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3. “*An Adaptive IMM for Tracking Maneuvering Target with High Variability of Environment,*” Fuzzy Systems and Data Mining X, DOI: 10.3233/FAIA241441.
4. “*Enhanced Multi- Target Tracking with Combination of Position, Power and Ambiguous Doppler Measurements,*” Fuzzy Systems and Data Mining IX, DOI: 10.3233/FAIA231011.
5. “*Ambiguity Resolution for Ground-based Pulse-Doppler Radars Using Multiple Medium PRF,*” Proc. Int. Conf. on Signal Processing Systems (ICSPS), Jiangsu, China, DOI: 10.1109/ICSPS58776.2022.00024.
6. “*A Discrete Clutter Reduction Method for Drone Detection with High Resolution Radars,*” Proc. 12th Int. Conf. on Electronics, Communications and Networks (CECNet 2022), DOI: 10.3233/FAIA220543.
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ORIGINAL RESEARCH

A design of a high-resolution frequency modulated continuous wave radar for drone detection based on spurious phase noise and discrete clutter reduction

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Abstract

The authors deal with the problem of the design and manufacture of a high-resolution FMCW radar for drone detection and classification. The difficulties of the problem are discrete clutter reduction and spurious phase noise mitigation. The discrete clutter is due to the reflected signals from land vehicles, birds etc., while the spurious phase noise is inherent in the radar signal due to the phase-locked loop component and leakage between the transmitting and receiving paths. Both spurious phase noise and clutter will increase the system noise level and hence reduce the probability of detection of small targets such as drones and induce false alarms on the radar screen. In order to reduce discrete clutter, the authors propose a method to separate a drone from discrete clutter based on the design of the radar system parameters for a drone and its propeller detection, target's Doppler dispersion and moving characteristics. For spur mitigation, a method that focuses on the design of the isolation coefficient between transmitting and receiving paths to decrease the power of spurs below the minimum power requirement at the input of the analogue-to-digital converter is introduced. The results were applied by the authors to the development and manufacture of a radar with the given specifications for drone detection and classification. Different laboratory and field tests show that the spurs are mitigated and the drones are separated from discrete clutter with a range and accuracy better than the one recently published.

KEYWORDS

phase noise, radar clutter, radar signal processing, radar target recognition

1 | INTRODUCTION

A radar is a complicated system that uses radio waves to detect objects (targets). In the radar signal echoes, beside the signals from considered objects, there are signals from unwanted objects and system noises. For example, for a drone detection frequency modulated continuous wave (FMCW) radar with a high range resolution ([1] ch9), the unwanted objects are land (or surface) clutter (grasses, trees and ground), volume clutter (precipitation and chaff) and discrete (or point) clutter (birds, insects, land vehicles, wind turbines, buildings and water tanks), while the major term of system noise is spurious phase noise due to leakage between transmitting and receiving paths. Both

spurs and clutter will increase the system noise level and hence reduce the probability of detection of small targets such as drones and induce false alarms on the radar screen, which degrade the system's performance. Figure 1 shows the false alarms from discrete clutter such as cars and motorbikes on a drone detection radar. Therefore, it is necessary to study both the methods of system parameter design and signal processing algorithms in order to mitigate spurs and discrete clutter for drone detection and false alarm reduction.

For the problem of reducing clutter from unwanted objects, the two most popular methods are moving target indication (MTI) and moving target detection (MTD). The MTI was first discussed by Ridenour [2] and Grisetti et al. [3], and it

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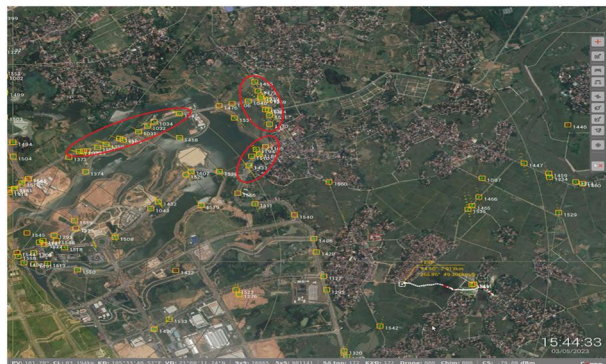


FIGURE 1 Illustration of false alarms from discrete clutter (cars and motorbikes in the red ellipses) on a high-resolution FMCW radar.

contains a delay line and a subtraction circuit that takes the difference between consecutive pulses. For a moving target, the Doppler shift of the carrier frequency will change the phase of the received pulse, whereas a ground or building echo will leave it essentially unchanged. Thus, the clutter will be cancelled in the output pulse.

The subsequent studies are extended to the cases of digital MTI [4] and MTI with staggered pulse repetition frequency [5, 6]. However, there are many causes, such as small movements of trees on the ground and the rotation of the radar antenna, that lead to the inefficiency of the MTI.

The MTD is a newer approach for the detection of moving targets than the MTI [7, 8]. One of the main blocks of the MTD system is the 'Doppler Filter Bank', which separates objects into different velocity levels (or, equivalently, different Doppler banks) in order to reduce clutter ([7] lecture 8).

The use of MTI and MTD is inefficient for separating drones from discrete clutter because of the similarity of their main Doppler features. Therefore, there is a need to explore new methods and features to avoid this difficulty. Among a large number of works concerning radar discrete clutter suppression or drone separation from discrete clutter, let us recall the work of Martin and Shapiro [9] with a method for discrimination of birds and insects for high-resolution weather radars using a combination of estimated radar cross section and density of targets, the work of Zaugg et al. [10] studied the problem of automatic identification of bird targets from insects and ground clutter for radars using wing flapping patterns and support vector classifiers, the work of He et al. [11] investigated the problem of wind farm discrete clutter suppression for air surveillance radar based on a clutter map and a generalising algorithm of the K-means clustering process, the work of Jatau et al. [12] for detecting birds and insects in the atmosphere using machine learning on patterns of bird and insect echoes based on dual polarisation variables and the study of Liu et al. [13] concerned the problem of drone separation from discrete clutter (birds) using motion characteristics. The reduction methods for another type of discrete clutter reflected from buildings were studied in refs [14–17].

Recently, the radar micro-Doppler signature of drones was studied by Chen et al. [18–20] and presented itself as a new feature to separate drones from discrete clutter [21, 22]. The

micro-Doppler shift of a drone is high enough due to the high rotation rate of its blades. Consequently, in order to detect such a high frequency, the radar pulse repetition interval (PRI) is very short, which leads to demands for radar hardware and processors. So, in practice, a continuous wave (CW) radar is usually used to extract the micro-Doppler information [23–28]. However, the CW radar cannot determine the target range, and hence it is rarely used for surveillance purposes. Although the extraction method of the micro-Doppler signature in an FMCW radar was presented in refs [29, 30], the periodicity in the spectrogram is not clearly visible. Other methods for detecting micro-Doppler signals from drones by using radar systems with different dwell times and multistatic radar can be found in refs [31–34]. All the methods mentioned above require detection of signals reflected from drone propellers. However, to the best of our knowledge, there has not been a study concerning the design of radar system parameters for drone propeller detection. Moreover, the use of micro-Doppler signatures for drone separation from discrete clutter has some drawbacks in practice, such as the unclear observation of micro-Doppler signatures in the spectrogram image due to noise and the increased computational requirement due to image processing and deep learning for classification [22].

The second problem studied in the present paper is spurious phase noise mitigation. Phase noise in a radar [35, 36] is the noise due to the phase fluctuations of a signal. These fluctuations manifest themselves as a noise spectrum spreading out on either side of the signal. As a result, the noise floor level is increased and the dynamic range of the receiver system is decreased, which might cause false targets on the radar screen and miss detection of small targets such as drones. Among the components of phase noise in an FMCW radar using separate transmitting and receiving antennas [37], such as random noise, harmonics, spurs due to the frequency instability of the oscillator, random noise phenomena, coupling from the transmitter to the receiver paths and the internal time delay, we focus on the mitigation of spurious phase noise in the received signal. In relation to this goal, Bakır et al. [38] investigated the effect of phase noise in FMCW radars and proposed some techniques to avoid it, such as by choosing the electronic components, using reflected power cancellers and using delay line cancellers. Siddiq et al. [35, 36] introduced detailed guidelines for the phase noise modelling of various components and sub-systems, such as phase noise in the frequency synthesiser, phase noise under frequency translation, phase noise in the received and down-converted signals and phase noise in the processed signals. Melzer et al. [39] proposed two methods for online phase-noise estimation for an FMCW radar: estimation in time domain (EMT) and (estimation in frequency domain (EMF). Park et al. [37] studied leakage mitigation in a heterodyne FMCW radar for small drone detection. The equations of phase noise in the received signal are derived. Then the authors proposed the stationary point concentration technique that alleviates the impact of the phase noise by using the exact IF beat frequency and IF constant phase of the leakage for the least LO, and hence, the term rising the noise floor is removed. Other techniques for phase noise mitigation can be found in refs [40, 41].

For a given receiver system gain $\hat{G}_{RX}$, the thermal noise density NSD_{ADC} at the input of the ADC is calculated by the following equation:

$$NSD_{ADC} = N_0 + \hat{G}_{RX} + NF. \quad (8)$$

The thermal noise density NSD_{rFFT} after range FFT processing is given by the following equation:

$$NSD_{rFFT} = NSD_{ADC} + 10 \times \log\left(\frac{f_s}{N_{rFFT}}\right), \quad (9)$$

where, N_{rFFT} is the number of range FFT points.

The minimum required power P_{ADC} at the ADC's input for detection can be estimated by the following equation:

$$P_{ADC} = NSD_{rFFT} + SNR_{\min} - 10 \times \log(N_p) + L_x, \quad (10)$$

where $SNR_{\min}$ is the minimum signal-to-noise ratio at the input of the CFAR detector for a desired probability of target detection and false alarm rate, N_p is the number of pulses for integration in the Doppler processing and L_x denotes the total loss of the signal processing.

If Iso_{Ant} is the antenna isolation improvement, then in order to mitigate spurs, the power of spurs P_{spurs} at the input of the transmitting antenna needs to be satisfied by the following equation:

$$Iso_{Ant} > P_{spurs} + \hat{G}_{RX} - P_{ADC}. \quad (11)$$

Section 3 will show how to use the relationships (2) and (11) to design a radar system for a drone and its propeller detection and spur mitigation. The new signatures of drones, including propeller and moving signatures, and classification algorithms are then proposed for drone separation from discrete clutter.

3 | PRACTICAL FRAMEWORK

3.1 | Designing radar system parameters

Assume that we need to design an FMCW radar with a 360-degree azimuth scan and the following requirements (Table 1). Note that the ranges for drone detection and classification follow from the battle request as well as the comparison with Robin's radar system 'Elvira', which detects and classifies a drone of 3.0 kg weight from 3.0 to 1.1 km, respectively [44]. With the recent software upgrade Robin's radar system 'Elvira' has been able to classify a drone up to 1.5 km [45]. The value of -36 dBsm RCS of propellers comes from ref. [46].

For a drone and its propeller detection, the radar system parameters, including the bandwidth of the transmitted signal, the sweep time, the maximum beat frequency and the power of the transmission, are calculated in Steps 1–3. For spur mitigation, the isolation coefficient between transmitting and receiving antennas is calculated in Step 4. The test results show

TABLE 1 Radar requirements.

Parameter	Unit	Value
Instrumented range $R_{\max}$	km	12
Range resolution ΔR	m	1.5
Azimuth resolution $\Delta\beta$	Degree	1.2
Frequency	GHz	8.9 ÷ 9.5
Drone detection:		
+RCS ~ -20 dBsm	km	≥ 3.3
Drone classification:		
+RCS of propellers ~ -36 dBsm	km	≥ 1.65
UAV detection:		
+RCS ~ -6 dBsm	km	≥ 8.0
Scan rate f_{scan}	Hz	0.1

that the radar satisfies the requirements of the drone and its propeller detection and spur mitigation.

Step 1. The bandwidth of the transmitted signal is

$$BW = \frac{c}{2\Delta R} = \frac{3 \times 10^8}{2 \times 1.5} = 100 \text{ MHz}.$$

As stated in ref. ([43] p. 53), the sweep time T_s needs to be satisfied by the following equation:

$$T_s \geq 5 \times \frac{2 \times R_{\max}}{c} = 5 \times \frac{2 \times 12 \times 10^3}{3 \times 10^8} = 400 \text{ } \mu\text{s}.$$

Step 2. Let $T_s = 2048 \text{ } \mu\text{s}$ and $\Delta T = 252 \text{ } \mu\text{s}$ be the sweep time and configuration time for the next sweep period. The reason for choosing $T_s = 2048 \text{ } \mu\text{s}$ is due to the trade-off between the maximum beat frequency and the number of pulses for Doppler processing. With T_s and ΔT above, the maximum beat frequency $f_{b\max}$ and the number of pulses N_p for Doppler processing are given as below:

$$\begin{aligned} f_{b\max} &= \frac{BW}{T_s} \times \frac{2R_{\max}}{c} \\ &= \frac{100 \times 10^6}{2048 \times 10^{-6}} \times \frac{2 \times 12 \times 10^3}{3 \times 10^8} \approx 3.9 \text{ MHz}, \\ N_p &= \frac{\Delta\beta}{\frac{f_{scan} \times 360}{T_s + \Delta T}} = \frac{1.2}{\frac{0.1 \times 360}{2300 \times 10^{-6}}} \approx 14. \end{aligned}$$

Step 3. The radar transceiver system is homodyne (Figure 3), and its parameters are measured in the laboratory and given in Table 2.

