An overview of the experimental settings and hardware is shown in Figure 9. The mmWave radar utilized is the Texas Instruments (TI) AWR2243 (Figure 9c), operating within the 77-81 GHz millimeter-wave frequency band. It integrates 7 onboard antennas, including 3 transmitters and 4 receivers. In the experiments, the transmitter antennas transmit FMCW signals starting at 77GHz with 4GHz bandwidth, and all receiver antennas receive the reflected signals. The chirp duration is $40\mu\text{s}$, with the ideal time being $7\mu\text{s}$ and the ramp end time being $33\mu\text{s}$. The chirp frequency slope is $50\text{MHz}/\mu\text{s}$. The raw data is collected through the TI DCA1000EVM data acquisition board with a sample rate of 10MHz.

The flights are conducted using the Holybro S500 quadcopter (Figure 9d), weighing 782g and measuring $38.3 \times 38.5 \times 24.0$ cm, equipped with a Pixhawk 4 autopilot running PX4 firmware. Additionally, the Crazyflie 2.1 quadcopter (Figure 9e), weighing 27g and measuring $9.2 \times 9.2 \times 2.9$ cm, is utilized with an autopilot control based on an STM32 microcontroller. To collect ground truth data, a companion computer, Raspberry Pi4, is installed on the Holybro drone and connected to the autopilot via UART for mavlink communication between the drone and a ground control station PC. The Raspberry Pi4 uses MAVROS to stream time-stamped information of VICON motion tracking to the drone. For Crazyflie drone, the Crazyradio is used for the communication between the drone, the ground control station PC, and VICON information streaming. The time synchronization between

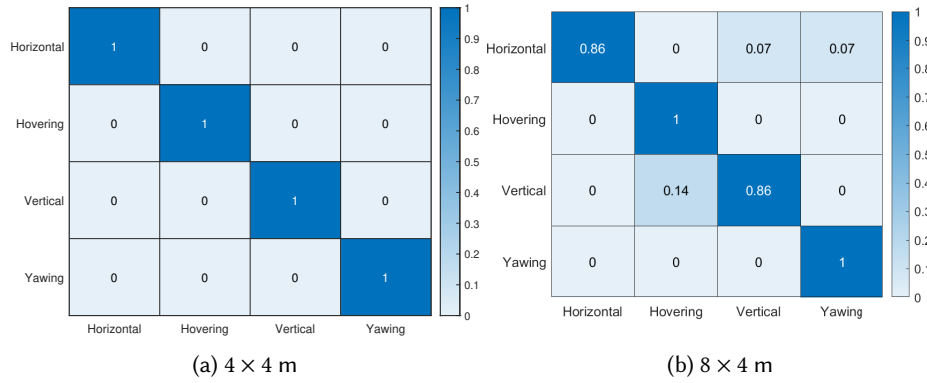


Fig. 10. Motion recognition confusion matrix of the four coarse-grained motions

different devices is maintained using the Network Time Protocol under the same network subnet. The default drone used to perform the experiments is Holybro, unless the other Crazyflie drone is mentioned.

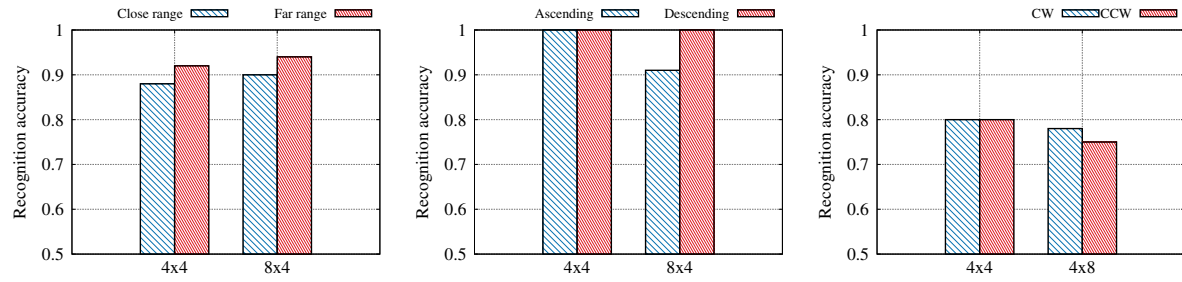
5.1.2 Experiments Settings. The experiments are conducted in two indoor flight arenas with sizes $L \times W \times H = 11 \times 6 \times 7$ m (Figure 9a) and $5 \times 5 \times 7$ m (Figure 9b). Throughout the experiments, each flight arena had a minimum of three individuals in motion nearby. The flight arenas have a range of obstacles including metallic stairs, cable trays, and stands, which serve as significant sources of distraction. The experiments involving flights covering an 8×4 m area are conducted in the large flight arena, while flights covering 4×4 m area are conducted in the small flight arena. Both arenas are equipped with VICON motion capture system to trace the ground truth of the drone position and attitude at a sample rate of 100Hz. A Tachometer is used to measure the propeller speed which is considered a reference for the rotation speed ground truth of the system.

