

Article

A Micro-Doppler Flash Detection Framework for Hovering UAV Detection

Tianxing Zhang , Rui Sun and Ye Yuan *

School of Information and Communication Engineering, University of Electronic Science and Technology of China, Chengdu 611731, China; zhangtx0807@163.com (T.Z.); 15128271661@163.com (R.S.)

* Correspondence: yeyuan@uestc.edu.cn

Abstract

This paper proposes a micro-Doppler flash detection framework for hovering unmanned aerial vehicle (UAV) detection with linear frequency modulated continuous wave (LFMCW) radar under the dual constraints of strong ground clutter and severe thermal noise conditions. In such scenarios, conventional methods fail not only due to the spectral overlap between hovering targets and clutter but also because of the visual disappearance of micro-Doppler features under heavy noise. The framework consists of three sequential modules. A prior-template orthogonal projection (PTOP) module suppresses clutter via a single-step orthogonal projection, preserving the micro-Doppler flash signature without distortion while approximately maintaining the Gaussian noise statistics required for subsequent detection. A flash power spectrum construction module then collapses the periodic blade flash energy onto a sharp spectral peak in a one-dimensional (1D) power spectrum via Gabor transform, power projection, and fast Fourier transform (FFT). A cell-averaging constant false alarm rate (CA-CFAR) detection module with an analytically derived threshold factor finally renders a reliable detection decision. Simulations under a signal-to-clutter ratio (SCR) of -21 dB and signal-to-noise ratio (SNR) of -23 dB confirm that the proposed framework achieves reliable detection even when the micro-Doppler flash signatures are visually obscured by residual noise in the time–frequency domain. Parametric SNR sweep curves and a two-dimensional (2D) SCR–SNR detection-probability heatmap under a non-stationary clutter model further quantify the practical performance boundaries of the framework. By transforming these concealed periodic features into a sharp spectral peak, the framework provides robust detection performance where conventional range-Doppler and moving target indication (MTI)-based methods both exhibit severe performance degradation.

Keywords: LFMCW radar; hovering UAV detection; micro-Doppler flash; clutter cancellation; CA-CFAR



Academic Editor: Emanuele Cardillo

Received: 27 April 2026

Revised: 18 June 2026

Accepted: 23 June 2026

Published: 25 June 2026

Copyright: © 2026 by the authors.

Licensee MDPI, Basel, Switzerland.

This article is an open access article distributed under the terms and conditions of the [Creative Commons Attribution \(CC BY\)](https://creativecommons.org/licenses/by/4.0/) license.

1. Introduction

With the rapid proliferation of unmanned aerial vehicles (UAVs) in various civilian and commercial applications, their unauthorized deployment poses increasingly severe threats to low-altitude airspace security, privacy, and urban surveillance [1–4]. These rotorcraft, typically characterized as “low-slow-small” (LSS) targets [5], present significant challenges for weak signal extraction and reliable target recognition within traditional air defense architectures [6,7]. To counter these LSS threats, linear frequency modulated continuous wave (LFMCW) radar has been widely adopted for low-altitude surveillance owing to its

high range resolution, low power consumption, and the ability to eliminate near-range blind zones caused by transmit-receive switching in pulsed radars [8–11]. In practical threat scenarios, unauthorized UAVs frequently execute strict hovering maneuvers to perform critical missions such as persistent covert surveillance, high-resolution target reconnaissance, and precise payload delivery. Nevertheless, a critical physical bottleneck remains when a UAV operates in this strict hovering state. In this scenario, the UAV body exhibits zero radial velocity, causing its Doppler frequency to overlap completely with strong ground clutter. Consequently, conventional moving target indication (MTI) filters or moving target detector (MTD) banks suppress the target return together with the clutter, leading to inevitable missed detection and severe degradation of the energy-domain detection chain [12,13]. To address this limitation, extensive research attention has pivoted toward exploiting rotor micro-Doppler signatures. Currently, investigations into the micro-Doppler features of UAVs can be systematically categorized into three main streams. First, regarding feature extraction and time–frequency (TF) analysis, advanced signal processing tools have been developed to capture non-stationary blade flashes. For instance, pseudo-Bayesian algorithms based on the short-time Fourier transform (STFT) [14] and wavelet coefficient enhancement [15] have been proposed to robustly extract instantaneous frequencies even under severe noise conditions [16–18]. Second, building upon extracted TF features, significant efforts have been dedicated to micromotion parameter estimation. Modern algorithms, such as complex Bayesian compressive sensing [19] and multi-domain feature fusion [20], have demonstrated efficacy in estimating rotation rates and blade lengths despite unstable hovering dynamics or low pulse repetition frequencies [21,22]. Finally, in the realm of target classification, micro-Doppler spectrogram images are harnessed as distinctive fingerprints. Both support vector machines (SVMs) [3] and deep learning frameworks, such as convolutional neural networks (CNNs) [23–26], have achieved high-accuracy discrimination between drones and biological clutter such as flying birds [27]. Despite the success of the aforementioned micro-Doppler analyses, most existing work implicitly presupposes that the range bin containing the target is already known, i.e., the detection decision has been completed in advance [28]. While some studies explore utilizing micro-Doppler information for detection [2,25,29], they predominantly target moving UAVs or rely on empirical thresholds. However, dedicated investigations into the detection under the dual constraints of extremely low signal-to-clutter ratio (SCR) and signal-to-noise ratio (SNR) conditions remain scarce. Most existing methods assume either a high-SNR environment or a clutter-free scenario, leaving the detection of hovering UAVs in practical, complex environments an open challenge. Once the body return is eliminated by conventional zero-Doppler filtering, energy-based detection architectures suffer severe degradation, rendering subsequent micro-Doppler classification networks highly ineffective. Detection approaches based on micro-Doppler energy statistics, such as the range-energy pre-screening and STFT pixel thresholding method of [29], also encounter fundamental limitations under the dual constraints considered here: strong clutter submerges the range-energy pre-screening step, while the short-window coherent gain of STFT-based detection is insufficient to lift the flash signature above the noise floor at extremely low SNR.

This paper proposes a micro-Doppler flash detection framework that fundamentally shifts the detection decision domain from the range-Doppler energy domain, where the criterion is whether the target moves to the flash frequency domain, where the criterion is whether the target exhibits periodic rotor blade flash. This paradigm shift renders hovering UAVs, whose zero-Doppler body return is indistinguishable from stationary clutter, detectable through their rotor modulation signature. The framework consists of three sequential modules: a prior-template orthogonal projection (PTOP) module for clutter suppression, a flash power spectrum construction module for energy concentra-

tion, and a cell-averaging constant false alarm rate (CA-CFAR) module for automated decision-making [30]. The main contributions of this work are as follows:

- We propose the PTOP module to address the strong ground clutter suppression challenge. By exploiting the slow-time stationarity of ground clutter, it eliminates the dominant clutter component via a single-step orthogonal projection. This ensures zero distortion to the micro-Doppler flash signature while approximately preserving the Gaussian noise statistics essential for subsequent weak signal detection, thereby enabling an analytically derived CA-CFAR threshold with a statistical guarantee.
- We develop a flash power spectrum construction module to achieve robust weak signal enhancement. It effectively overcomes the bottleneck of visual feature disappearance under extreme low-SNR conditions by aggregating concealed periodic energy into a sharp spectral peak. This transformation from the two-dimensional (2D) time–frequency plane to the one-dimensional (1D) flash frequency domain provides the necessary integration gain for detecting hovering targets.
- We derive an analytical threshold factor for the CA-CFAR detection module, providing a theoretically grounded framework that maintains robust detection resilience. This ensures reliable decision-making even when the target’s micro-Doppler signatures are entirely submerged by noise in traditional time–frequency representations.

The remainder of this paper is organized as follows. Section 2 formulates the mathematical models of the LFMCW radar echo, the hovering UAV target, and the ground clutter. Section 3 details the proposed micro-Doppler flash detection framework, including the PTOP clutter cancellation, the flash power spectrum construction, and the analytical CA-CFAR detection. Section 4 presents the numerical results and Monte Carlo simulations to demonstrate the effectiveness of the proposed framework. Section 5 provides the potential extensibility of the framework. Finally, Section 6 concludes the paper.

2. System Model

The geometric configuration is illustrated in Figure 1. The radar is located at the origin of the coordinate system. Let R_0 denote the initial slant range from the radar to the rotor center, α the azimuth angle, and β the elevation angle. To simplify the model, $\alpha = \beta = 0^\circ$ is assumed. The UAV body moves along the radar line of sight with initial radial velocity v_0 ; for the hovering scenario considered here, $v_0 = 0$. The UAV carries N_b blades of length L , uniformly distributed in the rotor plane and rotating at rotational frequency f_{rot} (in r/s), corresponding to angular velocity $\omega = 2\pi f_{\text{rot}}$.