To calculate the transmitting power, we use the following values: The standard noise temperature $T_0 = 290 \text{ K}$ ([43] p. 9), the signal processing loss $L_x = 8.6 \text{ dB}$ includes 1.6 dB of beam-shape loss ([1] p. 146), 3.0 dB of range straddle loss, 3.0 dB of

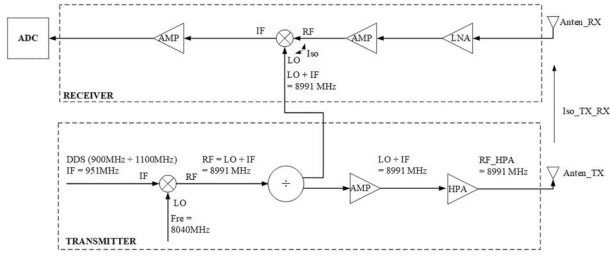


FIGURE 3 The design of the radar transceiver system.

TABLE 2 Radar transceiver system parameters.

Parameter	Unit	Value
Frequency	MHz	8991
Receiver's noise figure NF	dB	3.0
Transmitting line loss L_t	dB	1.0
Receiving line loss L_r	dB	1.0

Doppler straddle loss and 1.0 dB of CFAR loss ([47] pp. 55–56), the two-way atmospheric attenuation $L_{atm} \approx k_a R$ dB, where k_a is the two-way attenuation coefficient in dB/km, and R is the detection range. For the climate in Vietnam, the average humidity is 30 g/m³, and the coefficient $k_a \approx .04$ dB/km corresponds to the frequency of 8991 MHz. The value $k_a \approx 0.04$ dB/km comes from ([1] ch. 7), the signal-to-noise ratio at the CFAR detector $SNR = 14$ dB according to the requirement at the pulse level of probability of target detection $P_D = 0.7$ and probability of false alarm $P_{fa} = 10^{-4}$ for the Swerling 1 model ([1] p. 122).

Applying (2) we obtain the dependence of the transmitting power P_t on antenna gain G (Figure 4) to detect a drone with $RCS \approx -20$ dBsm from a range of 3.3 km (the black curve $P_{tDroneDetect}$), detect drone propellers with $RCS \approx -36$ dBsm from a range of 1.65 km (the blue curve $P_{tPropellerDetect}$) and detect an UAV with $RCS \approx -6$ dBsm from a range of 8.0 km (the magenta curve $P_{tUAVDetect}$). These curves show that for a given value of antenna gain $\hat{G}$, the minimum transmitting power P_t for detection requirements in Table 1 is given by the following equation:

$$P_t = \max \left\{ P_{tDroneDetect}(\hat{G}), P_{tPropellerDetect}(\hat{G}), P_{tUAVDetect}(\hat{G}) \right\}. \quad (12)$$

For a chosen antenna topology in Step 4, we can simulate the antenna radiation pattern and its gain (Figure 5).

The antenna gain by simulation without a radome is 31.3 dBi (Figure 5). Therefore, it will be approximately 30.3 dBi when measured with a radome after manufacturing. According to Equation (12) and Figure 4, the minimum transmitting power at the output of a high-power amplifier (HPA) is $P_t = 5$ W.

Step 4. In this step, we calculate the required isolation coefficient between transmitting and receiving antennas for spur mitigation. Since the maximum beat frequency f_{bmax} is

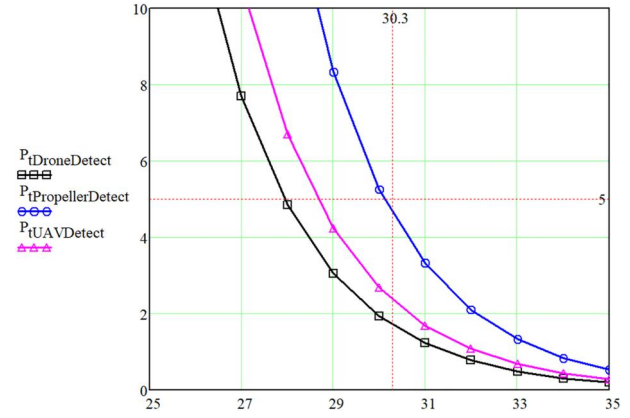


FIGURE 4 Dependence of P_t (W) on G (dB) for detection requirements.

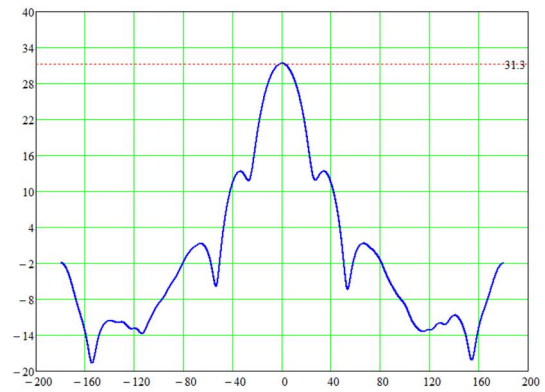


FIGURE 5 Antenna radiation pattern on the horizontal plane.

TABLE 3 Parameters of ADC LTC2386-16.

Parameter	Unit	Value
Maximum sampling rate f_{smax}	Msp	10
Resolution	bit	16
Input full scale	V_{pp}	8.192
Input resistance R_{in}	Ω	50

3.9 MHz, to satisfy Nyquist's theorem, we use the ADC LTC2386-16 with the features given in Table 3.

The full-scale power is evaluated by the following equation:

$$P_{FullScale} = 10 \times \log \left(\left(\frac{V_{pp}^2}{8R_{in}} \right) \right) + 30 \approx 22 \text{ dBm}.$$

Let the sampling rate be $f_s = 8.0$ MHz. Then the number N_{rFFT} of sample points in the 'RangeFFT processor' (Figure 2) is given by the following equation:

$$N_{rFFT} = f_s \times T_s = 8 \times 10^6 \times 2048 \times 10^{-6} \approx 2^{14} = 16384.$$

Applying (3–11) with $B = f_s/N_{rFFT}$, $G_{ctr} = [-10 \text{ dB}, 10 \text{ dB}]$, we obtain $N_0 = -174$ dBm/Hz and the following equation:

$$\begin{aligned}
SNR_{Nyq} &= 16 \times 6.02 + 1.76 = 98.08 \text{ dB}, \\
SNR_{ADC} &= 98.08 + 10 \times \log(16384/2) \approx 137 \text{ dB}, \\
NSD_{ADCFS} &= (22 - 1) - 137 = -116 \text{ dBm/Hz}, \\
G_{RX} &= -116 + 174 - 3 + 3 + [-10, 10] \\
&\approx [47 \text{ dB}, 67 \text{ dB}].
\end{aligned}$$

Set $\hat{G}_{RX} = 50 \text{ dB}$, then,

$$\begin{aligned}
NSD_{ADC} &= -174 + 50 + 3 = -121 \text{ dBm/Hz}, \\
NSD_{rFFT} &= -121 + 10 \times \log((8 \times 10^6)/16384) \\
&\approx -94 \text{ dBm/Hz}, \\
P_{ADC} &= -94 + 14 - 10 \times \log(14) + 8.6 \approx -91.2 \text{ dBm}.
\end{aligned}$$

As shown in Figure 3, we use a DDS (direct digital synthesis) to create an IF signal of frequency 951 MHz and a PLL (phase-locked loop) to create a signal of frequency 8040 MHz for mixing with the IF signal. As a result, we obtain the signal at 8991 MHz. The PLL induces spurs with frequencies of the form $(8040 + n \times 1) \text{ MHz}$ and $(8040 + n \times 0.7) \text{ MHz}$, where $n = 1, 2, 3, \dots$ and hence, in the transmitting signal, there are spurs of the form $(8991 + n \times 1) \text{ MHz}$ and $(8991 + n \times 0.7) \text{ MHz}$.

Let the transmitting power be 5 W, and measure the output power of the transmitting signal at the output of the HPA. There are two visible spurs at frequencies of 8992.4 and 8993 MHz with powers of -68.93 and -58.95 dBm , respectively. From Equation (11) we obtain the following requirement of antenna isolation coefficient Iso_{Ant} for the spur mitigation:

$$\begin{aligned}
Iso_{Ant} &> P_{phasenoise} + \hat{G}_{RX} - P_{ADC} \\
Iso_{Ant} &> -58.95 \text{ dBm} + 50 \text{ dB} + 91.2 \text{ dBm} \approx 82.25 \text{ dB}.
\end{aligned}$$

In many applications, the microstrip antenna is used due to its easy fabrication, low manufacturing cost, light weight and ability to be mounted with other integrated circuits on the same printed circuit board. However, the isolation coefficient of microstrip antennas is less than 80 dB [48]. To satisfy the above requirement of the isolation coefficient between TX and RX antennas, we use a slotted waveguide array antenna with flares (Figure 6). This type of antenna design was used in ref. [49] to reduce the vertical beamwidth and the cross-polarisation level and in ref. [50] to achieve an ultralow side lobe level.



FIGURE 6 The manufactured antenna with flares (in the red rectangles).

The measure of the isolation coefficient is given in Figure 7.

It is clear that the isolation coefficient between TX and RX antennas is greater than 85 dB at all frequencies from 8900 to 9500 MHz (Figure 7). Therefore, the spurs are mitigated.

The radar with the parameters designed in Steps 1–4 is manufactured. It detects almost continuously the DJI Phantom 4 from a distance of 3.5 km (Figure 8).

3.2 | New features for drone separation from discrete clutter

To separate drones from discrete clutter, we propose new features such as the target's Doppler dispersion level and moving characteristics. These features are easily estimated, do not require a short PRI to extract micro-Doppler and do not require a deep learning model for classification. Hence, they avoid the drawbacks of the use of micro-Doppler signatures in real-world applications.

3.2.1 | Doppler dispersion level

At each radar scan, a target will be detected as a group of hits. Each hit characterises an echo pulse from a part of the target

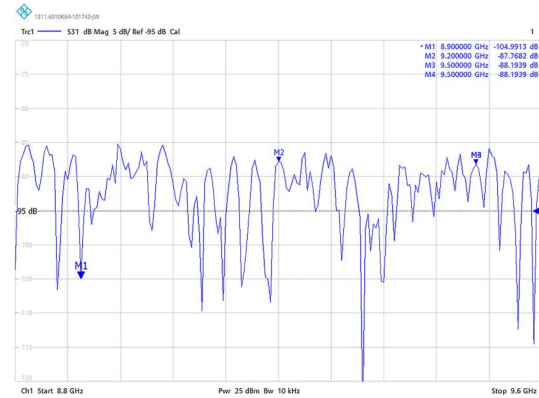


FIGURE 7 The measured result of the isolation coefficient between TX and RX antennas.



FIGURE 8 Detection of the DJI Phantom 4 by the radar (in the red ellipse).

and has its own Doppler. By counting the hits with the same Doppler and displaying the results in consecutive scans, we obtain the target's Doppler characteristic image (Figure 9). The target's Doppler dispersion level is defined by a vector (sample) of the form $(\overline{\Delta f_D}, \sigma_{\Delta f_D})$, where

$$\overline{\Delta f_D} = \text{mean}\{\Delta f_{D1}, \Delta f_{D2}, \dots, \Delta f_{DM}\} \quad (13)$$

$$\sigma_{\Delta f_D} = \text{std}\{\Delta f_{D1}, \Delta f_{D2}, \dots, \Delta f_{DM}\} \quad (14)$$

Δf_D is the spread of Doppler banks of the target's hits at i -th scan, and M is number of scans (in this study we use $M = 5$).

In the range of up to 1.7 km where the radar can detect drone propellers, we collect a dataset of 20,000 samples from radar targets (half of them from the drones Inspire 2, Phantom 4, and Mavic 2 Pro). Analysing the dataset, we obtain the following statistics about the target's Doppler dispersion levels (Figure 10).

The Doppler dispersion level of drones is statistically different from that of discrete clutter. Therefore, it is satisfied with drone separation from discrete clutter.

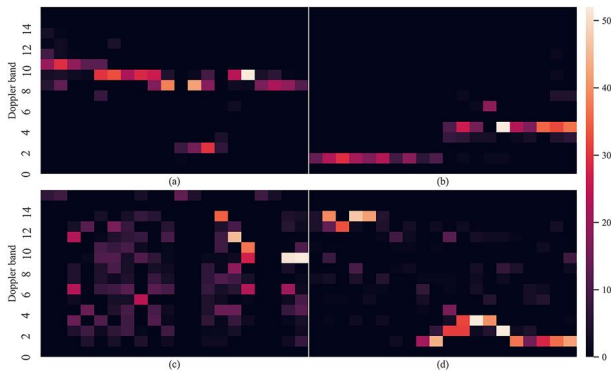


FIGURE 9 Doppler characteristic images of different types of targets. (a) Heatmap of the Doppler characteristic of a car in 40 consecutive radar scans. (b) Heatmap of the Doppler characteristic of a motorbike in 40 consecutive radar scans. (c) Heatmap of the Doppler characteristic of the drone DJI Inspire 2 in 40 consecutive radar scans. (d) Heatmap of the Doppler characteristic of the drone DJI Phantom 4 in 40 consecutive radar scans.