5.1.3 Metrics. The evaluation includes different experimental metrics to assess various parts of the system. These metrics include the true positive and false positive percentages of recognized motion type to evaluate the drone's motion recognition module. Revolution per minute (RPM) error and RPM relative error rate are used to judge the performance of the angular speed of the spinning propellers. The RPM relative error rate is calculated as $|\frac{\hat{C}-C}{C}| \%$, where $\hat{C}$ is the RaDro propeller speed measurement and C is the propeller speed ground truth. Additionally, a localization error metric is employed to evaluate the overall system performance. The error bars shown in the evaluation figures indicate the 95% confidence interval of the error distribution.

5.2 Motion Identification Performance

We first evaluate the system performance in terms of recognizing the drone's motion type. The drone performs the four movement types: horizontal, hover, vertical, and yawing, with each repeated approximately 10 ~ 15 times at random distances from the radar for each situation. Figure 10 shows the performance in two different areas to evaluate the impact of changing distance. In the small area of 4×4 m, RaDro accurately identifies the four basic movements of the drone without any false identifications (Figure 10a). In the larger area of 8×4 m, drone's movements are occasionally misidentified due to the susceptibility of the mmWave signal to noise and interference when the drone moves farther away from the radar (Figure 10b).

In the context of fine-grained motion direction identification, Figure 11 illustrates the system performance using true positive accuracy to recognize the different motion directions within the 4×4 m and 8×4 m areas. Fine-grained direction identification includes distinguishing between closer and far away horizontal directions,



(a) Horizontal motion closer and far away (b) Vertical motion ascending and descending from mmWave antenna (c) Yawing motion CW and CCW

Fig. 11. Fine-grained motion parameters recognition

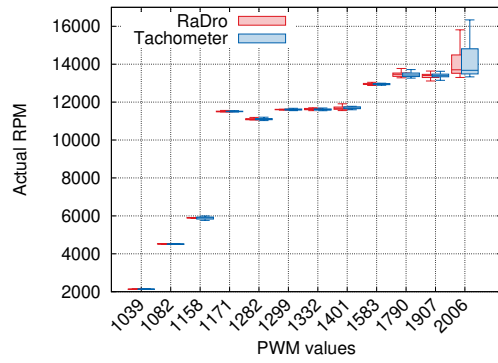


Fig. 12. Commanded PWM versus actual RPM measured by Tachometer and RaDro

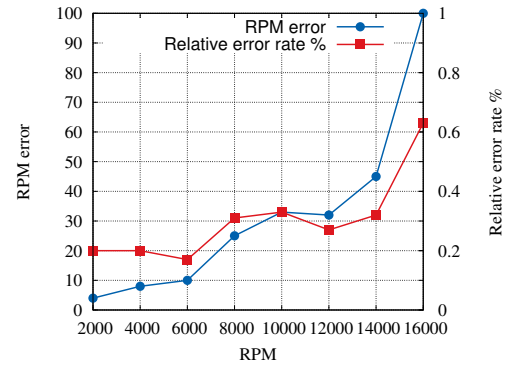


Fig. 13. RPM estimation error and relative error rate of RaDro speed sensing for the different flight speeds