The LFMCW radar transmits a linearly frequency modulated waveform within each sweep period T_p , with carrier frequency f_c , sweep bandwidth B , frequency modulation slope $K = B/T_p$, and wavelength $\lambda = c/f_c$, where c is the speed of light. The corresponding range resolution is $\Delta R = c/(2B)$. The m -th pulse ($m = 1, \dots, M$) corresponds to slow time $t_m = (m - 1)T_p$. For a point target with an initial range R_0 and a constant radial velocity v_0 , the instantaneous slant range is $R(t_m) = R_0 + v_0 t_m$. The down-converted beat signal after low-pass filtering is expressed as follows:

$$s_b(t, t_m) \approx A \exp \left\{ j \frac{4\pi R(t_m)}{\lambda} + j 2\pi \left(\frac{2KR(t_m)}{c} + \frac{2v_0}{\lambda} \right) t \right\}, \quad (1)$$

where t is the fast-time variable spanning each sweep interval $[-T_p/2, T_p/2]$ and A is the complex echo amplitude. Note that the residual video phase and the intra-pulse range walk terms have been ignored in this approximation. To extract the discrete slow-time sequences, the fast Fourier transform (FFT) is applied to Equation (1) along the fast-time axis t , yielding the range-domain point spread function (PSF), i.e., the compressed range response, $S_b(f_r, t_m; R(t_m))$, for a scatterer at instantaneous range $R(t_m)$:

$$S_b(f_r, t_m; R(t_m)) = \int_{-T_p/2}^{T_p/2} s_b(t, t_m) e^{-j2\pi f_r t} dt = \tilde{A} \cdot \text{sinc}[T_p(f_r - f_b(t_m))] \cdot \exp\left\{j \frac{4\pi R(t_m)}{\lambda}\right\}, \quad (2)$$

where $\tilde{A} = A \cdot T_p$ is the complex amplitude gain after fast-time coherent integration, and $f_b(t_m) = 2KR(t_m)/c + 2v_0/\lambda$ is the instantaneous beat frequency. By sampling S_b at the center frequency f_i of the i -th range bin, the discrete slow-time sequence $[s_{\text{body},i}]_m$ for the UAV body is obtained:

$$[s_{\text{body},i}]_m = S_b(f_i, t_m; R_{\text{body}}) = A_{\text{body}} \cdot \text{sinc}\left[T_p\left(f_i - f_{b,\text{body}}(t_m)\right)\right] \cdot \exp\left\{j \frac{4\pi(R_0 + v_0 t_m)}{\lambda}\right\}, \quad (3)$$

where A_{body} is the peak amplitude of the body return and $f_{b,\text{body}}(t_m)$ is its corresponding beat frequency. Adopting the full-length blade integration scattering model of [21], for the n -th rotating blade of length L , the slow-time sequence $[s_{\text{blade},n,i}]_m$ is derived by integrating Equation (2) over the blade span $r \in [0, L]$:

$$[s_{\text{blade},n,i}]_m = \int_0^L \frac{A_{\text{blade}}}{L \cdot \tilde{A}} \cdot S_b\left(f_i, t_m; R_n(t_m, r)\right) dr, \quad (4)$$

where A_{blade} denotes the scattering complex amplitude of a single blade. $R_n(t_m, r) = R_{\text{body}}(t_m) + r \cos \psi_n(t_m)$ is the instantaneous range of a scatterer at distance r from the hub. Substituting $R_n(t_m, r)$ into Equation (4) produces a coupled integrand in which both the range-domain sinc term and the exponential phase term depend on r . Under the narrowband assumption $L \ll \Delta R$, the argument of the range sinc varies by at most $T_p \cdot 2KL \cos \psi_n(t_m)/c \ll 1$ across the blade span, so the sinc term can be approximated as constant and evaluated at the blade midpoint $r = L/2$. The remaining phase integral over $r \in [0, L]$ admits the closed-form solution $L \cdot \text{sinc}(2L \cos \psi_n(t_m)/\lambda) \cdot \exp(j2\pi L \cos \psi_n(t_m)/\lambda)$, where the additional phase factor $\exp(j2\pi L \cos \psi_n(t_m)/\lambda)$ equivalently shifts the scattering reference from the blade root to the blade midpoint. Combining these results and absorbing constant factors into A_{blade} yields

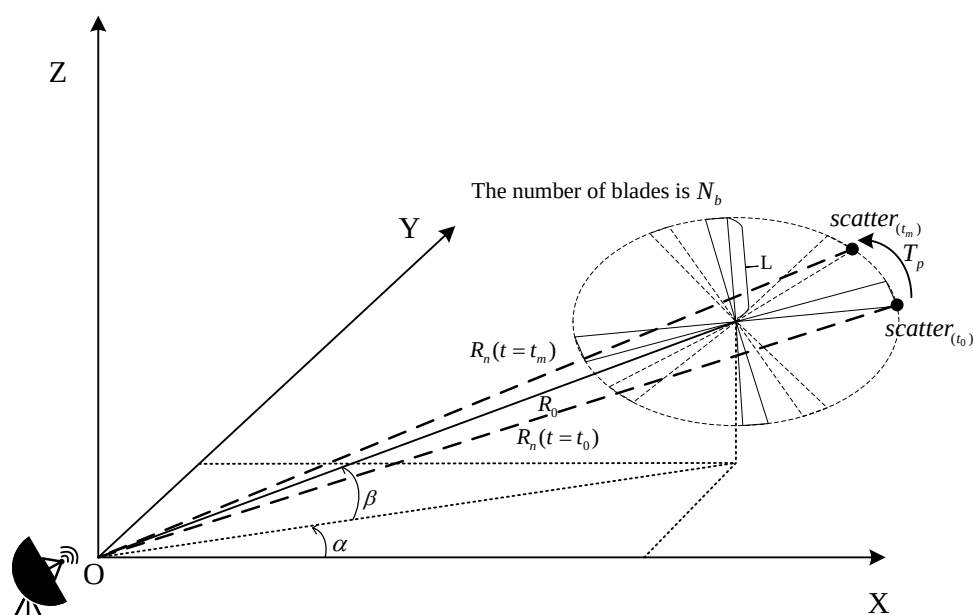
$$[s_{\text{blade},n,i}]_m = A_{\text{blade}} \cdot \text{sinc}\left[T_p(f_i - f_{b,n}(t_m, L/2))\right] \cdot \text{sinc}\left(\frac{2L}{\lambda} \cos \psi_n(t_m)\right) \cdot \exp\left\{j \frac{4\pi \tilde{R}_n(t_m)}{\lambda}\right\}, \quad (5)$$

where $\tilde{R}_n(t_m) = R_0 + v_0 t_m + \frac{L}{2} \cos \psi_n(t_m)$ is the distance to the effective phase center of the blade. The second sinc term specifically characterizes the micro-Doppler flash envelope induced by the spatial integration of the blade and attains its maximum at $\psi_n(t_m) = \pi/2$ and $3\pi/2$, generating periodic blade flash in the slow-time domain. In practice, UAV rotors typically employ an even number of blades. In this configuration, symmetrically distributed blade pairs flash synchronously, so the $2N_b$ theoretical flash instants collapse pairwise into N_b independent ones, giving a blade flash frequency of

$$f_{\text{flash}} = N_b \cdot f_{\text{rot}}. \quad (6)$$

The composite UAV slow-time vector is

$$\mathbf{s}_{\text{UAV},i} = \mathbf{s}_{\text{body},i} + \sum_{n=1}^{N_b} \mathbf{s}_{\text{blade},n,i}. \quad (7)$$



LFMCW Radar

Figure 1. Geometric configuration of LFM CW radar for UAV detection.

Ground clutter arises from the superposition of returns from numerous stationary scatterers. Because each scatterer is stationary, its beat signal remains constant across all M pulses. The m -th element of the clutter slow-time vector $\mathbf{s}_{\text{clutter},i}$ in the i -th range bin is

$$[\mathbf{s}_{\text{clutter},i}]_m = A_{c,i} \exp \left\{ j \frac{4\pi R_i}{\lambda} \right\}, \quad \forall m = 1, \dots, M, \quad (8)$$

where $A_{c,i}$ is the composite clutter scattering amplitude in the i -th range bin whose magnitude follows a Rayleigh distribution [1], and R_i is the range corresponding to the i -th bin. The received slow-time signal in the i -th range bin after range compression is

$$\mathbf{y}_i = \mathbf{s}_{\text{UAV},i} + \mathbf{s}_{\text{clutter},i} + \mathbf{w}_i, \quad (9)$$

where $\mathbf{w}_i \sim \mathcal{CN}(\mathbf{0}, \sigma_w^2 \mathbf{I})$ is complex Gaussian white noise with power σ_w^2 . Conventionally, target detection is performed directly on the slow-time sequence $\mathbf{y}_i$ in Equation (9) by applying Moving Target Indication (MTI) or Moving Target Detector (MTD) filters [12,13] to eliminate the ground clutter component $\mathbf{s}_{\text{clutter},i}$. However, for a hovering UAV ($v_0 = 0$), the body return $\mathbf{s}_{\text{body},i}$ remains constant across all M pulses, exhibiting the identical zero-Doppler property as the stationary ground clutter $\mathbf{s}_{\text{clutter},i}$. Consequently, traditional filters designed to suppress $\mathbf{s}_{\text{clutter},i}$ will simultaneously eliminate $\mathbf{s}_{\text{body},i}$, rendering the energy-domain detection chain inoperative [30]. To address this limitation, the proposed framework completely discards the reliance on the body return $\mathbf{s}_{\text{body},i}$, and instead shifts the detection focus to the periodic rotor micro-Doppler flash signature contained in the rotor component $\sum_{n=1}^{N_b} \mathbf{s}_{\text{blade},n,i}$.

3. Micro-Doppler Flash Detection Framework

The proposed detection framework consists of three sequential modules designed to transform the raw radar return into a reliable detection decision. First, the PTOP clutter cancellation module acts as a spatial-temporal filter to suppress the dominant ground clutter $\mathbf{s}_{\text{clutter},i}$ by projecting the received signal $\mathbf{y}_i$ onto a prior clutter subspace, ensuring the integrity of the weak rotor micro-Doppler flash signature. Second, the flash

power spectrum construction module serves as an energy concentrator; it maps the high-dimensional time–frequency information into a 1D flash frequency domain, effectively collapsing the periodic flash energy into a sharp spectral peak to enhance the signal-to-interference ratio. Finally, the CA-CFAR detection module provides the decision-making logic, utilizing an analytically derived threshold to distinguish the target peak from the residual noise floor under a constant false alarm rate constraint.