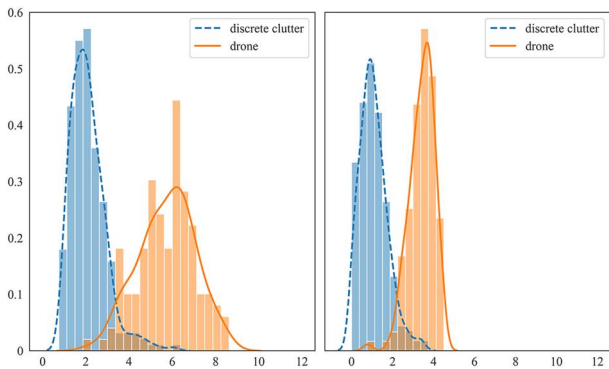


FIGURE 10 Distributions of $\overline{\Delta f_D}$ (on the left) and $\sigma_{\Delta f_D}$ (on the right) for drones and discrete clutter.

3.2.2 | Moving characteristic feature

The target's Doppler dispersion feature is not enough to reduce the discrete clutter because of its dependence on the range from the radar to the targets. For a small drone moving far from the radar, its Doppler dispersion level is the same as discrete clutter. Therefore, in this section, we introduce a method to create a street map that is used to extract the target's moving characteristics for discrete clutter reduction.

To create a street map, we need the well-known following converting formula. For a point A with range d (m) and azimuth α (rad), its latitude and longitude are defined as

$$\text{lon}_A = \text{lon}_{\text{root}} + \frac{d \times \text{hs} \times \sin \alpha}{\cos \frac{\text{lat}_{\text{root}} \times \pi}{180}}, \quad (15)$$

$$\text{lat}_A = \text{lat}_{\text{root}} + d \times \text{hs} \times \cos \alpha, \quad (16)$$

where, $(\text{lat}_{\text{root}}, \text{lon}_{\text{root}})$ is the latitude and longitude of the radar position and

$$\text{hs} = \frac{360}{2\pi \times R \times 1000}, \quad R = 6378.137 \text{ (}^\circ/\text{m)}.$$

For a point A $(\text{lat}_A, \text{lon}_A)$, its coordinates (x_A, y_A) in the Cartesian coordinate system are

$$x_A = \left(\frac{\text{lat}_A - \text{lat}_{\text{root}}}{\text{hs}} \right) / \text{scale}, \quad (17)$$

$$y_A = \left(\frac{\text{lon}_{\text{root}} - \text{lon}_A}{\text{hs}} \right) / \text{scale}, \quad (18)$$

where scale (pixel/m) is a given parameter.

The radar range resolution is 1.5 m (Table 1), hence we can use the value $\text{scale} = 1.5/\sqrt{2} \approx 1$ (pixel/m), that is, the street map has a resolution of 1.0 m in the Cartesian coordinate system.

The process of creating a street map is as follows:

Step 1. From the website www.openstreetmap.org, load the street data where the radar is set up. The street data contains a list of elements (or equivalent streets). Each element (or street) is constructed by connecting adjacent nodes (or points) together.

The area of the street data is determined by a square shape with length $2R_{\text{max}}$ (m) and centre in the radar position, where R_{max} is the radar instrumented range.

Step 2. Using formulas (15) and (16), calculate the latitude and longitude of Point A (top left corner of the square shape).

Step 3. For each street in the loaded data, convert the coordinates of all nodes into Cartesian coordinates using formulas (17) and (18), where the latitude and longitude of Point A are given as $(\text{lat}_{\text{root}}, \text{lon}_{\text{root}})$.

Step 4. Connect consecutive nodes of a street and interpolate values (coordinates) for other points in the street (according to the resolution of 1.0 m of the street map). Repeat for all other streets. We obtain the street map with (approximately) the same slant range resolution as the radar (Figure 11).

For analysing the moving characteristics of radar discrete clutter with respect to the street map, we collected 10,676 distance (to the nearest street on the street map) samples and 9311 moving direction (to the nearest street on the street map) samples from 380 radar discrete clutter (cars, motorbikes). The statistical results show that most discrete clutter has a distance and moving direction (to the nearest street on the street map) of less than 30 m and 30°, respectively (Figure 12). These characteristics will be used in the following to separate drones from discrete clutter.

Algorithms for drone detection and discrete clutter reduction

Now, we propose a system design and algorithms for the module drone detection and discrete clutter reduction (DDDCR) on the radar. The principle of the module is included in the classification of discrete clutter and drones. The design of the module is represented in Figure 13.

The data flow is as follows:

Step 1. From the 'Core' of the radar data processing, the target's data (such as ranges, azimuths, moving directions and Doppler features) are transferred into the 'Random Forest



FIGURE 11 A created street map (red colour) is displayed on the radar screen.

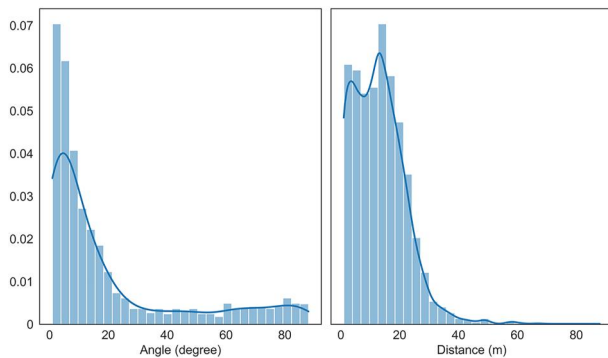


FIGURE 12 Statistical results on the moving characteristics of radar discrete clutter.

Model' and 'Street Model' via the 'Server' and 'Cache data' of the module DDDCR.

Step 2. Each of the models 'Random Forest Model' and 'Street Model' will predict the targets as 'drone', 'discrete clutter' or 'undefined' and send the label with confidence scores (probabilities of classification) back to the 'Top Model'.

Step 3. At the 'Top Model', a decision for each target is confirmed, and the results are returned to the 'Core' of radar data processing to display on the radar screen.

The 'Random Forest Model' is created by training 20 trees with the target's Doppler dispersion levels of 20,000 samples, 10,000 samples of drones and 10,000 samples of discrete clutter. The maximum depth value of each decision tree in the model is set to 5 to avoid overfitting. For a target at each radar scan, the 'Random Forest Model' will classify it as 'drone' or 'discrete clutter'.

The algorithms for 'Street Model' and 'Top Model' are described in Table 4 and Table 5, respectively.

4 | TEST RESULTS

The module DDDCR was integrated into the radar system and tested with different drones in different moving scenarios (such as radial flight and tangent flight). For performance evaluation, we use the metrics True Rate of Clutter Reduction (TRCR), True Rate of Drone Classification (TRDC) and Maximum Range for Drone Classification (MRDC):

$$TRCR = \frac{\text{number of true clutter classified}}{\text{number of discrete clutter}} \quad (19)$$

$$TRDC = \frac{\text{number of true drones classified}}{\text{number of all drones}}. \quad (20)$$

The results are given in Table 7 and Figures 14–16. For comparison, Table 8 shows the results of our study and those of Robin's radar system 'Elvira' [44, 45].

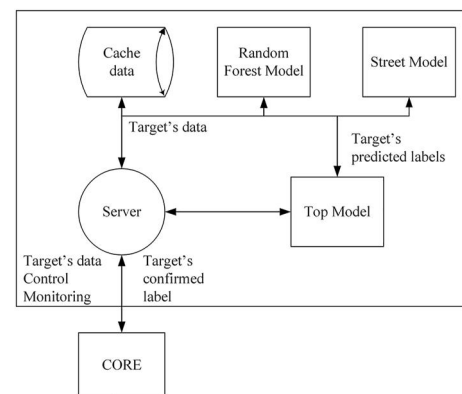


FIGURE 13 System design of the module DDDCR.

TABLE 4 Algorithm 1 (street model).

Input:	Target's data from the 'core' module of radar data processing and the parameter values given in Table 6.
Output:	Target's label ('drone' or 'undefined').
1:	Convert the radar target's ranges and azimuths to latitude and longitude coordinates using the formulas (15) and (16). Then, obtain the target's positions on the street map using formulas (17) and (18) with the root at point A (top left corner of the map).
2:	Open a square gate with the centre at the target's position and a radius of r on the street map. If there is a node (point) in the gate that belongs to a street, then the target's current position is considered 'near the street'.
3:	Repeat Step 2 for N consecutive radar scans. If there are at least M scans at which the target's position is 'near the street' and
$M \geq N \times \text{nearStreetRate},$	
then the target is called 'near the street'.	
4:	For a 'near the street' target, consider N last radar scans $(n - N + 1, n - N + 2, \dots, n)$ where n is the current radar scan. A window with length $k(k < N)$ is used to calculate the angles $\{\text{angle}_1, \text{angle}_2, \dots, \text{angle}_{N-k+1}\}$ between the target's moving direction and the nearest street. If
$\text{median}\{\text{angle}_1, \text{angle}_2, \dots, \text{angle}_{N-k+1}\} < \text{angleMax},$	
then the target is confirmed as 'moving along the street'.	
5:	If a target is moving along the street, it is classified as 'undefined', otherwise as 'drone'.

TABLE 5 Algorithm 2 (top model).

Input:	Target's labels from sub-modules 'random forest model' (for short: RFM) and 'street model' (for short: StM), active ranges of models (1.7 km for random forest model and 12 km for street model).
Output:	Target's confirmed label ('drone', 'discrete clutter', or 'undefined').
1:	If RFM is inactive, that is, the target's range is greater than 1.7 km, then StM is used: - If the current output of StM is 'drone', then use MN logic (in this study, $M = 6, N = 10$) to confirm the target as 'drone' or 'undefined'; - If the current output of StM is 'undefined', then confirm the target as 'undefined'.
2:	If RFM is active, that is, the target's range is less than 1.7 km, then use MN logic ($M = 6, N = 10$) to confirm the target as 'drone' or 'discrete clutter'.

TABLE 6 Parameter values for algorithm 1.

Parameter	Unit t	Value
r (radius of the square gate)	m	30
N (number of consecutive scans)	Scan	15
nearStreetRate	-	0.5
k (window size)	Scan	5
angleMax	Degree	30

TABLE 7 Test results.

Parameter	Unit	Value
TRCR	-	0.97
TRDC	-	1.0
MRDC for drones moving across the streets	km	3.5
MRDC for drones moving along the streets	km	1.7

5 | CONCLUSION AND FUTURE WORKS

The paper presented a design of a high-resolution FMCW radar for drone detection based on the new approaches of spurious phase noise mitigation and discrete clutter reduction. Both theoretical and practical frameworks are proposed towards this goal.

Spurs are inherent in the radar signal and can be mitigated by the use of the stationary point concentration technique,

which was recently introduced [37]. In the present paper, the spurs are mitigated by the use of an antenna design with the required isolation coefficient. It is shown that the slotted waveguide array antenna with flares achieves a high side lobe level and isolation.

To reduce discrete clutter, the radar system design is proposed for drone propeller detection, and then the Doppler dispersion feature is introduced. This feature is easier to estimate than the micro-Doppler feature and is more efficient at separating drones from discrete clutter such as vehicles and birds. In the case when a drone is far from the radar, the



FIGURE 14 ‘Discrete clutter’ and ‘Drone’ on the radar screen. Classification of a drone (in the red ellipse) from 3.5 km by using the ‘Street Model’.

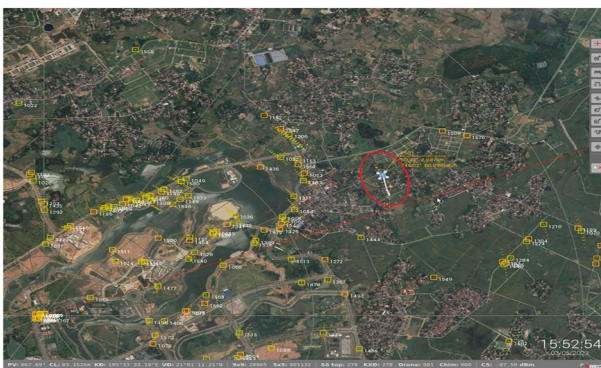


FIGURE 15 Classification of a tangential drone (in the red ellipse) at a range of 2.9 km.



FIGURE 16 Classification of a drone moving along the street (in the red ellipse) from a range of 1.7 km using the Doppler diversion feature.

TABLE 8 Comparison with Robin's radar system ‘Elvira’.

Parameter	Elvira radar	Proposed radar
TRCR	-	0.97
TRDC	-	1.0
MRDC	1.5 km	3.5 km

reflected power from drone propellers is lower than the minimum required power at the ADC's input for detection, and hence, the Doppler dispersion level of the drone is the same with the discrete clutter. To overcome this problem, a street map is created and used to study the target's moving characteristics.