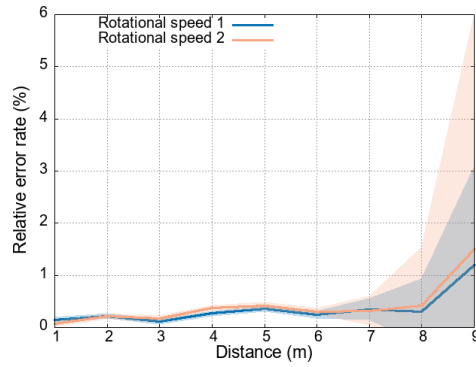


Fig. 14. RPM relative error rate at different distances from the mmWave antenna. Shadows represent the 95% confidence interval of the error distribution

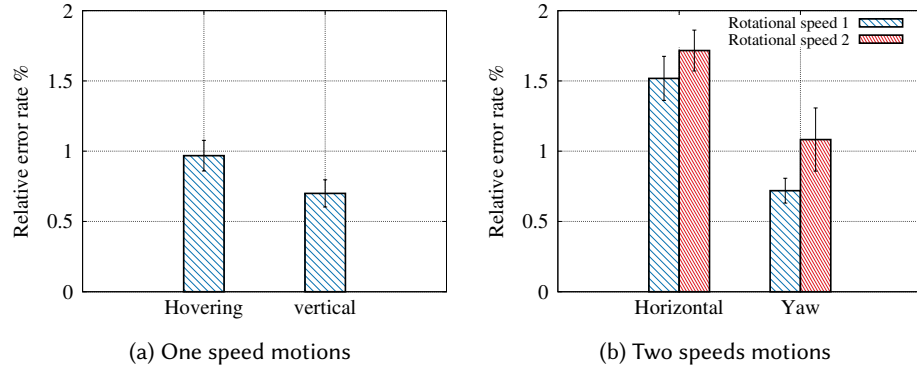


Fig. 15. RPM relative error rate for the four motions of the quadcopter

Area	Rotational speed 1 relative error rate (%)			Rotational speed 2 relative error rate (%)		
	Median	percentile 75	Maximum	Median	percentile 75	Maximum
4 × 4 m trace	0.32	0.6	6.9	1.37	3.37	18.37
8 × 4 m trace	0.09	0.57	2.18	0.52	0.97	39.82

Table 1. RPM relative error rate of propeller speeds during a flight

ascending and descending vertical directions, and CW and CCW yawing directions. The precise identification performance of the vertical motion direction shown in Figure 11b, is a result of the robustness of the micro-Doppler shift information (additional evaluation results are presented in Section 5.3). The horizontal motion direction is also recognized with a high accuracy of around 90% (Figure 11a). Conversely, the slightly reduced performance in identifying the yaw motion direction can be attributed to the sensitivity of the estimated angle information (yet this is still acceptable as the accuracy ranges from 75% to 80% which is then calibrated in the tracking module).

5.3 Rotational Speed Measuring Performance

Beyond movement detection, propeller speed detection plays a fundamental role in tracking drones. As a result, we provide an extensive evaluation of the propeller speed estimation performance using mmWaves. The experiments are conducted under two distinct settings: fixed-drone and flying-drone scenarios, involving various movements performed at different distances from the radar and following specific trajectories.

5.3.1 Capturing Different Rotational Speeds. A fixed-drone scenario is employed to evaluate the system's ability to capture different propeller rotation speeds in the range of flying scenarios. A hovering motion is manually commanded with different throttle levels for the fixed drone while positioned at a distance of 1m from the radar. Figure 12 shows the commanded pulse width modulation (PWM) received by the flight controller, which represents the magnitude of the commanded RPM, versus the actual RPM measurement using both RaDro and a Tachometer. The commanded PWM values are varied by changing the throttle level of a handheld radio remote control. The commanded PWM values in the range of 0 to 100% throttle level on the remote control are from 984 to 2006. As shown in the figure, each commanded PWM (throttle level) is mapped to variable propeller speed ranges. For lower PWM values, the actual RPM linearly changes with the commanded PWM. The actual RPM range then significantly increases with commanded PWM of 1171 (18% throttle) to be around 11000 RPM and continuously increases until it reaches around 14000 RPM with commanded PWM of 2006 (100% throttle).