3.1. Prior-Template Orthogonal Projection

With no target present, N_s independent pre-scans of the scene are performed. Since each pre-scan is corrupted by receiver thermal noise, the range FFT output of the k -th pre-scan ($k = 1, \dots, N_s$) in the i -th range bin is

$$\mathbf{y}_i^{(k)} = \mathbf{s}_{\text{clutter},i} + \mathbf{w}_i^{(k)}, \quad (10)$$

where $\mathbf{w}_i^{(k)} \sim \mathcal{CN}(\mathbf{0}, \sigma_w^2 \mathbf{I})$ are mutually independent thermal noise vectors across pre-scans. Averaging the N_s results along the slow-time direction yields the prior clutter template vector:

$$\mathbf{d}_i = \frac{1}{N_s} \sum_{k=1}^{N_s} \mathbf{y}_i^{(k)} = \mathbf{s}_{\text{clutter},i} + \frac{1}{N_s} \sum_{k=1}^{N_s} \mathbf{w}_i^{(k)}. \quad (11)$$

Since the pre-scan noise vectors are mutually independent, the residual noise power decays at a rate of σ_w^2/N_s . A larger N_s yields a cleaner estimate of the true clutter steering vector and thus improves the cancellation performance. For all N_{bins} range bins, the projection of the received signal $\mathbf{y}_i$ onto the clutter template direction is subtracted to obtain the cancellation residual:

$$\hat{\mathbf{s}}_i = \mathbf{y}_i - \frac{\mathbf{d}_i^H \mathbf{y}_i}{\|\mathbf{d}_i\|^2} \mathbf{d}_i. \quad (12)$$

Compared with conventional MTI filters, PTOP offers two advantages. First, the orthogonal projection eliminates exactly the $\mathbf{d}_i$ direction component with zero distortion to signals at all other frequencies, fully preserving the rotor micro-Doppler flash signature. Second, since orthogonal projection is a linear operation acting on a complex Gaussian input, the residual $\hat{\mathbf{s}}_i$ remains jointly complex Gaussian. Although the projection introduces rank deficiency along the template direction $\mathbf{d}_i$, the residual noise can be approximated as complex white Gaussian when $M \gg 1$, thereby providing the statistical foundation for CA-CFAR detection.

3.2. Flash Power Spectrum Construction

After clutter cancellation, $\hat{\mathbf{s}}_i$ contains the rotor micro-Doppler flash signature and residual noise. The following four steps concentrate the periodic blade flash energy into a sharp peak on a 1D power spectrum.

Step 1: Gabor Time–Frequency Transform. Following the time–frequency analysis framework of [16], a Gabor transform (Gaussian-windowed short-time Fourier transform) is applied to $\hat{\mathbf{s}}_i$ to obtain the complex time–frequency distribution (TFD):

$$Y_i(\tau, f) = \sum_{m=1}^M [\hat{\mathbf{s}}_i]_m g(t_m - \tau) e^{-j2\pi f t_m}, \quad (13)$$

where τ is the time center, f is the Doppler frequency, and $g(\cdot)$ is the Gaussian window function. The Gaussian window achieves the lower bound of the Heisenberg uncertainty principle, providing optimal joint time–frequency resolution.

Step 2: Frequency-Axis Power Projection. The instantaneous power of the TFD is integrated along the Doppler frequency axis to obtain a 1D instantaneous power time series:

$$E_i(\tau) = \sum_f |Y_i(\tau, f)|^2. \quad (14)$$

This step projects all energy information of the 2D TFD non-coherently onto the time axis. From Equations (5) and (6), the sinc amplitude envelope of the n -th blade has period $T_{\text{rot}} = 1/f_{\text{rot}}$. After summing the power contributions of all N_b uniformly distributed blades, the power peaks interleave uniformly on the time axis, shortening the dominant period of $E_i(\tau)$ to $T_{\text{flash}} = 1/(N_b f_{\text{rot}}) = 1/f_{\text{flash}}$.

Step 3: FFT Spectral Analysis. A discrete Fourier transform is applied to $E_i(\tau)$ to obtain the complex flash frequency spectrum:

$$C_i(f_m) = \sum_{\tau} E_i(\tau) e^{-j2\pi f_m \tau}, \quad (15)$$

where f_m denotes the frequency variable in the flash frequency domain. In the implementation, $E_i(\tau)$ is zero-padded to the next power of two, $N_{\text{fm}} = 2^{\lceil \log_2 N_{\tau} \rceil}$, prior to the FFT to improve frequency resolution.

Step 4: Flash Power Spectrum. The power spectrum of Equation (15) yields the 1D flash power spectrum used for detection:

$$P_C(f_m) = |C_i(f_m)|^2. \quad (16)$$

If a UAV target is presented in the i -th range bin, the periodicity of $E_i(\tau)$ causes $P_C(f_m)$ to exhibit a sharp peak at $f_m = \pm f_{\text{flash}}$; otherwise, $P_C(f_m)$ presents a statistically uniform noise floor.

Remark on Low-SNR Detection Gain: The necessity of the proposed cascade module extends beyond dimensional reduction; it fundamentally provides significant integration gain to overcome the extreme low-SNR bottleneck. Since the residual noise after PTOP cancellation is approximately complex white Gaussian, the Gabor transform in Equation (13) first provides a localized coherent integration gain determined by the effective window length. Subsequently, although the frequency-axis power projection in Equation (14) is a non-linear square-law operation that inevitably introduces squaring loss at low SNRs, the final FFT operation in Equation (15) acts as a global coherent integrator for the periodic flash envelope. Consequently, the magnitude of the target peak in $C_i(f_m)$ accumulates proportionally to the total number of pulses M , causing the flash peak power in $P_C(f_m)$ to scale as M^2 . In contrast, the noise power floor grows linearly with M . This cascaded hybrid integration ensures that the overall detection gain scales robustly with the coherent processing interval (CPI) length, effectively lifting the weak micro-Doppler signature out of the noise floor.

3.3. CA-CFAR Detection

CA-CFAR detection is performed on $P_C(f_m)$. As shown in Appendix A, the noise floor of $P_C(f_m)$ approximately follows an exponential distribution, from which the CA-CFAR threshold factor can be analytically derived from P_{fa} . Let M_r denote the number of reference cells on each side, giving a total reference cell count of $M_{\text{ref}} = 2M_r$. The noise power estimate is

$$\hat{P}_n = \frac{1}{M_{\text{ref}}} \sum_{k \in \mathcal{R}} P_C(f_k), \quad (17)$$

where $\mathcal{R}$ denotes the reference cell set. Under the constraint of false alarm probability P_{fa} , the detection threshold is

$$T = \alpha \hat{P}_n, \quad \alpha = M_{\text{ref}} \left(P_{fa}^{-1/M_{\text{ref}}} - 1 \right). \quad (18)$$

To avoid interference from the residual direct current (DC) peak of the body return, a guard band is set in the region $|f_m| < f_{\text{guard}}$, where f_{guard} is the guard band half-width, and these cells are excluded from detection. The detection is performed independently for all N_{bins} range bins. If any frequency bin in the i -th range bin satisfies $P_C(f_m) > T$, the bin is declared to contain a UAV target. The frequency of the peak with the highest SNR is reported as the estimated flash frequency $\hat{f}_{\text{flash}}$. If N_b is known, the rotor rotational frequency can be further estimated as

$$\hat{f}_{\text{rot}} = \hat{f}_{\text{flash}} / N_b. \quad (19)$$

Note that the peak location $\hat{f}_{\text{flash}}$ obtained directly from Equation (19) is constrained to the discrete FFT grid with spacing $\Delta f_m = 1/(N_{\text{fm}} \Delta \tau)$, where $N_{\text{fm}} = 2^{\lceil \log_2 N_{\text{f}} \rceil}$ is the zero-padded FFT length and $\Delta \tau$ is the hop step of $E_i(\tau)$. To overcome this quantization limit, a three-point parabolic interpolation is applied around the maximum bin index k_0 . Let $P_{\text{dB}}[k] = 10 \log_{10} P_C(k \Delta f_m)$ denote the discrete logarithmic power spectrum. The sub-bin offset is yielded by

$$\delta = \frac{1}{2} \cdot \frac{P_{\text{dB}}[k_0 - 1] - P_{\text{dB}}[k_0 + 1]}{P_{\text{dB}}[k_0 - 1] - 2P_{\text{dB}}[k_0] + P_{\text{dB}}[k_0 + 1]}, \quad (20)$$

so that the refined estimate becomes $\hat{f}_{\text{flash}} = (k_0 + \delta) \Delta f_m$.

To provide a comprehensive overview of the proposed methodology, the complete signal processing pipeline of the micro-Doppler flash detection framework is summarized in Figure 2.

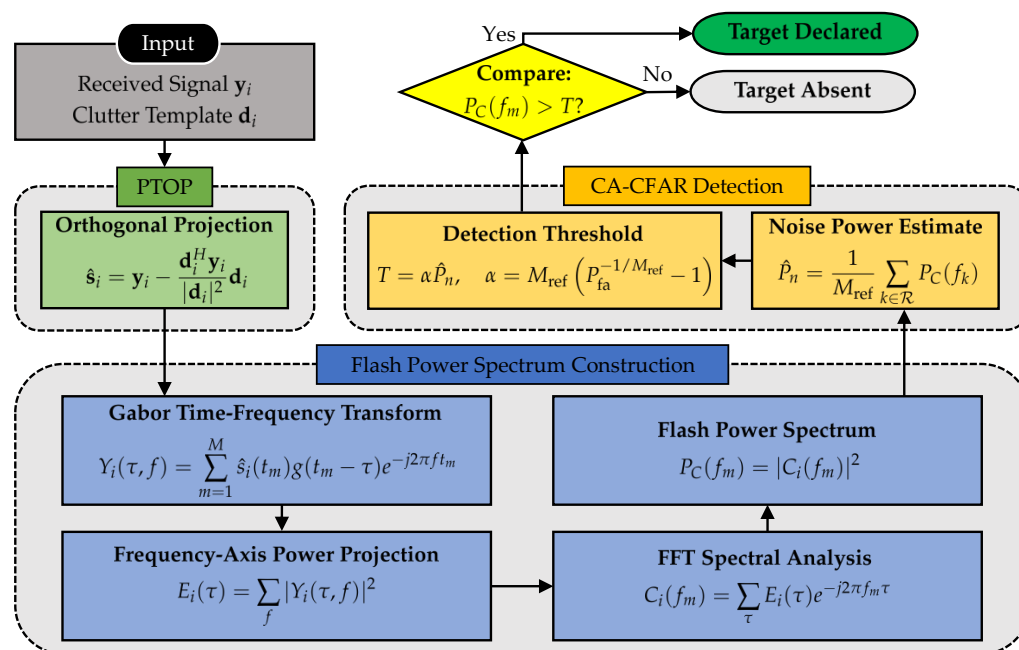


Figure 2. Flowchart of the micro-Doppler flash detection framework.