By combining the target's Doppler dispersion feature and moving characteristics, 97% of the discrete clutter was rejected, while 100% of the drones were exactly recognised. This result is better than in recent publications [22, 44, 45]. In future work, we will extend the study to recognise more different types of targets, such as drones, helicopters and UAVs, from discrete clutter.

AUTHOR CONTRIBUTIONS

Tran Vu Hop: Project administration (lead); conceptualisation (equal); data curation (lead); formal analysis (lead); investigation (lead); methodology (lead); software (lead); validation (lead); visualisation (lead); writing – original draft (lead); writing – review and editing (lead). **Tran Cao Quyen:** Conceptualisation (equal); validation (supporting); writing – review and editing (supporting); supervision (equal). **Nguyen Van Loi:** Conceptualisation (equal); data curation (supporting); validation (supporting); writing – review and editing (supporting); supervision (equal).

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CONFLICT OF INTEREST STATEMENT

The authors declare that they have no conflicts of interest.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

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Improving aerial target detection for 3D radar based on a two-stage CFAR method with adaptive clutter distribution estimation

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This study deals with the problem of enhancing aerial target detection for 3D radar. A novel approach which incorporates both signal and data processing is introduced. In order to increase the target's SNR (signal-to-noise ratio), two consecutive transmit beams are used; for each, three beams are received simultaneously. All received beams are then processed. A two-stage constant false alarm rate (CFAR) algorithm is proposed for improving target detection. At the first-stage CFAR, the global CA-CFAR is applied to identify all possible target candidates (plots). Then, unsupervised machine learning is used to separate interference regions. For each interference region, the truncated probability density function of interference is estimated, and then a local CFAR (second-stage CFAR) is applied to reduce false plots while retaining target plots. The proposed approach is an extension of that given in recent publications. Tests on a 3D surveillance radar show the effectiveness of the proposed approach on aerial target detection in comparison with previous methods.

KEYWORDS

radar target detection, radar signal processing, constant false alarm rate, DBSCAN, clutter distribution estimation

1 Introduction

The major role of a radar system is target detection by transmitting signals and processing the reflected signals from targets. A constant false alarm rate (CFAR) algorithm is used to decide the presence or absence of a target in a cell under test (CUT). One of the most popular CFAR algorithms is cell-averaging CFAR (CA-CFAR). CA-CFAR works well for target detection in the case of target isolation (i.e., targets are separated by at least the reference window size) and a homogeneous Gaussian environment (i.e., samples in reference cells are independent and identically distributed, and the distribution is Gaussian, like the distribution of interference in CUT) (Richard, 2005). However, in real-world scenarios, the environment is often complex (non-homogeneous) due to clutter (such as echo from surfaces, trees, meteorology, and terrain) and target masking (i.e., targets in reference cells reflect higher powers than the target in CUT). This leads to an increase in the false alarm rate and degrades the performance of CA-CFAR.

To mitigate the masking effect, smallest-of cell-averaging CFAR (SOCA-CFAR) and greatest-of cell-averaging CFAR (GOCA-CFAR) have been investigated (Hansen, 1973; Weiss, 1982). Unlike CA-CFAR, which evaluates the threshold using all reference cells, GOCA-CFAR and SOCA-CFAR only estimate the threshold using half the reference cells. They therefore need to use more reference cells than CA-CFAR.

Ordered-statistic CFAR (OS-CFAR) (Rohling, 1983) is another approach to improve classical CA-CFAR against the target masking problem. The data (reflected signal) from reference cells are arranged in an ascending sequence. Then, the k -element of the sequence is selected as the noise level. Blake (1988) has shown that the losses of OS-CFAR are lower than those of CA-CFAR.

Subsequent studies have extended CFAR in various directions, such as CFAR with different clutter distributions, with additional statistical tests, or with machine learning to recognize the homogeneity of the environment in reference cells. Among a larger number of works, we review some.

For CFAR with different clutter distributions, Rifkin (1994) and Baadeche and Soltani (2015) are relevant with CFAR thresholding in Weibull clutter, and Xu et al. (2015) and Zhou et al. (2018) refer to CFAR with K and gamma distributions, respectively.

For using CFAR with additional statistical tests, Finn (1986) worked with CFAR under the assumption that data from the CFAR window (including CUT) span into two different statistical regions. Smith and Varshney (2000) investigated the combination of CA-CFAR, GOCA-CFAR, and SOCA-CFAR based on second-order statistics (variability index) and the ratio of mean values of the leading and lagging reference windows. Sarma and Tufts (2001) investigated non-parametric CFAR, introducing a threshold setting algorithm without knowledge of the distribution of interference. Norouzi et al. (2007) studied detection in non-coherent radar in the case of Weibull and log-normal clutter based on goodness-of-fit tests (Kolmogorov–Smirnov, Cramer–von Mises, and Anderson–Darling tests). Zhou et al. (2017) proposed a novel CFAR combining the advantages of CA-, GOCA-, and OS-CFAR using an iterative process by sorting and amplitude-weighted averaging to estimate background level and detection in gamma distribution clutter. Mehanaoui et al. (2019) detected non-Gaussian background using the Pietra index as a measure of statistical heterogeneity instead of the variability index. Other studies in this direction are Tien et al. (2018), Zhou et al. (2019), Subramanyan et al. (2019), Lv et al. (2024), and Coluccia et al. (2024) and the references therein.

Machine learning and deep learning approaches have been intensively investigated in recent years for improving radar detection in non-homogeneous environments. Various machine learning techniques, from simple models such as support vector machines and neural networks to more complex models such as recurrent neural networks, convolutional neural networks, and YOLO, have been studied. For more details, we refer readers to Wang et al. (2017), Lu et al. (2018), Zhang et al. (2013), Perd'ock et al. (2024), and Jiang et al. (2022).

In almost all the literature mentioned above, CFAR is studied in combination with signal processing algorithms such as moving target indicator (MTI) and moving target detection (MTD) (Richard, 2005; Skolnik, 2008; Barton, 2013; Budge and German, 2015) and with the pre-defined interference distribution (for example, Gaussian distribution for noise in the entire space region and the Weibull distribution for ground clutter in the near-radar region). MTI and MTD increase the signal-to-noise ratio and hence improve the probability of detection while reducing false alarms.

However, from a practical point of view, the interference is unknown in both the type of distribution and where it may appear. It may change from region to region and scan to scan. Therefore, the

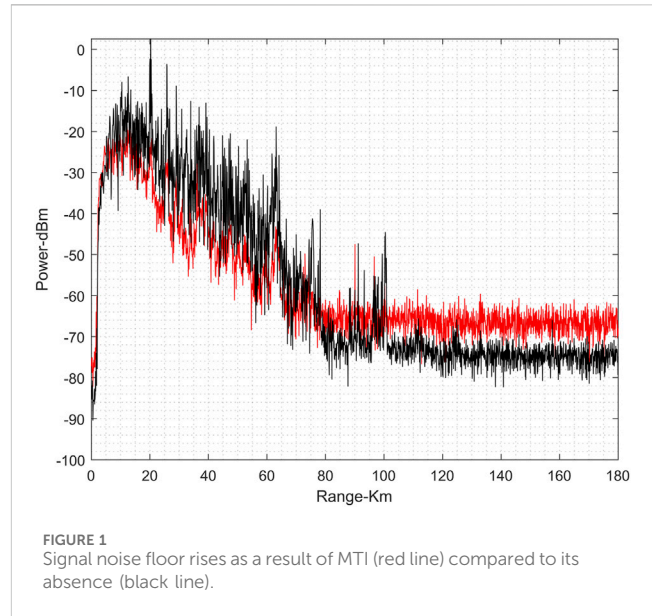


FIGURE 1
Signal noise floor rises as a result of MTI (red line) compared to its absence (black line).

use of the classical signal processing methods (MTI, MTD, and CFAR) with the same pre-defined interference distribution is not suitable. In fact, the use of MTI will increase the noise floor level in non-clutter regions (Figure 1). Moreover, the probabilities of detection (P_d) and of a false alarm (P_{fa}) are related (Richard, 2005). Thus, in the case of complex interference environments, the choice of an interference level to maintain a required probability of detection may lead to an increased false alarm rate (Figure 2).

In this study, we extend the results of Tien et al. (2018) and Li et al. (2025) to propose a new approach for improving aerial target detection. The suggested method focuses on a two-stage CFAR process comprising a global CFAR in the first stage and a local CFAR based on interference distribution estimation in the second stage to improve target detection in non-homogeneous environments. This study is organized as follows: Section 2, we give a detailed statement of the problem. The proposed approach is presented in Section 3. The test results and comparison are given in Section 4. Section 5 contains the conclusion and future work.

2 Statement of the problem

In radar, detecting a target is equivalent to deciding whether “target absent” (null hypothesis, H_0) or “target present” (alternative hypothesis, H_1) is valid in the CUT (cell under test) based on measured data. Let $\mathbf{y}$ be the measured data from CUT and $p(\mathbf{y}|H_0)$ and $p(\mathbf{y}|H_1)$ be the probability density functions (PDFs) of $\mathbf{y}$ given that a target was not present (respectively, a target was present) in CUT. The probabilities of detection and of false alarms are thus evaluated (Richard, 2005; Skolnik, 2008; Barton, 2013; Budge and German, 2015):

$$P_d = \int_{\Omega} p(\mathbf{y}|H_1) d\mathbf{y}, \quad (1)$$

$$P_{fa} = \int_{\Omega} p(\mathbf{y}|H_0) d\mathbf{y}, \quad (2)$$

where Ω denotes the set of $\mathbf{y}$ for which hypothesis H_1 will be chosen.

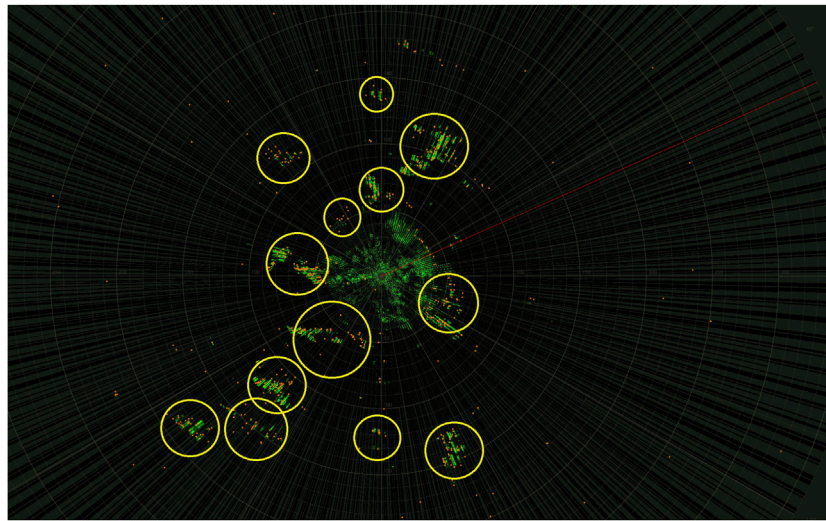


FIGURE 2
False alarms (in yellow circles) on a radar screen due to non-homogeneous environments.

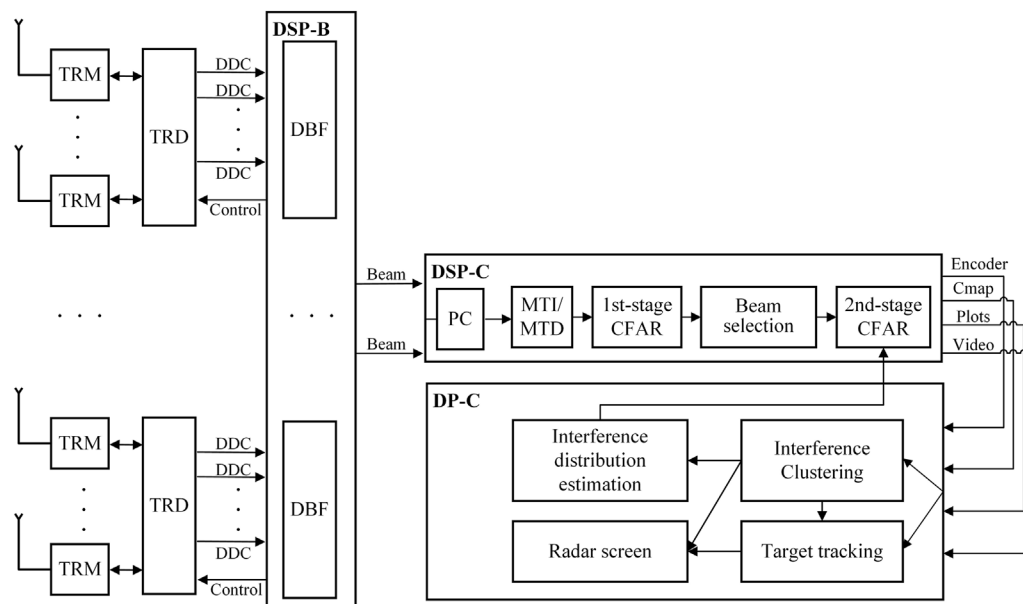


FIGURE 3
Diagram of the proposed approach.