Area	RaDro localization error (m)			Point cloud localization error (m)		
	Median	percentile 75	Maximum	Median	percentile 75	Maximum
4×4 m trace	0.11	0.15	1.07	0.61	0.79	2.6
8×4 m trace	0.4	0.5	2	0.76	0.98	5.85

Table 2. Drone localization errors in 2 different areas

Figure 13 shows the relative error rate of estimating the propeller rotational speed using RaDro (relative to the Tachometer). It shows the ability of RaDro to accurately capture the rotation speed even for the high speeds of ~ 16000 RPM with a relative error rate of 0.63%.

We also perform experiments to evaluate the impact of distance on propeller speed sensing performance. Figure 14 illustrates the performance while applying a pitch-back horizontal motion command to the drone, thus the front pair and the rear pair of propellers are in different speeds, at different distances from the radar. The horizontal motion results in two frequency peaks that map to two rotational speeds. The two speeds can be captured with stable accuracy while the distance is less than 8m where the mean relative error rate is maintained less than 0.5%. Errors begin to increase after 8m, likely due to surrounding obstacles in the flight arena during the experiments. Based on these results, we define the operational range of the experiments to be up to 8m. However, this range can be expanded using multi radar arrays.

5.3.2 Capturing Rotation Speeds while Flying. This experiment evaluates the system capability to estimate the propeller speeds during flight. Because of the complexity of using tachometer with a flying drone, we use the relationship between the RPM and PWM to obtain the ground truth of the rotational speeds from the commanded PWM. Figure 15 shows the impact of different motion types on the accuracy of the rotational speed sensing. The speeds can be accurately captured for all motions types with RPM relative error rate ranges between 0.6% to 1.7%. To evaluate the impact of changing the distance, the drone flies in 4×4 m and 8×4 m quadrilateral trajectories. As shown in Table 1, the system can maintain a median RPM relative error rate of less than 1.37% for both the 4×4 m and 8×4 m trajectories. On the other hand, the maximum relative error increases when the distance is increased due to the weakening energy of the corresponding frequency peak in far distances.

5.4 Drone Tracking

5.4.1 Impact of Flight Range. To evaluate the overall performance of the system, the drone flies in 4×4 m and 8×4 m quadrilateral trajectories. The ground truth is obtained from the VICON system and the localization error of RaDro is compared with the performance of a Point Cloud based method [60]. Table 2 shows that the median localization error experienced more than 50% reduction with RaDro compared to the point cloud-based method. For both areas, the maximum estimation error is significantly reduced with RaDro due to the stability of micro-Doppler information used in our system compared to the angle information as explained in Section 3.1.

5.4.2 Localization of Different Drone Models. To evaluate the system's robustness to different drone sizes, we compare the localization accuracy for two drones, the Holybro S500 V2 with dimensions of $38.3 \times 38.5 \times 24.0$ cm and a much smaller one, the Crazyflie 2.1 with dimensions of $9.2 \times 9.2 \times 2.9$ cm (W x H x D). The experiments are conducted in the $5 \times 5 \times 7$ m flight arena. Figure 16a shows the localization errors for both drones while hovering at different distances from the radar. The localization error of the Crazyflie drone slightly increases at 4m distance. Figure 16b shows that the median localization error for both drones during a trace-following flight is less than 10cm with a slight increase in maximum error for Crazyflie. These results can be justified by the fact that the radar cross section depends on the target size, influencing the amount of radar energy reflected back to the source [27], and consequently, affecting the localization accuracy.