3.4. Applicability to Non-Stationary Clutter

The framework derivation in Sections 3.1–3.3 assumes slow-time stationary ground clutter. In practice, wind-induced vegetation motion introduces a time-varying alternating current (AC) component. A straightforward extension to handle such non-stationary clutter is to apply a notch filter in the time–frequency domain to $Y_i(\tau, f)$ in Equation (13), excluding low-frequency bins $|f| < f_{\text{notch}}$ from the power projection:

$$E_i^{\text{notch}}(\tau) = \sum_{|f| \geq f_{\text{notch}}} |Y_i(\tau, f)|^2, \quad (21)$$

where f_{notch} is set to cover the residual AC clutter bandwidth. Although this notch filters out low-Doppler components in the time–frequency plane, the maximum blade tip micro-Doppler frequency (analytically $f_{d,\text{max}} \approx 1885$ Hz for the considered parameters) far exceeds typical notch boundaries. Thus, the high-Doppler flash energy remains largely intact, ensuring sufficient integration gain. Furthermore, since this operation merely reduces the number of participating Doppler bins from N_f to $N_{\text{eff}} < N_f$ without altering the i.i.d. complex Gaussian property of the remaining noise terms, the statistical derivation in Appendix A remains valid. Consequently, the analytical CA-CFAR threshold Equation (18) remains directly applicable without any structural modification to the detector.

4. Numerical Results

Simulation results are presented in this section to demonstrate the effectiveness of the proposed micro-Doppler flash detection framework under strong ground clutter. The radar parameters are set as follows: carrier frequency $f_c = 5$ GHz, sweep bandwidth $B = 100$ MHz, corresponding to a range resolution of $\Delta R = 1.5$ m, sweep period $T_p = 100$ μ s, and CPI duration 0.25 s comprising $M = 2500$ pulses. The UAV target is placed at an initial range of 100 m, with body radar cross-section (RCS) $\sigma_{\text{body}} = 0.1$ m², rotor rotational frequency $f_{\text{rot}} = 30$ r/s, $N_b = 4$ blades per rotor, blade length $L = 0.3$ m, blade RCS $\sigma_{\text{blade}} = 0.01$ m², and theoretical blade flash frequency $f_{\text{flash}} = 120$ Hz. Ground scatterers following a Rayleigh distribution model are distributed from 0 to 200 m. The clutter cancellation template is obtained by time-averaging $N_s = 5$ target-free pre-scans. The CA-CFAR parameters are false alarm probability $P_{\text{fa}} = 10^{-6}$, reference cells per side $M_r = 8$, and guard band half-width $f_{\text{guard}} = 10$ Hz. The Gabor transform employs a Gaussian window with window length 128 points, overlap ratio 0.97, FFT size 512, and Gaussian window parameter $\alpha_g = 2.5$. With these Gabor parameters, the CPI of $M = 2500$ pulses yields $N_\tau = \lfloor (2500 - 128)/4 \rfloor + 1 = 594$ frames in the flash power projection sequence; zero-padding to $N_{\text{fm}} = 2^{\lceil \log_2 594 \rceil} = 1024$ points gives a flash frequency resolution of $\Delta f_m = 2500/1024 \approx 2.44$ Hz. To ensure clarity, both SCR and SNR are defined based on the average power of the UAV body return relative to the corresponding interference power, measured at the beat signal prior to range compression. Mathematically, they are expressed as

$$\text{SNR} = 10 \log_{10} \left(\frac{P_{\text{body}}}{P_w} \right), \quad \text{SCR} = 10 \log_{10} \left(\frac{P_{\text{body}}}{P_c} \right), \quad (22)$$

where P_{body} , P_w , and P_c denote the average power of the UAV body beat signal, thermal noise, and ground clutter beat signal, respectively. We utilize the body return as the power reference because the body radar cross-section (RCS) is a stable, macroscopic metric, whereas the blade flash energy is inherently coupled to the body return via a fixed ratio determined by the physical blade dimensions and the spatial integration envelope.

Under these parameters, the maximum range-sinc argument variation across the blade span evaluates to $T_p \cdot 2KL/c = 2BL/c = 0.2$. This corresponds to a negligible maximum amplitude attenuation of less than 7%, justifying the extraction of the sinc

term from the spatial integral. Furthermore, the maximum micro-Doppler frequency at the blade tip induces a range-Doppler coupling error (equivalent range shift) of $\Delta R_{eq} = cf_{d,max}/(2K) \approx 0.283$ m. Since this equivalent range shift is strictly smaller than the range resolution ($\Delta R_{eq} \approx 0.19\Delta R$), no range cell migration occurs during the sweep. Both physical constraints confirm the validity of the spatial and kinematic narrowband approximations in Equation (5).

Figure 3 illustrates the performance limitation of conventional methods for hovering UAV detection. Figure 3a shows the raw range-Doppler (RD) map of the hovering target ($v_0 = 0$): under $SCR = -21$ dB, a strong clutter ridge occupies the zero-Doppler bin, severely masking the target return and preventing energy-domain detection. Figure 3b shows the result of applying 2D CA-CFAR to the RD map after MTI filtering: although MTI suppresses the zero-Doppler clutter, the hovering target Doppler frequency $f_{d,body} \approx 0$ Hz overlaps completely with the clutter, causing the target to be eliminated together with the clutter and resulting in target missed detection accompanied by pure false alarms.

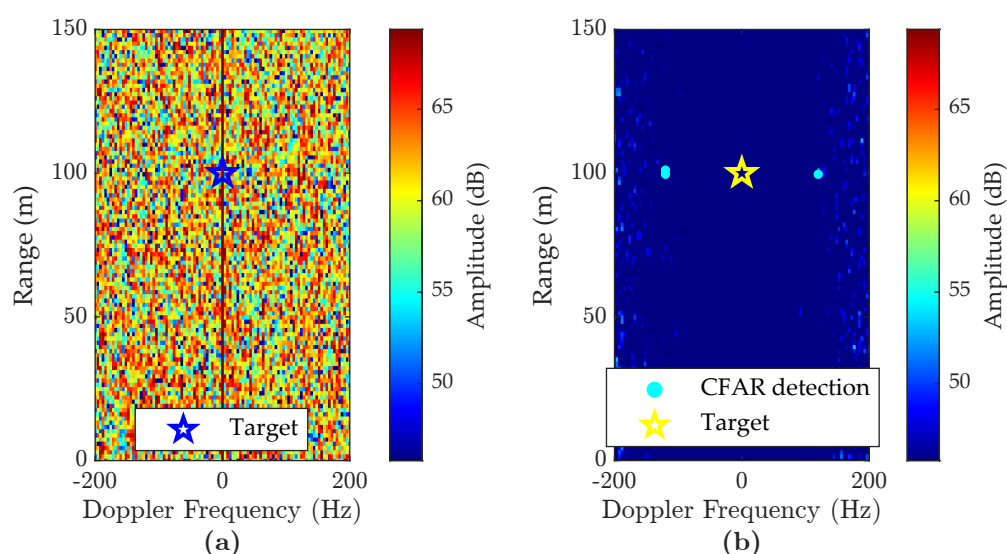


Figure 3. Conventional method failure analysis for hovering UAV detection under $SCR = -21$ dB. (a) Raw range-Doppler map. (b) 2D CA-CFAR detection result after MTI filtering.

Figure 4 presents a comprehensive comparison of the Gabor spectrograms before and after the PTOP cancellation for both the target range bin and a clutter-only bin. As observed in Figure 4a,c, before cancellation, the severe ground clutter ($SCR = -21$ dB) manifests as a dominant, continuous energy ridge concentrated at the zero-Doppler frequency ($f = 0$ Hz). This overwhelming DC component severely compresses the dynamic range of the spectrograms, effectively masking the weak micro-Doppler signatures of the hovering UAV. However, after applying the PTOP module, the vertical clutter ridges in Figure 4b,d are visually eliminated. The energy becomes statistically uniformly distributed across the Doppler domain, confirming that the PTOP module successfully suppresses the stationary clutter by projecting the signal onto the subspace orthogonal to the prior template. Notably, in the target bin (Figure 4b), although the clutter is removed, the rotor micro-Doppler flashes remain visually indiscernible due to the extreme noise floor ($SNR = -23$ dB). This highlights the necessity of the subsequent transformation into the flash frequency domain, which provides the requisite integration gain to extract the concealed periodic features. This visual indiscernibility highlights a fundamental vulnerability of conventional time-frequency image-based classification networks: they inherently fail when instantaneous signal energy cannot penetrate the noise floor. The proposed framework overcomes this

dual constraint (strong clutter and extreme low SNR) by strictly shifting the detection paradigm from instantaneous observation to global energy accumulation. The subsequent frequency-axis power projection and FFT effectively exploit the temporal periodicity of the flashes, aggregating the concealed energy across all M pulses. Meanwhile, the clutter bin in Figure 4d exhibits a uniform noise background after cancellation, qualitatively confirming that PTOP suppresses the clutter component while fully preserving the statistical foundation for subsequent CFAR detection.