The Neyman–Pearson decision rule (or likelihood ratio test) is as follows:

$$\frac{p(\mathbf{y}|H_1)}{p(\mathbf{y}|H_0)} \underset{H_0}{\overset{H_1}{\gtrless}} \lambda. \quad (3)$$

To use Equation 3, the explicit forms of $p(\mathbf{y}|H_1)$ and $p(\mathbf{y}|H_0)$, defined in Equation 1, 2, are required. Then, the threshold λ will be estimated from P_{fa} .

In order to determine the pdfs $p(\mathbf{y}|H_1)$ and $p(\mathbf{y}|H_0)$, the pre-defined model of measured data $\mathbf{y}$ is given. Usually, the model of $\mathbf{y}$

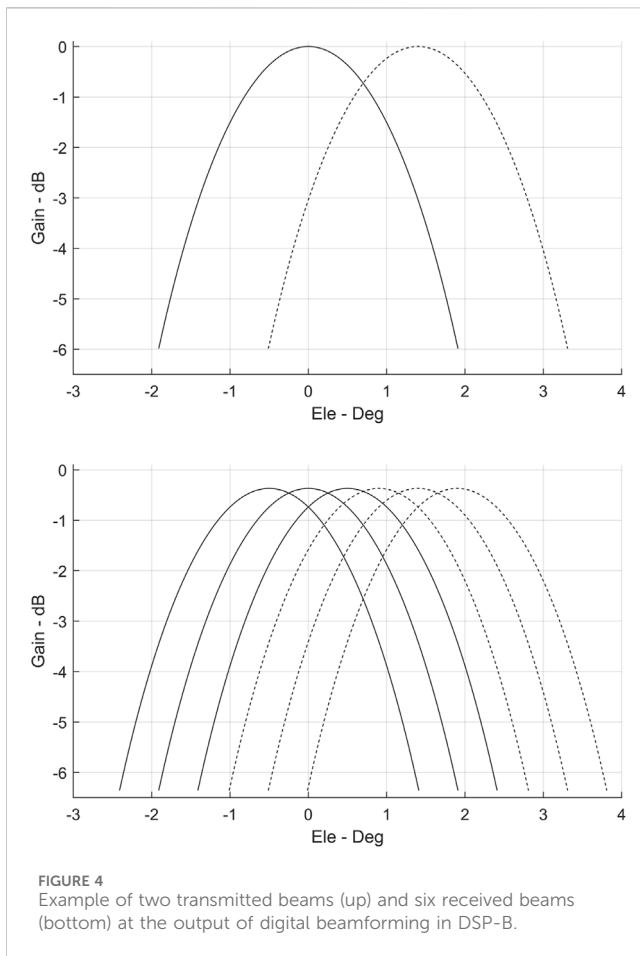
used in a radar system is of the form (Richard, 2005; Skolnik, 2008; Barton, 2013; Budge and German, 2015):

$$H_0: \mathbf{y} = \mathbf{n}, \quad (4)$$

$$H_1: \mathbf{y} = \mathbf{s} + \mathbf{n}, \quad (5)$$

where $\mathbf{s}$ and $\mathbf{n}$ denote the reflected signal from CUT and system noise (Gaussian noise), respectively. Another model is added with a clutter component $\mathbf{c}$ into the right-hand side of Equations 4, 5:

$$H_0: \mathbf{y} = \mathbf{n} + \mathbf{c}, \quad (6)$$



$$H_1: \mathbf{y} = \mathbf{s} + \mathbf{n} + \mathbf{c}, \quad (7)$$

where clutter $\mathbf{c}$ follows the predefined distribution such as Weibull, K, or gamma.

Assuming that interference (noise, clutter) in the adjacent range cells has the same PDFs and characteristics as that in the CUT, we propose a general model of Equations 6, 7 for target detection:

$$H_0: \mathbf{y} = \mathbf{i}, \quad (8)$$

$$H_1: \mathbf{y} = \mathbf{s} + \mathbf{i}, \quad (9)$$

where interference $\mathbf{i}(t, x)$ at time t and position x has the representation

$$\mathbf{i}(t, x) = \sum_{k=1}^m \chi(x, A_k) p^{(k)}(t, x). \quad (10)$$

Here, A_k is the disjoint region (i.e., $A_k \cap A_{k'} = \emptyset$ for $k \neq k'$) at which the PDFs of interference are $p^{(k)}(t, x)$, and

$$\bigcup_{k=1}^m A_k = \text{all the surveillance space}, \quad (11)$$

$$\chi(x, A_k) = 1, \quad \text{if } x \in A_k, \quad (12)$$

$$\chi(x, A_k) = 0, \quad \text{otherwise.}$$

The probability density function $p^{(k)}(t, x)$ might be the sum of different PDFs of interference that occur in the CUT:

$$p^{(k)}(t, x) = \sum_{j=1}^{n(k)} \alpha_j(k) p^{(k_j)}(t, x), \quad \alpha_j(k) \in \mathbb{R}. \quad (13)$$

Models Equations 8-13 mean that the reflected signal from a position x at time t could be the sum of signals reflected from targets and from various types of interference with different distributions $p^{(k_j)}$ and weights $\alpha_j(k)$. Therefore, the CFAR with the predefined interference distribution mentioned in Section 1 degrades its performance in this situation.

In the next section, we propose a new approach to solve the detection problem Equations 8-13. The main ideas of the proposed approach are:

- a. multiple beams processing for maximizing SNR;

TABLE 1 Algorithm 1 (processing in DSP-C and DP-C).

Main steps	Pseudo code
Input	Received beams after digital beamforming, global probability of false alarms P_{fa} for global CFAR (first stage), and local probability of false alarms p_{fa} for local CFAR (second stage); the set of interference regions = empty (initial condition)
Output	Target's plots and trajectories, interference regions, and their distributions
1	Take pulse compression for all received pulses corresponding to received beams
2	Integration using MTI and MTD
3	Detect possible target candidates using CA-CFAR (first-stage CFAR) with the global probability of false alarms P_{fa}
4	Select the beam with maximum SNR at CUT and transfer detected target candidates (plots) to DP-C
5	Process plots into two parallel streams for interference clustering and target tracking. The interference regions determined from interference clustering will be added to the set of interference regions
6	If the set of interference regions is non-empty, then approximate the interference PDF for each region (algorithm 2) in the set of interference regions. The interference PDFs are then used for the second-stage CFAR (step 7)
7	If the set of interference regions is non-empty, then for each interference region A_k and its PDF $p^{(k)}(t, x)$, evaluate the second threshold λ_k using local probability of false alarms p_{fa} : $\lambda_k = F_k^{-1}(1 - p_{fa})$ (15) where F_k is the cumulative distribution function corresponding to the interference PDF $p^{(k)}$. Then remove all plots in A_k with powers less than λ_k

TABLE 2 Algorithm 2 (interference probability density function estimation).

Main steps	Pseudo code
Input	The order n of approximation polynomial and data $\{y_i^{(k)}\}_{i=1}^{N_k}$
Output	Approximation polynomials using moments and Bernstein's methods
1	Take the truncated histogram for data $\{y_i^{(k)}\}_{i=1}^{N_k}$
2	Determine the Bernstein's approximation of the interference PDF using Supplementary Appendix Equations S1-S3
3	Calculate the moments from m_0 to m_{2n} and determine the polynomials from $P_0(y)$ to $P_n(y)$ using Supplementary Appendix Equation S5
4	Evaluate the values from c_0 to c_n
5	Determine the moments approximation of the interference PDF using Supplementary Appendix Equation S8

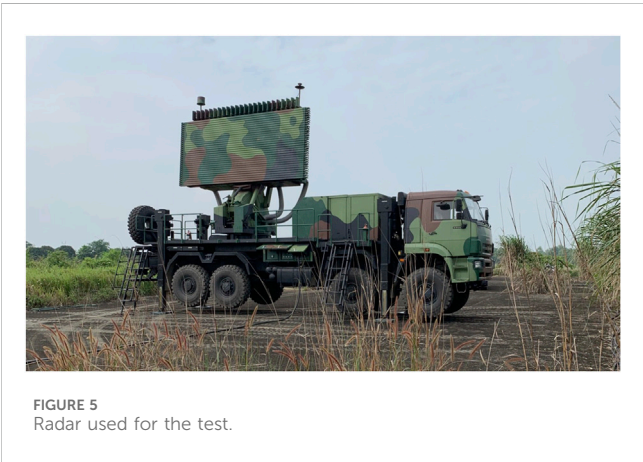


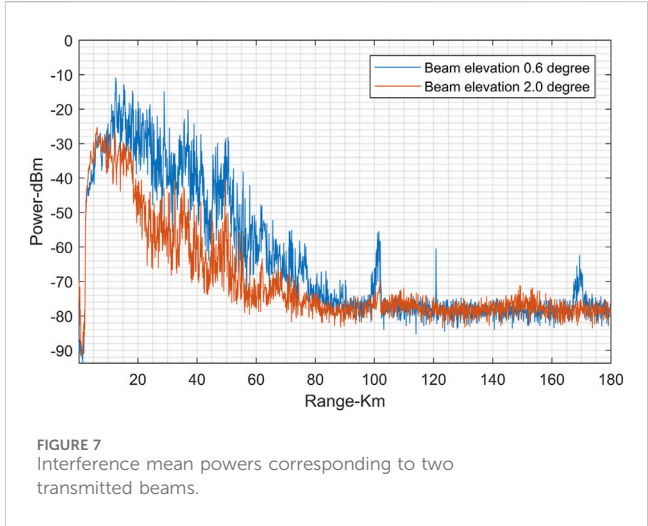
TABLE 3 Radar system parameters used for the test.

Parameter	Unit	Data
Instrumented range	km	360
Frequency		S band
Elevation beamwidth	degree	≤ 3.5
Scan rate	Hz	0.1
Global probability of false alarms P_{fa}		10^{-3}
Local probability of false alarms p_{fa}		0.1

- b. using CA-CFAR (first-stage CFAR) with a global P_{fa} to determine possible target candidates;
- c. application of unsupervised machine learning to separate interference regions A_k from all possible target candidates;
- d. interference distribution estimation for each region A_k ;
- e. false candidate reduction using second-stage CFAR with a local p_{fa} .

3 Proposed approach

The diagram of the proposed approach is given in [Figure 3](#). Two consecutive beams are formed in the DSP-B (digital signal



processing on board) block and up-converted to operating frequency. Then, the beams are radiated into space via TRMs (transmit/receive modules) and antennas. The received signals from TRMs are passed through TRD (transmit/receive digitization) blocks in which the signals are digitized, down-converted, and then passed to the DSP-B block for digital beamforming. For each transmit beam, three beams are received

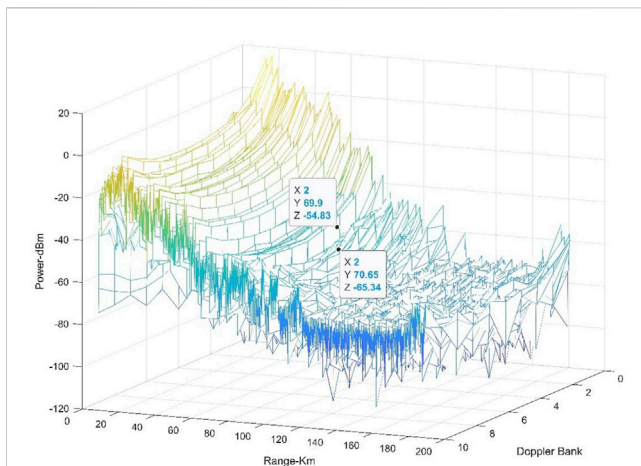


FIGURE 8
At range of 70 km, target's SNR corresponding to the beam at an elevation of 0.6 degree is 10 dB.

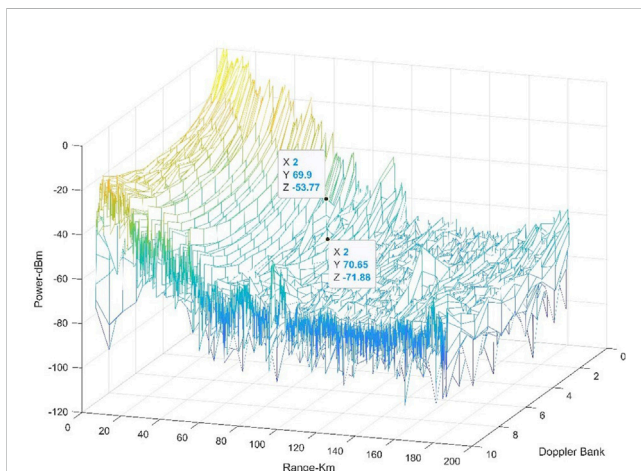


FIGURE 9
At range of 70 km, target's SNR corresponding to the beam at an elevation of 2.0 degree is 18 dB.

in DSP-B (Subsection 3.1). These are then processed in DSP-C (digital signal processing on computer) and DP-C (data processing on computer) blocks (Subsection 3.2).