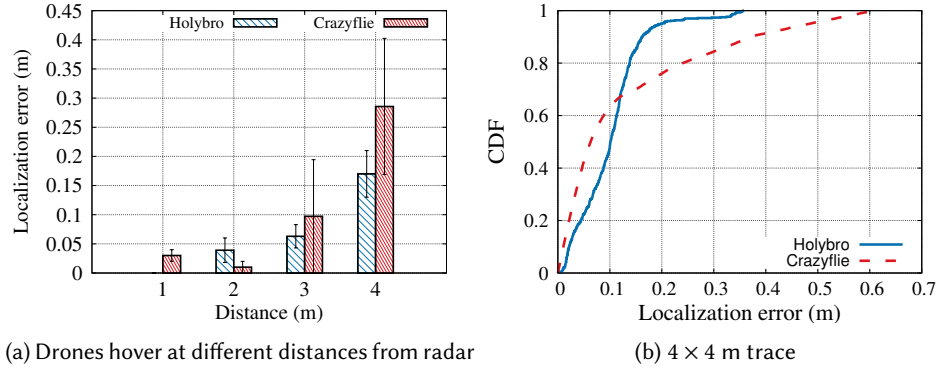


Fig. 16. Localization errors for different drone models

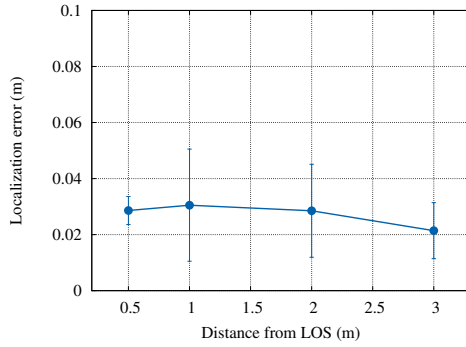


Fig. 17. Localization error with interfering human at different distances from the LoS

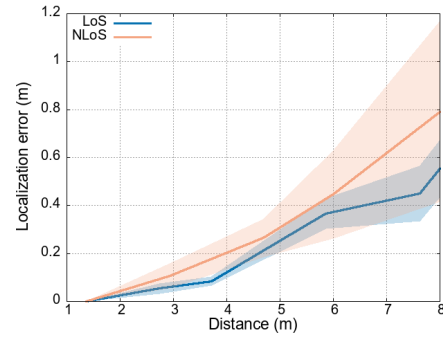


Fig. 18. Through-the-wall localization performance. Shadows represent the 95% confidence interval of the error distribution

5.4.3 Localization with Interfering Human. Since RaDro relies on the changes in mmWave signals, humans affecting the LoS between the radar and target drone may severely affect drone detection accuracy. To evaluate RaDro's localization accuracy, we perform an experiment where the distance between the mmWave radar and the flying Crazyflie drone is set to 2m. An interfering individual, performing in-location random activities (moving hands, holding a phone, and rotating body), moves in different positions along the line perpendicular to the line joining the radar and drone. Figure 17 illustrates the results, indicating that the localization error remains stable around 3cm, highlighting the robustness of RaDro's detection method as presented in Section 4.1.

5.4.4 NLoS Scenario. We also evaluate the system performance in NLoS scenarios. In NLoS setup, a vertical block stand is deployed in front of the radar array to block all the LoS paths while hovering the drone at different distances from the radar. The results are shown in Figure 18. The localization error slightly increases proportional to the distance between the drone and the radar while maintaining a maximum mean localization error of 0.8m in the operational area. These findings highlight RaDro's substantial potential for through-the-wall localization applications, encompassing intruder detection and security-related purposes across diverse lighting conditions.

6 Discussion and Outlook

In the future, we will extend the system in multiple directions including the following:

Area Expansion: RaDro operates in a passive manner to achieve indoor drone localization using a single mmWave radar array. While the experimental results highlight its effectiveness in a flight arena, there is potential for expanding its sensing capabilities by deploying distributed radar arrays to accommodate various layouts and environments. Maintaining the optimal distance between each two radar arrays is essential for real-world deployment, particularly for accurate drone tracking with the shortest operational range. This deployment process is simpler compared to other technologies; for instance, UWB-based systems require precise installation of at least three anchors in the environment, along with attaching a tag to the target body for localization based on pairwise distance estimation. In contrast, the potential approach to expand the working area of RaDro simplifies installation and calibration processes, as each mmWave array chip can independently estimate the target location within its coverage area.