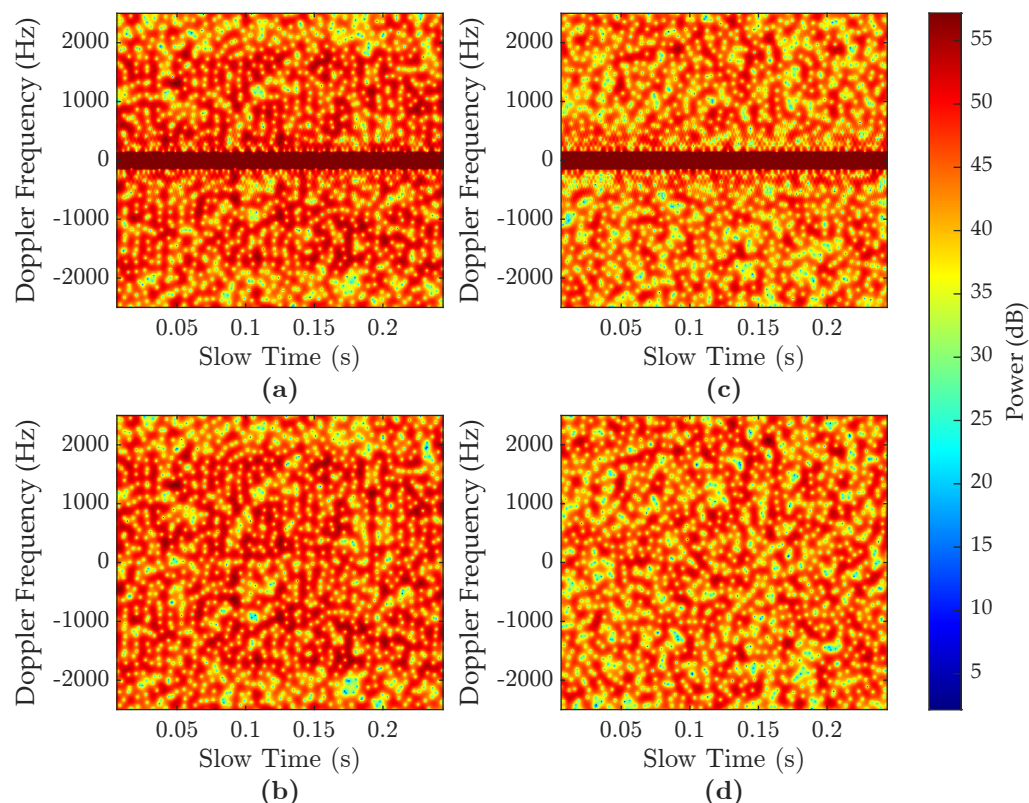


Figure 4. Comparison of Gabor spectrograms before and after PTOP cancellation: (a) Target bin before PTOP. (b) Target bin after PTOP. (c) Clutter-only bin before PTOP. (d) Clutter-only bin after PTOP.

Figure 5 shows the flash power spectrum $P_C(f_m)$ of the target range bin together with the CA-CFAR detection threshold. A sharp peak clearly exceeds the threshold at $f_m \approx \pm f_{\text{flash}}$, and the target is correctly declared in this bin (100 m) with a peak SNR of 19.97 dB. Owing to the discrete nature of the FFT in Equation (15), the peak location is subject to picket-fence quantization with a grid spacing of Δf_m . A three-point parabolic interpolation is therefore applied around the maximum bin to achieve sub-bin frequency resolution. The refined estimate yields $\hat{f}_{\text{flash}} \approx 119.97$ Hz, from which Equation (19) gives $\hat{f}_{\text{rot}} \approx 29.99$ r/s. This represents a relative error of approximately 0.03% compared with the ground truth, confirming that the proposed framework not only renders a reliable detection decision but also provides an accurate estimate of the rotor rotational frequency.

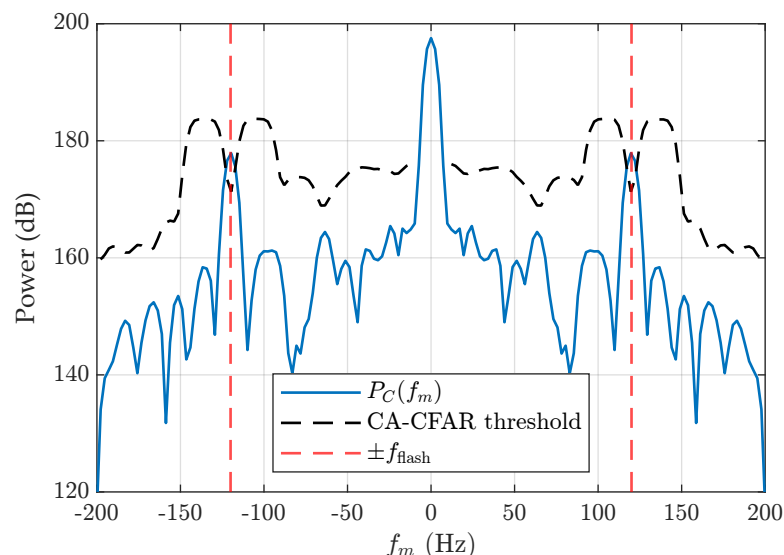


Figure 5. Flash power spectrum $P_C(f_m)$ of the target range bin and CA-CFAR detection threshold.

Figure 6 presents $P_C(f_m)$ under two representative conditions. Figure 6a shows $P_C(f_m)$ of the target range bin after MTI processing: the body and rotor components are attenuated by the MTI zero-Doppler notch, and the pulse-to-pulse subtraction operation transforms white noise into high-pass colored noise, elevating the local noise floor estimated by CA-CFAR. These two effects jointly prevent the flash peak from exceeding the detection threshold, confirming that conventional MTI-based processing exhibits severe performance degradation in the flash frequency domain. Figure 6b shows $P_C(f_m)$ of a clutter-only bin after PTOP cancellation: only a statistically uniform noise floor is present and no detection is triggered, verifying the constant false alarm rate property of the proposed framework.

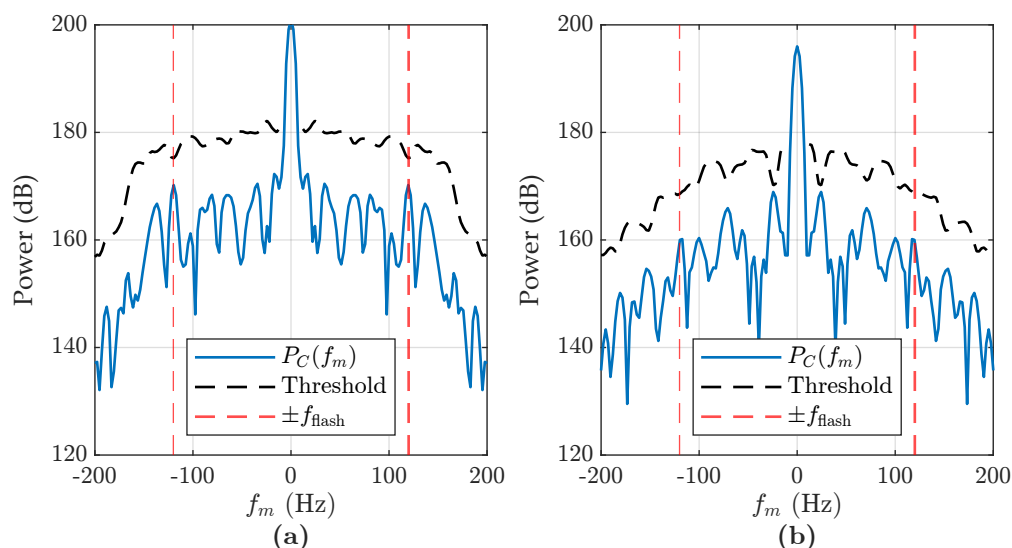


Figure 6. Flash power spectra $P_C(f_m)$ under two conditions. (a) Target range bin after MTI processing. (b) Clutter-only bin after PTOP cancellation.

Figure 7 shows the effect of the pre-scan count N_s on detection performance at $\text{SNR} = -23$ dB and $\text{SCR} = -21$ dB. As N_s increases, the noise in the template is progressively averaged out, causing the peak SNR to increase monotonically and the detection rate to rise steadily. Specifically, the mean peak SNR increases from 11.52 dB at $N_s = 1$ to 17.60 dB at $N_s = 10$, while the standard deviation narrows from 4.47 dB to 3.50 dB. $N_s = 5$

provides a reasonable trade-off between performance and pre-scan overhead, achieving a detection rate of 80%, and it is adopted as the operating point in this paper.

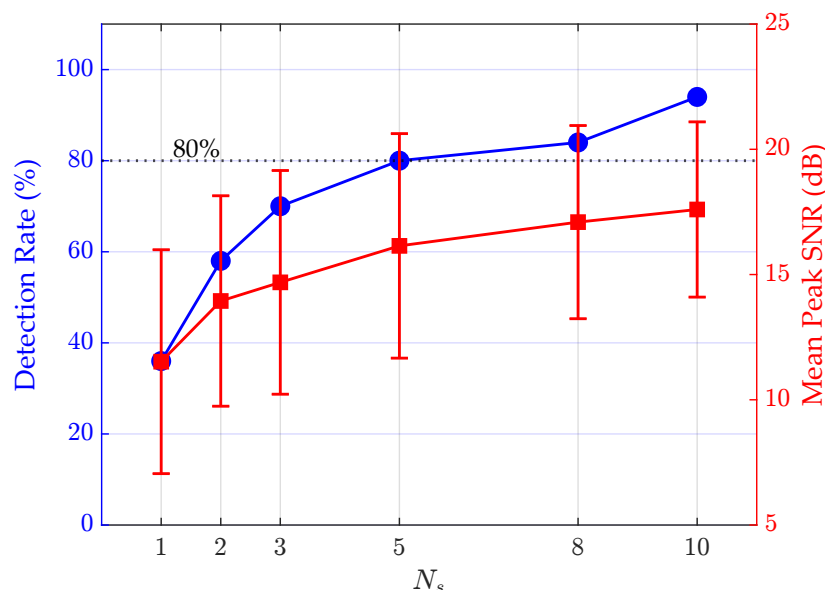


Figure 7. Effect of pre-scan count N_s on detection performance over 50 Monte Carlo trials.

To characterize the practical performance boundary of the proposed framework under stationary clutter, Figure 8 presents the detection-probability curve as a function of SNR at a fixed SCR = −21 dB, obtained from 50 independent Monte Carlo trials per point. The detection probability increases monotonically from near zero at SNR = −30 dB to 92% at SNR = −20 dB. The 80% detection-probability threshold is reached at SNR = −23 dB, which is adopted as the stationary-clutter operating point throughout this paper.