3.1 DSP-B

The radar system transmits two consecutive beams separated by different elevation angles, with the maximum angle-distance between them being half of the elevation beamwidth. For each transmitted beam, two sets of beams (the sum, and elevation difference beams) are received in Equation 14 below:

$$b_s^{(i)}(t) = \sum_{n=1}^N w_s^{(i)}(n) r_n(t), \quad b_{\Delta E}^{(i)}(t) = \sum_{n=1}^N w_{\Delta E}^{(i)}(n) r_n(t), \quad i = 1, 2, 3, \quad (14)$$

where $\{r_n(t)\}_{n=1}^N$, $\{w_s^{(i)}(n)\}_{n=1}^N$, $\{w_{\Delta E}^{(i)}(n)\}_{n=1}^N$ are the digital sub-array data and beamforming weights, respectively. The maximum angle-distance between simultaneously received beams (corresponding to each transmitted beam) is equal to one-fourth of the elevation beamwidth (Figure 4).

3.2 DSP-C and DP-C

Received beams are then processed in DSP-C, including PC (pulse compression), MTI/MTD (for pulse integration), and first-stage CFAR (using CA-CFAR with a given global P_{fa}). The beam with maximum detection performance (Yu, 2009, Scheme 3) is selected in “beam selection” (Figure 3).

In the case of non-homogeneous environments, false alarms occur after the first-stage CFAR. For air-defense radars, most popular false alarms are due to reflected echoes of surface or meteorology and have some typical characteristics, such as higher density (the density of plots in clutter regions is higher than in other non-clutter regions) and stability (the false plots due to clutter remain in the clutter regions are longer than in non-clutter regions). Based on these characteristics, density-based clustering based on the hierarchical density estimates (HDBSCAN) algorithm is used for “interference clustering” in DP-C. The main steps of the HDBSCAN algorithm are given in Campello et al. (2013). The output of the interference clustering is the set of interference regions A_k , $k = 1, \dots, m$, $m \geq 1$. For each region A_k , let N_k be the number of plots in A_k and $\{y_i^{(k)}\}_{i=1}^{N_k}$ be the set of plot powers in A_k . The interference PDF in A_k is approximated using polynomials in Algorithm 2 (Table 2). Here, we use the polynomial approximation in order to simplify execution while keeping a satisfactory result. The main steps processed in DSP-C and DP-C are given in Algorithm 1 (Table 1). We note that in formula 15, the function F_k is the cumulative distribution function corresponding to the interference PDF $p^{(k)}$, which by virtue of which Algorithm 2 (Table 2) is a polynomial. Therefore, F_k is a continuous and strictly increasing function. This implies that it is invertible, with formula 15 being consistent (Table 1).

4 Test results and comparison

The radar used for the test is an air-defense 3D surveillance radar (Figure 5) with system parameters given in Table 3. The value p_{fa} will be used for interference regions to reduce false alarms. This value is the default false alarm rate used in Li et al. (2025). Elevation scanning is achieved by electronically adjusting the phase of signals across an antenna array, while azimuth scanning is accomplished by physically rotating the antenna. At each steering angle, two consecutive beams are transmitted and six are received (Figure 4). The angle-distance between two consecutive transmitted beams equals 1.4° , while the angle-distance between simultaneously received beams (corresponding to each transmitted beam) equals 0.5° (Figure 4). The target used for the test is a light-sport aircraft, the ATEC 321 Faeta (Figure 6), which flies at a velocity of 160 km per hour at an altitude of 1000 m. The tests were carried out on an Ubuntu system and the C++ software platform. For DSP-C and for DP-C, we use three computers with Intel Xeon Gold 6242R 3.1 GHz (20 cores, 40 threads) and 24 GB of RAM. The computational time required in DSP-C is less than 1 ms,

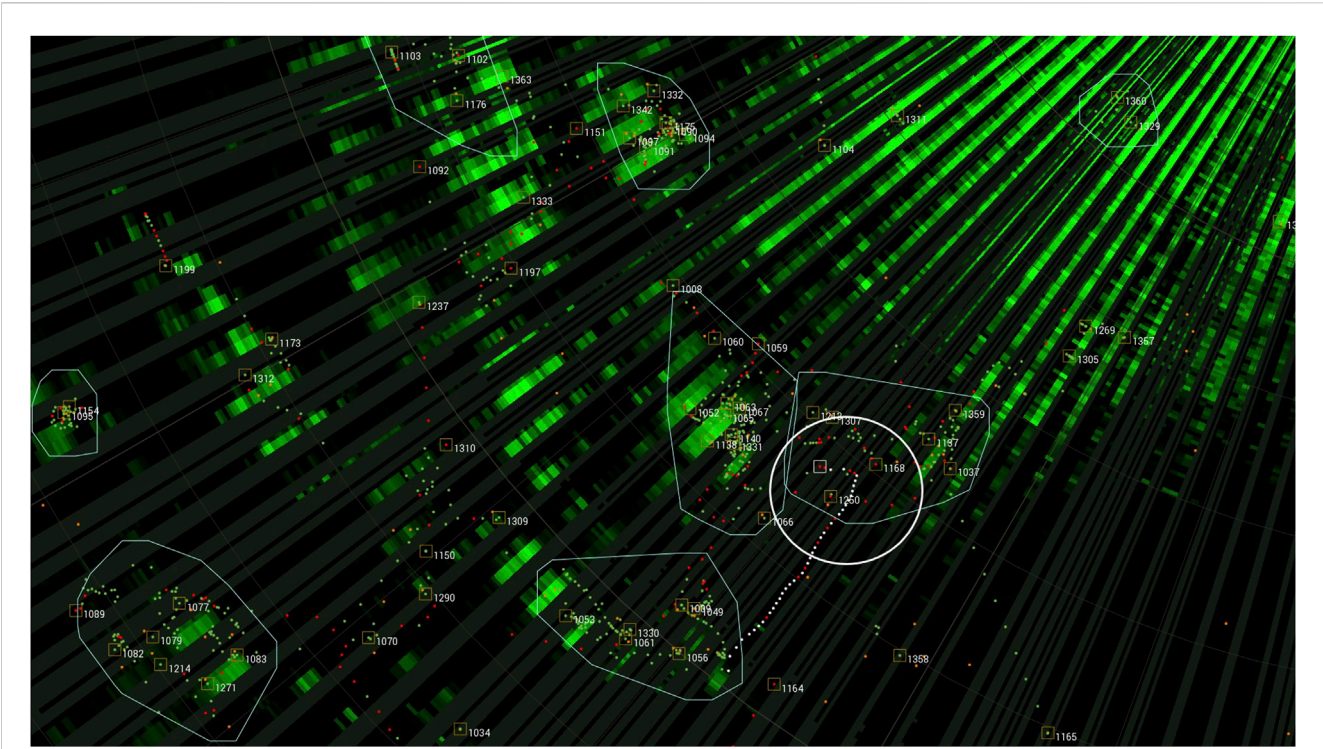


FIGURE 10
Result of first-stage CFAR: test target (in white circle) and false alarms due to interference (in polygons).

TABLE 4 Parameters for HDBSCAN algorithm used in the tests.

Parameter	Value
Value	All plots of k th radar scan, where
	$k = 1, 7, 13, 19, \dots$
minPts	5
minClusterSize	5

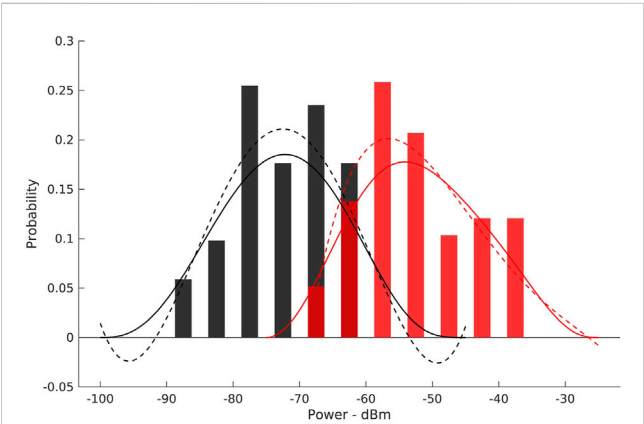


FIGURE 11
PDFs of the target (red curves) used for test and of interference (black curves) by Bernstein's (solid lines) and moment (dashed lines) methods.

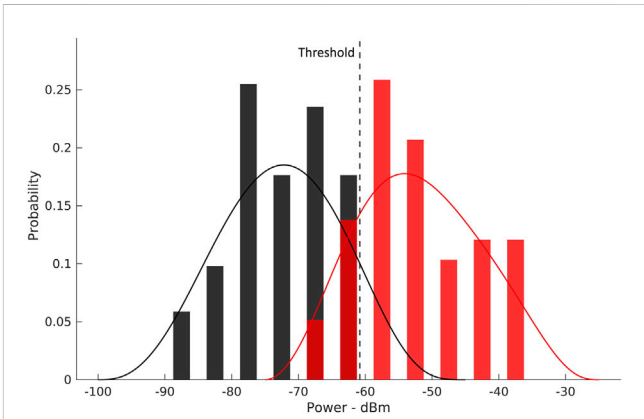


FIGURE 12
Threshold for second-stage CFAR of the interference region having the test target.

and that in DP-C is less than 0.3 s. This approach guarantees that the online processing for the radar system since the time of one radar scan is 10 s (Table 3).

The test showed that the interference mean powers between 13 km and 80 km with respect to the transmitted beams at 0.6° and 2.0° are approximately 33 dB and 18 dB, respectively (Figure 7). This induces an increase of the target's SNR with an averaging value of 11 dB (Figures 8, 9) and hence improves target detection at the first-stage CFAR (Figure 10). Since the threshold of the first-stage CFAR is chosen for the case of Gaussian noise, there are false plots in



TABLE 5 Comparison of proposed approach with other CFAR algorithms.

Parameter	Proposed	OS	SOCA	GOCA	VI	PI
α	8.6	6.1	12.6	7.5	-	-
P_{d_c}	0.86	0.23	0.14	0.32	0.26	0.26
FTr_c	7	31	53	52	56	74
TDr_c	0	1	1	1	1	1

interference regions due to the difference of interference PDFs from normal. Furthermore, in the radar data processing, the false plots are clustered using the HDBSCAN algorithm with parameters given in Table 4. The values of k mean that the first radar scan is used for interference clustering, and then every minute (equivalently every 6 radar scans) these interference regions are checked and updated. The results of interference clustering are shown in Figure 10 (in polygons).

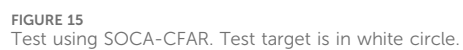
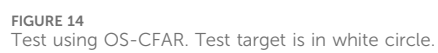
For each interference region, the interference PDF can be estimated using Algorithm 2. The results of probability density function approximation show (Figures 11) that the method using Bernstein’s polynomial performs better than that using probability moments. Here, for the false plot reduction in the second-stage CFAR, we use Bernstein’s approximation with $n = 6$, the local probability of false alarms $p_{fa} = 0.1$ for all interference regions, and the thresholds evaluated by (15) (Figure 12). The result of second-stage CFAR is given in Figure 13.

For comparison, note that the interference probability density function is estimated using Bernstein’s polynomial, which could be

more suitable for various types of interference than the use of kernel density estimation in Budge and German (2015). Additionally, we look at the situation where other CFAR algorithms like OS, SOCA, GOCA, VI, and PI, which have thresholds listed in Supplementary Appendix 2, are applied in the first-stage CFAR, while the second-stage CFAR is not used. The following detection performance parameters are used for comparison (Sunnen et al., 1997).

- a. P_{d_c} : probability of target detection in the interference region, which is defined by the number of target reports over the number of antenna scans in the interference region.
- b. FTr_c : false target reports are defined by the average number of such reports in clutter regions per antenna scan.
- c. TDr_c : track drop rate in the clutter region. $TDr_c = 1$ where the track is dropped when the test target is moving in a clutter region; otherwise, $TDr_c = 0$.