Multiple Drone Tracking: When multiple drones are concurrently within the radar's field of view, their trajectories are typically distinct enough to ensure flight safety. Differences in range, Doppler and angle dimensions can be utilised to differentiate between multiple drones where each drone would have a different cluster in the RDA map (Section 4.1). Thus, each drone can be individually tracked using RaDro system approach. In scenarios where drone trajectories intersect, their unique micro-Doppler features can assist in distinguishing their respective paths, each characterized by a distinct micro-Doppler signature. Algorithms like the JPDAF and Multi-hypothesis Tracking (MHT) [8] can be employed in such intricate scenarios where these algorithms have demonstrated resilient performance in multiple target tracking tasks. Further investigation of RaDro's capability for multiple drone tracking will be considered as interesting future research.

Drones and Humans Sharing Spaces: RaDro can operate in dynamic environments where the discernible signatures resulting from the propeller rotations are distinguished from those of other moving objects, including humans, as shown in Sections 4.1 and 5.4.3. The human signature (Figure 4a) can be further leveraged to detect humans and their activities concurrently with drone localization. This highlights RaDro's ability to enable the secure coexistence of drones and humans in shared spaces for various applications.

Identifying Drone Structures: While assuming known drone specifications is acceptable for working environments such as warehouses, given their standardization among well-known companies, It is worth exploring the possibility of automatically identifying the drone structure for intruder detection applications. RF waves have already been employed to estimate the drone's model and weight by extracting the drone's body vibration profile [34]. Several studies have demonstrated the capabilities of mmWave radar in extracting vibration characteristics [16, 23]. This highlights the potential of the mmWaves to passively identify the drone structure, thus enabling RaDro to operate independently of drone parameters identification.

Complex Environments: Another issue is the deployment in highly cluttered spaces such as industrial environments for mining tasks. These environments are characterized by numerous obstacles that can significantly impact the radio waves through distraction and interference. Examples of such obstacles include machinery, equipment, and structures, all of which can obstruct or distort the signal, posing challenges for accurate drone localization and tracking. Moreover, the presence of metallic objects in industrial settings can exacerbate signal interference, further complicating the deployment of the radio-based sensing system in these environments. Addressing these challenges requires careful consideration of signal propagation dynamics and the implementation of robust signal processing techniques tailored to operate effectively in such cluttered spaces, where the proposed methodology for modelling the multipath reflections in [11] can be used. The proposed RaDro's drone detection

approach in Section 4.1.2 depends on propeller rotation harmonics detection, demonstrating high accuracy even in dynamic environments with various obstacles, including metallic objects and moving humans. This approach has the potential to operate in highly cluttered industrial spaces, warranting further investigation in future research.

7 Conclusion

In this paper, we have presented RaDro for passive indoor drone localization using a single mmWave radar array. RaDro is cost-effective, doesn't require attaching tags or anchors to drones, and works effectively in different LoS and NLoS scenarios independent of lighting conditions. It achieves 3D tracking with a single radar point, resulting in a simpler deployment, indeed the drone can deploy the mmWave sensor itself; useful for several applications such as search and rescue missions and mining tasks. The system captures the micro-Doppler signature corresponding to the drone's propeller speeds which are incorporated into the drone's dynamic model to improve the performance of the mmWave tracking system. Extensive evaluation of RaDro in different scenarios has been conducted using commercial off-the-shelf mmWave radar and drones. The results show that there is a significant reduction in localization error compared to the baseline. The results also demonstrate the robustness of the system performance in the presence of interfering objects, including moving people around the experimental space. Our system demonstrates that it has the potential to detect humans and some of their behaviours concurrently while providing drone location. This highlights the further potential of the approach to facilitate the secure coexistence of drones and humans in shared spaces. Additionally, the system exhibits its capability to accurately localize drones through the wall with an average localization error of less than 0.8m at distances up to 8m without attaching any reflector to the drone body, a task where conventional state-of-the-art optical technologies face limitations. This underscores the effectiveness of RaDro for intruder detection and security applications under varying lighting conditions.

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