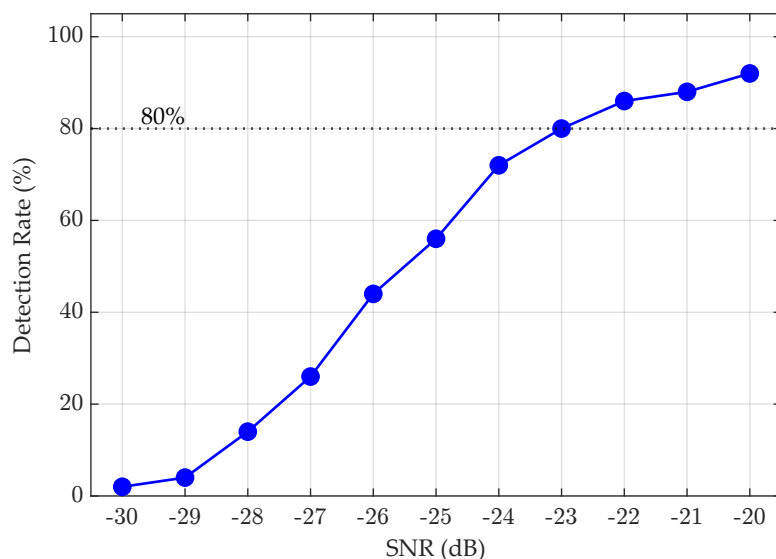


Figure 8. Detection probability as a function of SNR under stationary clutter at a fixed SCR = −21 dB.

To further assess the detection capability of the proposed framework, we compare it against the range-screening and STFT pixel thresholding (RSPT) method of Hoffmann et al. [29], which proceeds in two steps: (1) a range-energy pre-screening step that applies CA-CFAR to the 1D range profile energy—obtained by integrating the received power across all pulses in a CPI—to identify candidate range bins whose integrated energy exceeds

the detection threshold; (2) a micro-Doppler discrimination step that computes the STFT spectrogram of each candidate bin and counts the number of time–frequency pixels whose intensity exceeds an empirically set power level and whose Doppler frequency lies beyond an empirically set velocity offset from the main Doppler response, and a UAV detection is declared if this count exceeds an empirical threshold. Both the power level and the velocity offset in step (2) are empirically determined from training data without analytical derivation. As shown in Figure 9a, the range-energy pre-screening step completely fails under the strong distributed ground clutter. It should be noted that the RSPT method was originally designed for scenarios where the target occupies a range cell with dominant scattering energy standing above the background—a condition that naturally holds when isolated strong scatterers are distributed sparsely across range cells. In the distributed Rayleigh clutter model considered here, every range cell contains severe clutter returns, rendering the range-energy pre-screening step inherently inapplicable: even if the target is present, its body return energy is uniformly submerged below the clutter fluctuation level across all range cells. This makes it impossible to trigger the 1D CA-CFAR threshold and identify a candidate target bin through energy pre-screening alone. To evaluate the second step independently of the clutter masking, we bypass the pre-screening failure and apply the STFT pixel thresholding step directly to the PTOP-canceled signal of the target bin. The corresponding time–frequency representation, annotated with the empirical velocity exclusion bounds (± 10 m/s) utilized in the RSPT method, is illustrated in Figure 9b. Simulation results confirm that even under this favorable condition, the method still fails to declare the target. As previously discussed in the context of Figure 4, the instantaneous signal energy of the blade flashes cannot penetrate the extreme noise floor at such a low SNR. Consequently, attempting to detect the target by counting spectrogram pixels that exceed an empirical power threshold outside the predefined velocity bounds is inherently ineffective, as the micro-Doppler signatures are visually and statistically indiscernible in the time–frequency domain. The proposed framework overcomes this limitation by strictly shifting the detection paradigm from instantaneous observation to global energy accumulation, effectively exploiting the temporal periodicity of the flashes to successfully extract the target. In terms of computational cost (evaluated for a single range bin on a standard personal computer), the proposed method (18.60 ms) and the RSPT baseline (19.90 ms) are comparable, while the conventional 2D RD+CFAR pipeline (dominated by the 2D sliding window search) (818.03 ms) is approximately 44× slower.

To evaluate the extended framework described in Section 3.4, Figure 10 shows the Gabor time–frequency distribution of the target range bin under non-stationary intrinsic clutter model (ICM) clutter [31] before PTOP cancellation. In this scenario, the residual AC clutter energy spreads across low-frequency Doppler bins. The applied notch band is delineated by $f_{\text{notch}} = 333$ Hz, which corresponds to a maximum radial velocity fluctuation of ± 10 m/s (significantly lower than the maximum blade tip micro-Doppler frequency of $f_{d,\text{max}} \approx 1885$ Hz, ensuring the vast majority of the high-frequency flash energy is preserved). Figure 11 compares two methods at $\text{SCR} = -21$ dB and $\text{SNR} = -22$ dB: (A) MTI with time–frequency domain notch, and (B) PTOP with time–frequency domain notch. Method A fails, yielding a peak SNR of only 4.88 dB, well below the CA-CFAR threshold, as the MTI notch attenuates both the non-stationary clutter residual and the flash signature. Method B successfully detects the target with a peak SNR of 16.07 dB, demonstrating that PTOP-based cancellation followed by notch-based power projection maintains reliable detection robustness under non-stationary clutter conditions. Figure 12 presents the 2D SCR–SNR detection-probability heatmap under the ICM model, with each cell obtained from 50 Monte Carlo trials. The 80% contour defines the practical performance boundary, and the operating point ($\text{SCR} = -21$ dB, $\text{SNR} = -22$ dB) lies on this boundary.

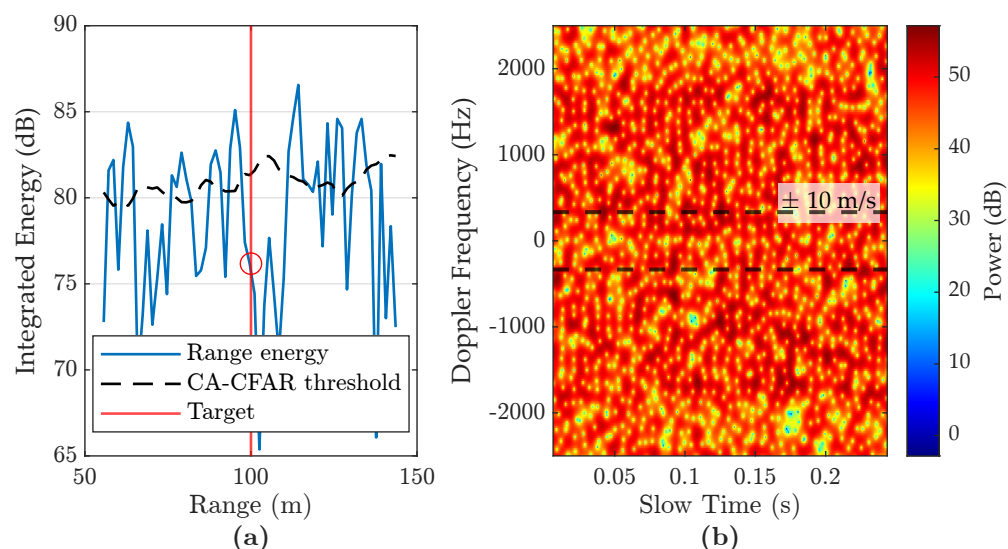


Figure 9. Failure mechanism analysis of the RSPT baseline method. (a) Range-energy pre-screening step under distributed clutter (the red circle highlights the integrated energy of the target range cell). (b) STFT spectrogram of the target bin after PTOP cancellation, annotated with the empirical velocity threshold bounds of the RSPT method.

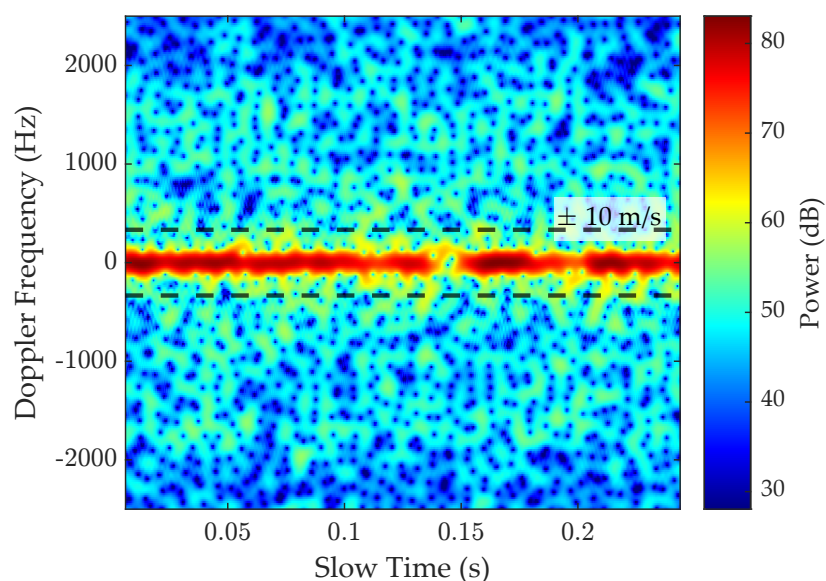


Figure 10. Gabor time–frequency distribution of the target range bin under non-stationary ICM clutter before PTOP cancellation.

To numerically corroborate the statistical derivation in Appendix A, Figure 13 compares the empirical probability density function (PDF) of $P_C(f_m)$ against the theoretical exponential distribution. To evaluate the statistical properties, the empirical samples are extracted from an arbitrary fixed non-DC frequency bin across 3000 independent Monte Carlo trials. Furthermore, it is generally assumed that the background cells within a narrow local CA-CFAR reference window satisfy the independent and identically distributed (i.i.d.) condition. As shown in Figure 13a, under stationary clutter, the Kolmogorov–Smirnov (KS) test yields a p -value of 0.8105 (well above the standard 0.05 significance level, thus supporting the exponential null hypothesis) with a variance-to-mean-squared ratio of 1.0026 (theoretical value 1.0), confirming an excellent exponential fit. As shown in Figure 13b, under non-stationary ICM clutter with the time–frequency domain notch extension, the KS test yields a p -value of 0.6769 with a ratio of 1.0474, indicating that the exponential

approximation remains valid despite the mild deviation introduced by the non-stationary ICM clutter. Both results support the applicability of the analytically derived CA-CFAR threshold Equation (18) under the respective clutter conditions.