With the same value $P_{fa} = 10^{-3}$, the coefficient α (Supplementary Appendix 2) for CFAR threshold calculating and



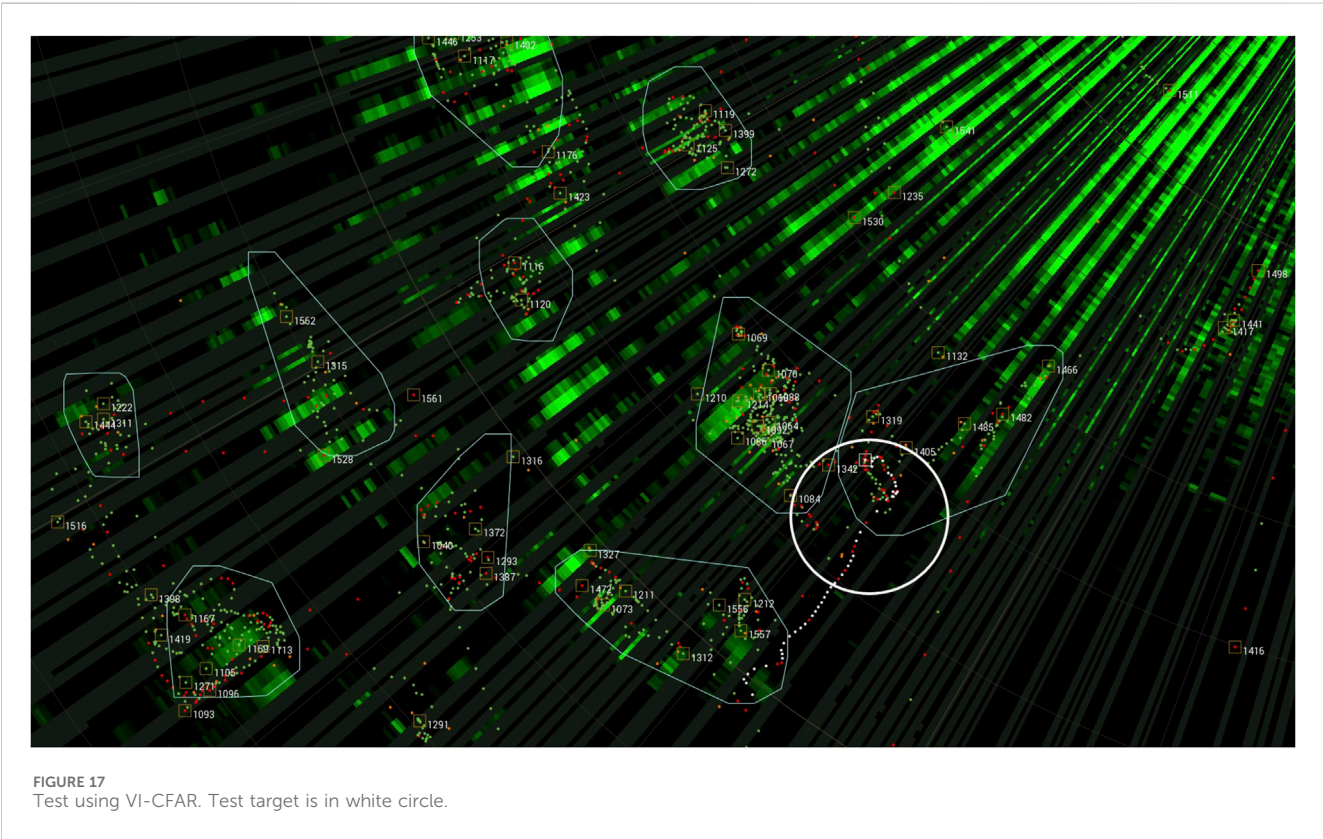
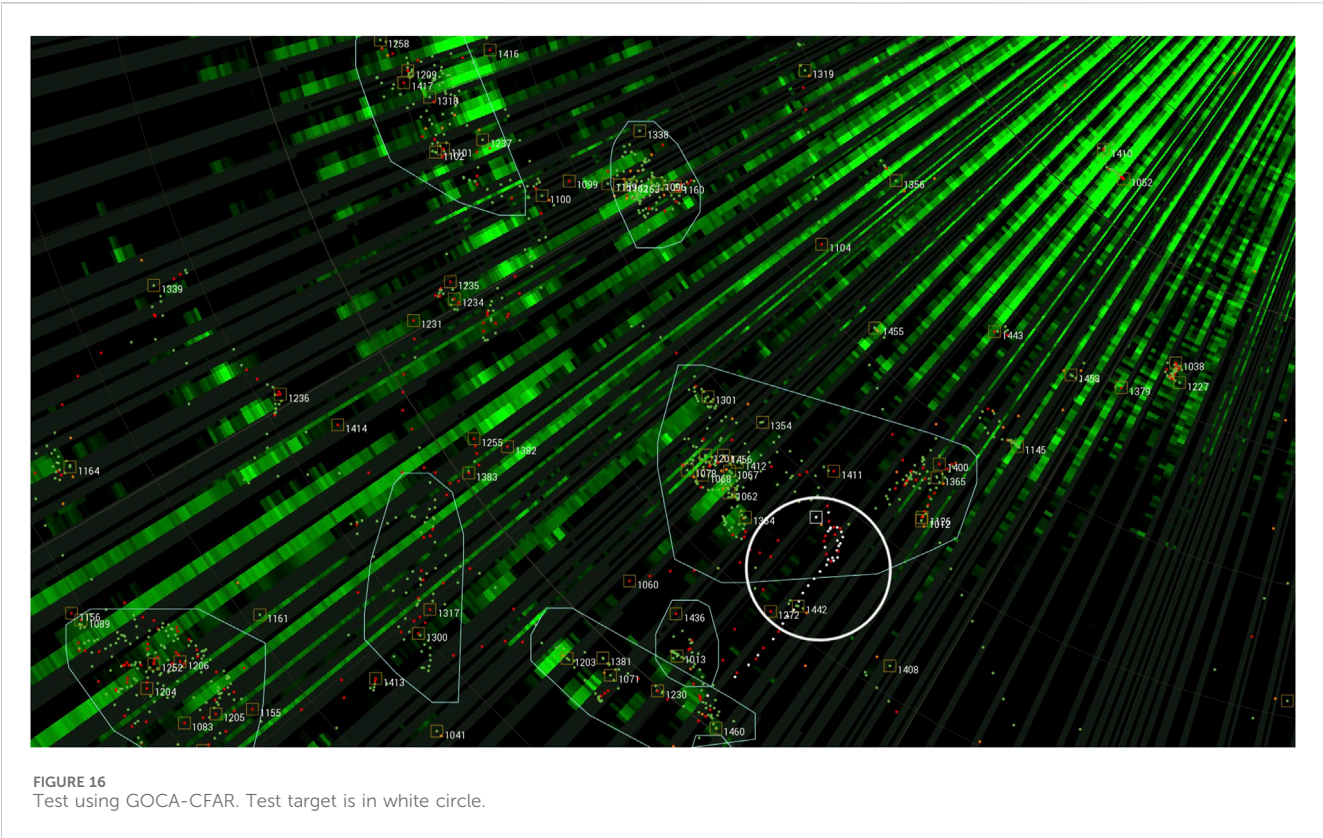




FIGURE 18
Test using PI-CFAR. Test target is in white circle.

detection performance is given in Table 5 and Figures 14–18. Note that the α value of the proposed approach given in Table 5 is of the first-stage CFAR (CA-CFAR). The threshold for second-stage CFAR is approximately -61 dBm (Figure 12). The thresholds of VI-CFAR are $K_{VI} = 5.3$ and $K_{MR} = 2.1$, while the thresholds of PI-CFAR are $T_{PI} = 3$ and $T_{MR} = 1.5$. The test results show that by using the proposed approach, we can track the target over the interference region, while with other methods the track is dropped when the target moves into the interference region. Moreover, the false track reports (per antenna scan) of the proposed approach are much fewer than others.

Compared with the machine learning approach (Perd'ock et al., 2024), we note that in our test, the target's SNR is only approximately 10 dB (Figure 8), and hence the approach in Perd'ock et al. (2024) gives the value $P_{d_c} \approx 0.6$ according to $P_{fa} = 0.1$ [Perd'ock et al. (2024), Figures 19, 22]. This value shows the superior performance of our proposed approach.

5 Conclusion and future work

This study presents a new approach for improving aerial target detection for 3D radars while working in non-homogeneous environments based on multiple beam processing, interference clustering, and its PDF approximation. Although the problem of PDF estimation is well-known and has been studied for more than a century, the discovery that the target's and the interference PDFs are truncated for a radar system guarantees that the approximations are consistent—there are no other PDFs with the same approximations as Supplementary Appendix

Equations A2, A14. The test and comparison show the effectiveness of the proposed approach.

In future research, instead of using the same value $p_{fa} = 0.1$ for all interference regions as in this study, we will apply optimization theory to select the optimal local probability of false alarms p_{fa} value for each interference region. In addition, new results in the probability distribution estimation problem will be considered for enhancing radar detection performance.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Author contributions

TV: Conceptualization, Data curation, Formal Analysis, Project administration, Software, Validation, Visualization, Writing – original draft, Writing – review and editing. TC: Conceptualization, Supervision, Validation, Writing – review and editing. NV: Conceptualization, Data curation, Supervision, Validation, Writing – review and editing.

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Generative AI statement

The authors declare that no Generative AI was used in the creation of this manuscript.

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Supplementary Material

1 SUPPLEMENTARY APPENDIX 1: FUNCTION APPROXIMATION

Let $[a, b]$ be a given interval. Denote by $C[a, b]$ the set of all continuous functions defined on $[a, b]$.

Theorem 1 [Hausdorff's theorem (Sury, 2011)]. If $f, g \in C[a, b]$ such that

$$\int_a^b x^k f(x) dx = \int_a^b x^k g(x) dx,$$

for all $k \geq 0$, then $f \equiv g$ on $[a, b]$.

Theorem 2 [Bernstein's theorem (Sury, 2011)]. Let $f: [0, 1] \rightarrow \mathbb{R}$ be continuous and for every $n \in \mathbb{N}$ define Bernstein's polynomial $B_n(x, f)$ by

$$B_n(x, f) = \sum_{k=0}^n \binom{n}{k} x^k (1-x)^{n-k} f(k/n). \quad (\text{S1})$$

Then $B_n(x, f) \rightarrow f(x)$ uniformly on $[0, 1]$, i.e.,

$$\lim_{n \rightarrow \infty} \left(\sup_{x \in [0, 1]} |B_n(x, f) - f(x)| \right) = 0. \quad (\text{S2})$$

For the case of $f: [a, b] \rightarrow \mathbb{R}$, we define the function $g: [0, 1] \rightarrow \mathbb{R}$, $g(x) = f\left(\frac{x-a}{b-a}\right)$. Then, the function $f(x)$ can be approximated by the polynomial $B_n(a + (b-a)x, g)$.

Now, let X be a random variable with the probability density and cumulative distribution functions $p(x)$ and $F(x)$, respectively. If the value of X outside the interval $[a, b]$ cannot be observed, then the distribution $F(x)$ is said to be truncated at a and b . The truncated density function $p(x; a, b)$ is determined by

$$p(x; a, b) = \frac{p(x)}{F(b) - F(a)} I_{(a,b)}(x), \quad (\text{S3})$$

where $I_{(a,b)}(x) = 1$ if $x \in [a, b]$ and $I_{(a,b)}(x) = 0$ if $x \notin [a, b]$.

For a radar system, the use of the truncated density functions has arisen naturally since the reflected signals could be detected by the radar receiver system only in the power range between sensitivity level (the value of a) and saturation level (the value of b) of the radar receiver system.

If $p(x)$ is continuous, then the truncated density function $p(x; a, b)$ is continuous on $[a, b]$. Hence, applying Theorem 2, we can approximate $p(x; a, b)$ by Bernstein's polynomial.

If $p(x)$ is not continuous, but square-integrable, i.e.,

$$\int_{-\infty}^{\infty} |p(x)|^2 dx < \infty,$$

then the function $p(x; a, b)$ belongs to the space $L^2[a, b]$ of all square-integrable functions on the interval $[a, b]$. Therefore, we can approximate the density function $p(x; a, b)$ in the space $L^2[a, b]$ by a polynomial

using the moments of $p(x; a, b)$. Toward this goal, denote the inner product and the norm in the space $L^2[a, b]$ by

$$\langle p, q \rangle = \int_a^b p(x)q(x)dx, \quad (\text{S4})$$

and $\|p\| = \sqrt{\langle p, p \rangle}$, respectively.

Let $m_k = \int_a^b x^k dx$, $k = 0, 1, \dots$. Define the polynomials $P_0(x) = m_0$ and

$$P_n(x) = \det \begin{pmatrix} m_0 & m_1 & \cdots & m_n \\ m_1 & m_2 & \cdots & m_{n+1} \\ \vdots & \vdots & \ddots & \vdots \\ m_{n-1} & m_n & \cdots & m_{2n-1} \\ 1 & x & \cdots & x^n \end{pmatrix} \quad (\text{S5})$$

where $\det(A)$ denotes the determinant of matrix A .

Theorem 3. For any $n, r \in \mathbb{N}, r \neq n$, the polynomials $P_n(x)$ and $P_r(x)$ are orthogonal in the space $L^2[a, b]$, i.e.,

$$\langle P_n, P_r \rangle = \int_a^b P_n(x)P_r(x)dx = 0, \quad (\text{S6})$$

and the set of polynomials

$$\mathbb{S} = \left\{ \frac{P_0(x)}{\|P_0\|}, \frac{P_1(x)}{\|P_1\|}, \dots, \frac{P_n(x)}{\|P_n\|}, \dots \right\}$$

forms an orthonormal basis of the space $L^2[a, b]$.

Proof. Without loss of generality, assume that $0 \leq r < n$ and $P_r(x) = \sum_{j=0}^r \alpha_j x^j$, $P_n(x) = \sum_{i=0}^n \beta_i x^i$. Therefore, by applying (S4)-(S5) we have

$$\begin{aligned} \langle P_n, P_r \rangle &= \sum_{j=0}^r \alpha_j \langle P_n(x), x^j \rangle \\ &= \sum_{j=0}^r \alpha_j \sum_{i=0}^n \beta_i \langle x^j, x^i \rangle \\ &= \sum_{j=0}^r \alpha_j \sum_{i=0}^n \beta_i m_{i+j} \\ &= \sum_{j=0}^r \alpha_j \det \begin{pmatrix} m_0 & m_1 & \cdots & m_n \\ m_1 & m_2 & \cdots & m_{n+1} \\ \vdots & \vdots & \ddots & \vdots \\ m_{n-1} & m_n & \cdots & m_{2n-1} \\ m_j & m_{j+1} & \cdots & m_{j+n} \end{pmatrix} \\ &= 0. \end{aligned}$$

In order to prove that the set $\mathbb{S}$ is an orthonormal basis of the space $L^2[a, b]$ we assume that there is a function $h \in L^2[a, b]$ such that

$$\left\langle h, \frac{P_n}{\|P_n\|} \right\rangle = 0, \quad \text{for all } n = 0, 1, \dots$$

Now we prove that $h \equiv 0$ on $[a, b]$.