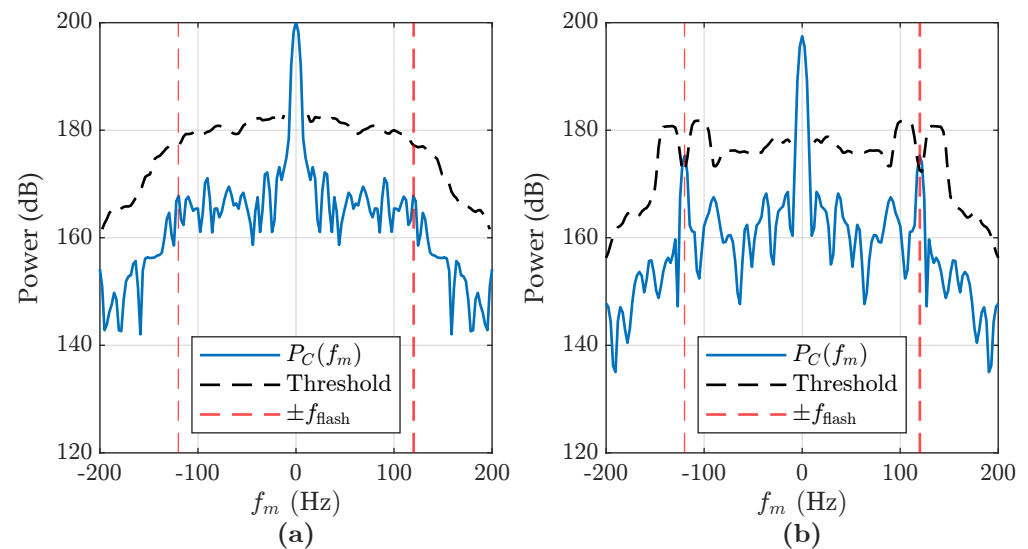


Figure 11. Flash power spectra $P_C(f_m)$ under non-stationary ICM clutter. (a) MTI with time–frequency domain notch filter. (b) PTOF with time–frequency domain notch filter.

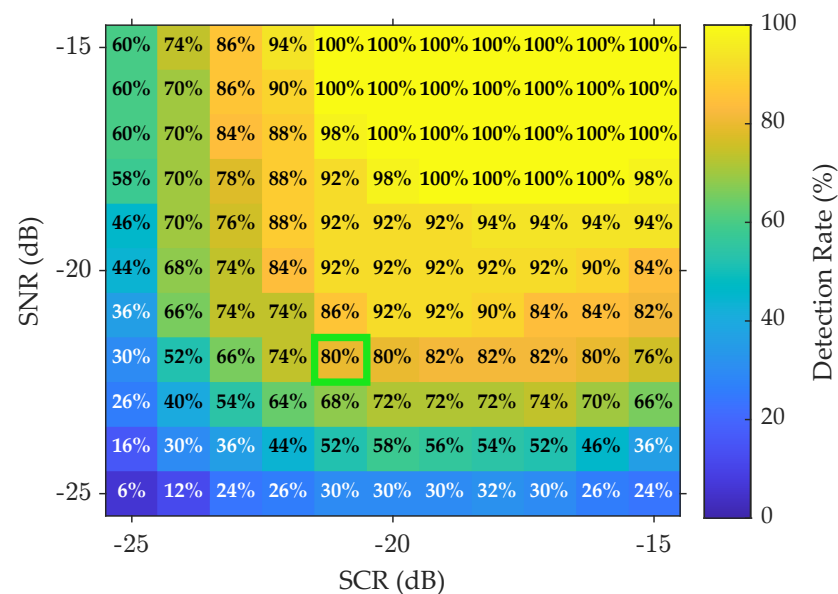


Figure 12. 2D SCR–SNR detection-probability heatmap under non-stationary ICM clutter, where the green frame marks the 80% detection-probability operating point.

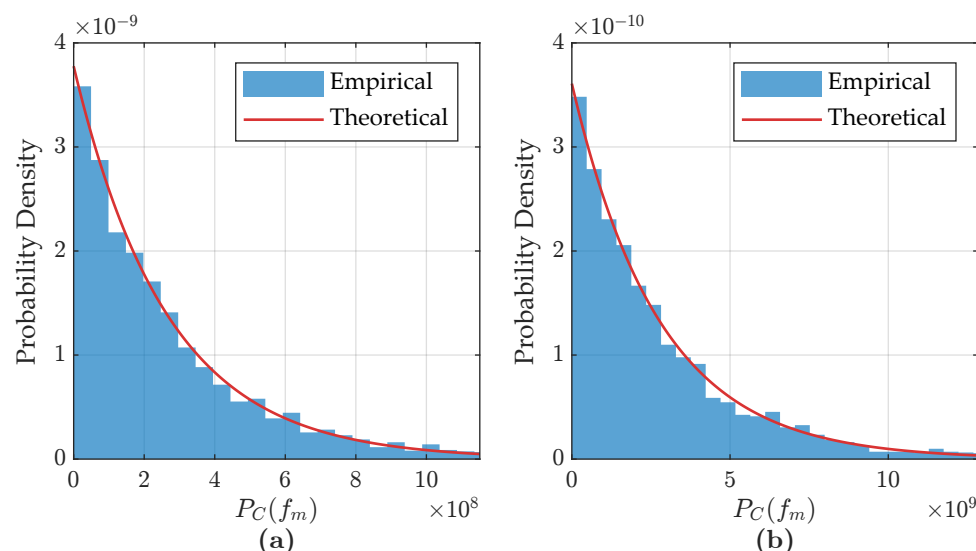


Figure 13. Empirical PDF of $P_C(f_m)$ at non-DC frequency bins versus the theoretical exponential distribution. (a) Under stationary clutter conditions. (b) Under non-stationary ICM clutter with the time–frequency domain notch extension.

5. Discussion

The primary contribution of this paper is a detection framework that exploits the periodicity of rotor blade micro-Doppler flash—rather than target radial velocity—to detect hovering UAVs. The PTOP module is specifically designed for stationary ground clutter, where the slow-time clutter steering vector remains constant across the CPI. Under this condition, a single-step orthogonal projection suffices to suppress the dominant clutter component while preserving the flash signature and the Gaussian noise statistics required for the analytical CA-CFAR threshold. For non-stationary clutter scenarios, such as wind-induced vegetation motion, the time–frequency domain notch extension introduced in Section 3.4 provides a compatible remedy: by excluding the low-frequency Doppler bins from the power projection, the residual AC clutter energy is suppressed without altering the detector structure or invalidating the CA-CFAR threshold derivation. Simulation results confirm that this extension achieves reliable detection performance under the ICM non-stationary clutter model. Looking further ahead, replacing the single clutter template with a multi-atom redundant dictionary constructed via the orthogonal matching pursuit (OMP) algorithm [21], combined with an empirically calibrated detection threshold, represents a promising direction toward more adaptive detection under diverse and rapidly varying clutter environments. The PTOP module also relies on the prior availability of target-free pre-scan observations to construct the clutter template. This requirement is most naturally satisfied in fixed-deployment surveillance scenarios, where the radar is mounted at a stationary post and the ground clutter scene remains stable over extended periods, making it straightforward to acquire reliable pre-scan templates before the monitoring mission begins. When the clutter environment changes significantly, for instance, due to platform motion or seasonal vegetation changes, the template can be periodically refreshed using observations collected during confirmed target-free intervals. For deployments where such intervals cannot be guaranteed, additional prior knowledge about the clutter structure (e.g., from digital elevation maps or historical observations) could be incorporated to initialize the template, combined with an online update strategy that progressively refines the estimate as new target-free observations become available. The present parametric analysis characterizes detection performance along the SNR axis at a fixed SCR and across the joint SCR–SNR plane under non-stationary clutter. A more comprehensive characterization

would further sweep the pre-scan count N_s jointly with SCR and SNR to map the full three-dimensional performance boundary, which would provide quantitative guidance for selecting the optimal trade-off among detection sensitivity, pre-scan overhead, and clutter suppression capability in practical deployment scenarios. This joint parametric analysis is left for future work.

6. Conclusions

This paper proposed a micro-Doppler flash detection framework for hovering UAV detection with LFM CW radar under strong ground clutter, consisting of three sequential modules: PTOP clutter cancellation, flash power spectrum construction, and CA-CFAR detection. The PTOP module exploits the slow-time stationarity of ground clutter to eliminate the clutter component via a single-step orthogonal projection with zero distortion to the rotor micro-Doppler flash signature, preserving the statistical foundation for the analytically derived CA-CFAR threshold. Simulation results confirm that the proposed framework achieves reliable target detection even when the micro-Doppler flash signatures are visually obscured by residual noise in the time–frequency domain. The proposed framework effectively overcomes the dual challenges of clutter masking and noise submergence. By cascading PTOP-based clutter cancellation with frequency-domain energy integration, we provide a holistic solution that maintains high detection sensitivity even when the target’s micro-Doppler signature is visually indiscernible in the time–frequency domain. The framework is further shown to remain applicable under non-stationary clutter conditions through a time–frequency domain notch extension, with simulation results confirming that the analytical CA-CFAR threshold remains valid without modification to the detector structure.

Appendix A. Statistical Justification for the CA-CFAR Threshold

We establish that the noise component of $P_C(f_m)$ at $f_m \neq 0$ approximately follows an exponential distribution, which is the statistical basis for the CA-CFAR threshold in Equation (18). Since $\mathbf{w}_i \sim \mathcal{CN}(\mathbf{0}, \sigma_w^2 \mathbf{I})$ and the PTOP operation Equation (12) is a linear orthogonal projection, the residual noise $\hat{\mathbf{w}}_i$ within the clutter-canceled received vector $\hat{\mathbf{s}}_i$ satisfies $\hat{\mathbf{w}}_i \sim \mathcal{CN}(\mathbf{0}, \sigma_w^2 \mathbf{I})$ under a large number of integrated pulses $M \gg 1$. Since the Gabor transform Equation (13) is linear, the noise component in $Y_i(\tau, f)$ satisfies

$$W(\tau, f) = \sum_{m=1}^M [\hat{\mathbf{w}}_i]_m g(t_m - \tau) e^{-j2\pi f t_m} \stackrel{\text{i.i.d.}}{\sim} \mathcal{CN}(0, \sigma_Y^2), \quad (\text{A1})$$

where $\sigma_Y^2 = \sigma_w^2 \sum_m g^2(t_m - \tau)$.

The noise contribution to $E_i(\tau)$ in Equation (14) is

$$E_N(\tau) = \sum_{k=1}^{N_f} |W(\tau, f_k)|^2, \quad (\text{A2})$$

where N_f is the number of Doppler bins. Since $|W(\tau, f_k)|^2 \stackrel{\text{i.i.d.}}{\sim} \text{Exp}(\sigma_Y^2)$, by the Central Limit Theorem (CLT),

$$E_N(\tau) \xrightarrow{d} \mathcal{N}(N_f \sigma_Y^2, N_f \sigma_Y^4), \quad N_f \gg 1. \quad (\text{A3})$$

It is worth noting that the high overlap ratio of the Gabor transform introduces local time-domain correlation in the sequence $E_N(\tau)$. However, since the coherent processing interval contains a large number of pulses ($M \gg 1$) and the correlation length is significantly shorter than the total observation time, the global FFT operator effectively mixes these

weakly dependent samples. By virtue of the central limit theorem for weakly dependent sequences (mixing processes), and considering that the FFT Equation (15) is linear where the DC mean $N_f \sigma_Y^2$ contributes only to $f_m = 0$, the noise contribution to $C_i(f_m)$ at $f_m \neq 0$ asymptotically maintains complex Gaussianity:

$$C_N(f_m) = \sum_{\tau} [E_N(\tau) - N_f \sigma_Y^2] e^{-j2\pi f_m \tau} \sim \mathcal{CN}(0, \sigma_C^2), \quad f_m \neq 0. \quad (\text{A4})$$

Consequently, the noise power spectrum $P_C(f_m)|_{\text{noise}}$ at non-DC frequency bins can be asymptotically derived as

$$P_C(f_m)|_{\text{noise}} = |C_N(f_m)|^2 \sim \text{Exp}(\sigma_C^2), \quad f_m \neq 0, \quad (\text{A5})$$

which yields the closed-form threshold factor $\alpha = M_{\text{ref}}(P_{\text{fa}}^{-1/M_{\text{ref}}} - 1)$ in Equation (18).

Author Contributions: Conceptualization, T.Z. and Y.Y.; methodology, T.Z. and Y.Y.; software, T.Z. and R.S.; validation, T.Z. and R.S.; investigation, T.Z.; resources, R.S. and Y.Y.; writing—original draft preparation, T.Z.; writing—review and editing, R.S. and Y.Y.; supervision, Y.Y.; funding acquisition, Y.Y. All authors have read and agreed to the published version of the manuscript.

Funding: This work was supported in part by the National Natural Science Foundation of China under Grant 62301127, in part by the Natural Science Foundation of Sichuan Province under Grant 2026NSFSC1422, in part by the Fundamental Research Funds for the Central Universities under Grant ZYGX2025XJ004.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data presented in this study are available on request from the corresponding author due to institutional policies.

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. Garvanov, I.; Garvanova, M.; Borissova, D.; Cvjetkovic, M.; Nikic, J.; Tomov, M. Analysis of micro-Doppler signatures for drone detection. In Proceedings of the 19th Conference on Electrical Machines, Drives and Power Systems (ELMA), Sofia, Bulgaria, 19–21 June 2025; pp. 1–5.
2. Yang, Z.; Wang, Q.; Liu, G.; Ma, Z. UAV detection based on OTFS ISAC system. In Proceedings of the 2025 IEEE 101st Vehicular Technology Conference (VTC2025-Spring), Oslo, Norway, 17–20 June 2025; pp. 1–7.
3. Narayanan, R.M.; Tsang, B.; Bharadwaj, R. Classification and Discrimination of Birds and Small Drones Using Radar Micro-Doppler Spectrogram Images. *Signals* **2023**, *4*, 337–358.
4. Zhang, Y.D.; Xiang, X.; Li, Y.; Chen, G. Enhanced micro-doppler feature analysis for drone detection. In Proceedings of the 2021 IEEE Radar Conference (RadarConf21), Atlanta, GA, USA, 7–14 May 2021; pp. 1–4.
5. Ji, G.; Song, C.; Huo, H. Detection and identification of low-slow-small rotor unmanned aerial vehicle using micro-doppler information. *IEEE Access* **2021**, *9*, 99995–100008.
6. Gong, J.; Yan, J.; Li, D. Radar challenges and solutions for drone detection. In Proceedings of the 2025 26th International Radar Symposium (IRS), Hamburg, Germany, 21–23 May 2025; pp. 1–8.
7. Knott, E.F. *Radar Cross Section*, 2nd ed.; Artech House: Norwood, MA, USA, 2004.
8. Chen, X.; Guan, J.; Li, J.; Chen, W. Micro-motion classification of rotor UAV and flying bird via CNN and FMCW radar. In *Artificial Intelligence for Communications and Networks*; Springer: Cham, Switzerland, 2021; pp. 55–67.
9. Xu, Z.; Chen, C.; Tian, S.; Deng, M.; Zhao, Z. Decoupled parameter estimation of small UAV rotors using FMCW radar. *IEEE Trans. Instrum. Meas.* **2025**, *74*, 8507512.
10. Oh, B.-S.; Lin, Z. Extraction of global and local micro-doppler signature features from FMCW radar returns for UAV detection. *IEEE Trans. Aerosp. Electron. Syst.* **2021**, *57*, 1351–1360.
11. Skolnik, M.I. *Introduction to Radar Systems*, 3rd ed.; McGraw-Hill: New York, NY, USA, 2001.

12. Mughal, A.M.; Shahid, A.; Shaukat, M.Z.; Ashraf, M.A.; Ullah, T. Drone detection and classification on micro-Doppler signatures using FMCW radar. In Proceedings of the 20th International Bhurban Conference on Applied Sciences and Technology (IBCAST), Murree, Pakistan, 22–25 August 2023; pp. 456–460.
13. Richards, M.A. *Fundamentals of Radar Signal Processing*, 2nd ed.; McGraw-Hill Education: New York, NY, USA, 2014.
14. Legros, Q.; Fourer, D. Pseudo-bayesian approach for robust mode detection and extraction based on the STFT. *Sensors* **2023**, *23*, 85.
15. Qin, X.; Deng, B.; Wang, H. Micro-doppler feature extraction of rotating structures of aircraft targets with terahertz radar. *Remote Sens.* **2022**, *14*, 3856.
16. Fang, X.; Xiao, G. Rotor blades micro-Doppler feature analysis and extraction of small unmanned rotorcraft. *IEEE Sens. J.* **2021**, *21*, 3592–3601.
17. Hou, H.; Yang, Z.; Pang, C. Rotor UAV's micro-Doppler signal detection and parameter estimation based on FRFT-FSST. *Sensors* **2021**, *21*, 7314.
18. Wei, J.; Ma, D.; He, F.; Zhang, Q.; Feng, Z.; Liu, Z.; Liang, T. UAV's rotor micro-Doppler feature extraction using integrated sensing and communication signal. *IEEE Trans. Wirel. Commun.* **2025**, *24*, 10166–10182.
19. Yang, B.; Zhao, Y.; He, F.; Zhang, Q.; Yu, L. Micro-doppler parameter estimation based on complex bayesian compressive sensing for micro UAVs identification. *IEEE Sens. J.* **2025**, *25*, 31144–31151.
20. Zhao, X.; Li, K.; Luo, Y.; Zhao, D.; Zhang, Q. Micromotion parameters estimation for helicopter under low-pulse repetition frequency condition. *IEEE Trans. Aerosp. Electron. Syst.* **2024**, *60*, 9324–9341.
21. Fan, S.; Wu, Z.; Xu, W.; Zhu, J.; Tu, G. Micro-Doppler signature detection and recognition of UAVs based on OMP algorithm. *Sensors* **2023**, *23*, 7922.
22. Chen, V.C. *The Micro-Doppler Effect in Radar*, 2nd ed.; Artech House: Norwood, MA, USA, 2019.
23. Dey, A.; Cabanes, Y.; Rajan, S.; Balaji, B.; Damini, A.; Chanchlani, R. Radar-based drone detection using complex-valued convolutional neural network. In Proceedings of the IEEE Sensors Applications Symposium (SAS), Ottawa, ON, Canada, 18–20 July 2023; pp. 1–5.
24. Sun, Y.; Abeywickrama, S.; Jayasinghe, L.; Yuen, C.; Chen, J.; Zhang, M. Micro-Doppler signature-based detection, classification, and localization of small UAV with LSTM. *IEEE Trans. Geosci. Remote Sens.* **2021**, *59*, 6285–6300.
25. Raval, D.; Hunter, E.; Lam, I.; Rajan, S.; Damini, A.; Balaji, B. Detecting drones with radars and convolutional networks based on micro-Doppler signatures. In Proceedings of the 2022 IEEE Radar Conference (RadarConf22), New York, NY, USA, 21–25 March 2022; pp. 1–6.
26. Goodfellow, I.; Bengio, Y.; Courville, A. *Deep Learning*; MIT Press: Cambridge, MA, USA, 2016.
27. Yan, J.; Hu, H.; Gong, J.; Kong, D.; Li, D. Exploring radar micro-doppler signatures for recognition of drone types. *Drones* **2023**, *7*, 280.
28. Jiang, X.; Li, J.-J.; Zhu, S.; Yang, S. Sequential UAVs detection and micro-Doppler parameters estimation with distributed radar. In Proceedings of the IEEE 15th International Conference on Signal Processing, Communications and Computing (ICSPCC), Hong Kong, China, 18–21 July 2025; pp. 1–6.
29. Hoffmann, F.; Ritchie, M.; Fioranelli, F.; Charlish, A.; Griffiths, H. Micro-doppler based detection and tracking of UAVs with multistatic radar. In Proceedings of the 2016 IEEE Radar Conference (RadarConf), Philadelphia, PA, USA, 2–6 May 2016; pp. 1–6.
30. Finn, H.M.; Johnson, R.S. Adaptive detection mode with threshold control as a function of spatially sampled clutter-level estimates. *RCA Rev.* **1968**, *29*, 414–464.
31. Monti-Guarnieri, A.; Manzoni, M.; Giudici, D.; Recchia, A.; Tebaldini, S. Vegetated target decorrelation in SAR and interferometry: Models, simulation, and performance evaluation. *Remote Sens.* **2020**, *12*, 2545.

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.