In fact, by assumption we have

$$\int_a^b x^n h(x) dx = \langle h, x^n \rangle = 0,$$

for all $n = 0, 1, \dots$.

If h is continuous, then applying Theorem 1 we obtain $h(x) = 0$ for all $x \in [a, b]$. In other cases (when h is not continuous), consider the bilateral Laplace transform of h (Beerends, 2003):

$$\mathcal{L}[h](s) = \int_{-\infty}^{\infty} e^{-sx} h(x) dx. \quad (\text{S7})$$

The function $\mathcal{L}[h](s)$ is convergent and hence is analytic for all complex values of s . Differentiating both sides of (S7) with respect to s , we obtain the following relation

$$\begin{aligned} \frac{d^n \mathcal{L}[h](s)}{ds^n} &= (-1)^n \int_a^b e^{-sx} x^n h(x) dx \\ &= \langle e^{-sx} x^n, h \rangle \end{aligned}$$

for all $n = 0, 1, \dots$.

Therefore, $\frac{d^n \mathcal{L}[h](0)}{ds^n} = \langle x^n, h \rangle = 0$ for all $n = 0, 1, \dots$. Hence, $\mathcal{L}[h] \equiv 0$ for all complex values $s \in \mathbb{C}$. For the special case $s = i2\pi\omega$:

$$\begin{aligned} 0 &= \mathcal{L}[h](i2\pi\omega) = \int_{-\infty}^{\infty} h(x) e^{-i2\pi\omega x} dx \\ &= \mathcal{F}[h](\omega), \end{aligned}$$

where $\mathcal{F}[h]$ denotes the Fourier transform of the function h (Beerends, 2003). Taking the inverse Fourier transform, we conclude that $h \equiv 0$, and so $h \equiv 0$, on $[a, b]$. $\square$

Applying Theorem 3 for the density function $p(x; a, b)$ we obtain that the density function $p(x; a, b)$ can be uniquely represented as

$$p(x; a, b) = \sum_{n=0}^{\infty} c_n \frac{P_n(x)}{\|P_n\|}, \quad c_n = \left\langle p(\cdot; a, b), \frac{P_n}{\|P_n\|} \right\rangle, \quad (\text{S8})$$

i.e., c_k is evaluated from moments of the PDF $p(x; a, b)$.

The formula (S8) means that the PDF $p(x; a, b)$ could be approximated by its moments.

2 SUPPLEMENTARY APPENDIX 2: THRESHOLD CALCULATION FOR CFAR ALGORITHMS

The CFAR threshold (Richard, 2005; Skolnik, 2008) is calculated by $T = \alpha \times \beta$, where β characterizes the interference power level and α is the coefficient estimated from P_{fa} :

a) CA-CFAR:

$$\alpha_{CA} = N \times (P_{fa}^{-1/N} - 1).$$

b) SOCA-CFAR:

$$P_{fa} = 2(2 + \frac{\alpha_{SO}}{N/2})^{-N/2} \times \sum_{k=0}^{N/2-1} \binom{N/2-1+k}{k} \left(2 + \frac{\alpha_{SO}}{N/2}\right)^{-k}.$$

where

$$\binom{N/2-1+k}{k} = \frac{(N/2-1+k)!}{k! \times (N/2-1)!}.$$

c) GOCA-CFAR:

$$P_{fa} = 2(1 + \frac{\alpha_{GO}}{N/2})^{-N/2} - 2(2 + \frac{\alpha_{GO}}{N/2})^{-N/2} \times \sum_{k=0}^{N/2-1} \binom{N/2-1+k}{k} \left(2 + \frac{\alpha_{GO}}{N/2}\right)^{-k}.$$

d) OS-CFAR:

$$P_{fa} = k \binom{N}{k} \frac{(k-1)! \times (\alpha_{OS} + N - k)!}{(\alpha_{OS} + N)!}.$$

e) VI-CFAR (Smith, 2000):

$$VI_A^* = N_A \frac{\sum_{i=1}^{N_A} [X_A]_i^2}{(\sum_{i=1}^{N_A} [X_A]_i)^2}$$

$$VI_B^* = N_B \frac{\sum_{i=1}^{N_B} [X_B]_i^2}{(\sum_{i=1}^{N_B} [X_B]_i)^2}$$

$$MR = \frac{\sum_{i=1}^{N_A} [X_A]_i}{\sum_{i=1}^{N_B} [X_B]_i}.$$

where $[X_A]_i$ and $[X_B]_i$ are the data (powers) of the reference cells in the leading and lagging windows, N_A (N_B) is the number of reference cells in the leading (lagging) windows.

If

$$VI_A^* \leq K_{VI}, VI_B^* \leq K_{VI}, MR \leq K_{MR}, MR \geq \frac{1}{K_{MR}},$$

then use CA-CFAR with both reference cells in the leading and lagging windows.

If

$$VI_A^* \leq K_{VI}, VI_B^* \leq K_{VI}, MR > K_{MR}, \text{ or } MR < \frac{1}{K_{MR}},$$

then use GOCA-CFAR.

If

$$VI_A^* \leq K_{VI}, VI_B^* > K_{VI},$$

then use CA-CFAR with reference cells in the leading window.

If

$$VI_A^* > K_{VI}, VI_B^* \leq K_{VI},$$

then use CA-CFAR with reference cells in the lagging window.

If

$$VI_A^* > K_{VI}, VI_B^* > K_{VI},$$

then use SOCA-CFAR.

f) PI-CFAR (Mehanaoui, 2019):

$$\begin{aligned} PI_A &= \frac{1}{N_A} \sum_{i=1}^{N_A} \max\left(0, \frac{[X_A]_i}{E[X_A]} - 1\right) \\ PI_B &= \frac{1}{N_B} \sum_{i=1}^{N_B} \max\left(0, \frac{[X_B]_i}{E[X_B]} - 1\right) \\ LGMR &= \frac{1}{N_A} \sum_{i=1}^{N_A} \log[X_A]_i - \frac{1}{N_B} \sum_{i=1}^{N_B} \log[X_B]_i \\ &= \frac{2}{N} \left(\sum_{i=1}^{N/2} \log X_i - \sum_{i=N/2+1}^N \log X_i \right) (N_A = N_B = N/2). \end{aligned}$$

If

$$PI_A < T_{PI}, PI_B < T_{PI}, LGMR \leq T_{MR}, LGMR \geq \frac{1}{T_{MR}},$$

then use a threshold with $\alpha = \left(\prod_{i=1}^N X_i\right)^{1/N} \times P_{fa}^{-1/\epsilon}$, where ϵ is the parameter of Pareto distribution.

If

$$PI_A < T_{PI}, PI_B < T_{PI}, LGMR > T_{MR}, \text{ or } LGMR < \frac{1}{T_{MR}},$$

then use GOCA-CFAR.

If

$$PI_A \geq T_{PI}, PI_B < T_{PI},$$

then use a threshold with $\alpha = \left(\prod_{i=1}^{N_B} [X_B]_i\right)^{1/N_B} \times P_{fa}^{-1/\epsilon}$, where ϵ is the parameter of Pareto distribution.

If

$$PI_A < T_{PI}, PI_B \geq T_{PI},$$

then use a threshold with $\alpha = (\prod_{i=1}^{N_A} [X_A]_i)^{1/N_A} \times P_{fa}^{-1/\epsilon}$, where ϵ is the parameter of Pareto distribution.

If

$$PI_A \geq T_{PI}, PI_B \geq T_{PI},$$

then use a threshold with

$$\alpha = \left(\prod_{i=1+T_1}^{N-T_2} X_i \right)^{1/(N-T_1-T_2)} \times P_{fa}^{-1/\epsilon},$$

where ϵ is the parameter of Pareto distribution.

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An Adaptive IMM for Tracking Maneuvering Target with High Variability of Environment

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Abstract. This paper introduces a novel approach for tracking maneuvering targets in highly variable environments. An adaptive interacting multiple model algorithm, which is a combination of the modified adaptive Kalman algorithm and the interacting multiple model algorithm, is proposed to enhance tracking performance. One notable aspect of this method is its ability to continuously adjust the residual values of each sub-filter in the interacting multiple model algorithm, leading to improved adaptation to the target's high mobility and increased accuracy in position estimation. In comparison to the classical interacting multiple model algorithm, the results from both simulation and real data suggest that the proposed adaptive interacting multiple model algorithm has shown a 38.3% increase in overall tracking accuracy in position and approximately 28% in velocity.

Keywords. Maneuvering target, highly variable environments, Kalman algorithm, adaptive interacting multiple model, residual adjustment

1. Introduction

In recent years, tracking and estimating the positions of moving targets has become an extremely important and increasingly necessary problem in many different fields such as military and aerospace, traffic management and many other applications [1]. However, with the increase in structural complexity and flexible movement of targets in complex terrain conditions, accurate and effective tracking of targets is posing great challenges for both technology and science worldwide.

The Kalman filter (KF) is a commonly used technique in target tracking, providing an optimal solution to linear filtering problems in state-space dynamical systems. The effectiveness of Kalman filters relies on the assumption that the linear dynamic system model is accurately known beforehand, and the process and measurement noises are zero-mean, jointly standard Gaussian with known covariance matrices. On the other hand, a conventional linear system model may fail to represent the true sensor measurements in many actual applications [2-3], such as an intermittent sensor fault. The sensor measurement may on occasion only contain noise and be unaffected by the system being observed, and the performance of the KF may degrade when this pure noise is presented in the measurement update [4]. Moreover, many studies have also shown that the

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traditional Kalman filter and its modified versions, still face difficulties when the target is mobile and changes velocity rapidly or is nonlinear [5-7].

The interacting multiple model (IMM) algorithm is a technique that combines different state hypotheses from various filter models to improve the estimation of targets with dynamic behavior [8]. Filter models are chosen based on the target's characteristics and a Markov chain controls the switching between these models. The final output is a weighted average of tracking results from all models. The IMM Kalman filter incorporates multiple states of target movement, each with a certain weight that influences the final fusion results. Throughout the target's movement, the IMM Kalman filter is able to promptly adjust the weight for each model, particularly when the target's motion state undergoes a change. Nevertheless, the IMM Kalman filter may have limitations when not all target motion models are included, leading to weakened tracking or divergence, particularly when targets exhibit unpredictable and nonlinear maneuvers [9].

The literatures [10-11] use a neural network to correct the filter result of IMM Kalman filter, to achieve the goal of improving the performance of IMM Kalman filter in maneuvering target tracking. Compared with the traditional IMM, maneuvering target tracking using IMM Kalman filter aided by Elman neural network is more valid. Application of fuzzy interacting multiple model unscented Kalman filter (FUZZY-IMMUKF) approach to integrated navigation processing for maneuvering vehicles has been proposed in [12]. The FUZZY-IMMUKF algorithm displays notable enhancements in navigation estimation accuracy when compared to the UKF and IMMUKF approaches. A nonlinear tracking solution for maneuvering aerial targets based on an adaptive IMM framework and unscented Kalman filters (AIMM-UKF) has been studied in [13] to obtain more accurate estimates, better consistency of the tracker, and more robust prediction during sensor outages. The study demonstrated that the AIMM-UKF exhibited rapid adaptation to the maneuver, as evidenced by a decrease in velocity settling time. The AIMM-UKF produces a noise reduction factor ranging from 0.36 to 0.43. A novel adaptive Kalman filter (AKF) to estimate the unknown probability of measurement loss using the IMM filtering framework has been investigated in [14]. The state, Bernoulli random variable, and measurement loss probability are jointly inferred based on the variational Bayesian approach. Reference [15] developed a tracking method using IMM algorithm combined with Probabilistic Data Association algorithm to solve the problem of low data-rate measurement. The experimental results indicate that the algorithm is capable of significantly enhancing the accuracy of target tracking, as well as effectively addressing issues related to incorrect tracking and loss of maneuvering targets. However, the application of those methods to conditions of inaccurate measurement has not been fully mentioned.

Recently, the association of physical sensors and computational models to enhance additional information about system states, inputs, and/or parameters has been termed virtual sensing. The virtual sensing is gaining popularity in various industries, including machinery, robotics and especially in the control of unmanned devices [16]. In a recent study published in [17], researchers have proposed a new method using deterministic artificial intelligence to effectively control the movement of unmanned underwater vehicles. The approach aims to eliminate errors in tracking motion trajectories by accurately following user commands, even if they are unknown or arbitrary. This innovative approach involves learning from parameters that are traditionally assumed to be constant in classical linear, time-invariant (LTI) methods, allowing for more precise control of the vehicles. The study in literature [18] utilizes a computational model which

is formulated using Pontryagin’s treatment of Hamiltonian systems to obtain optimal and near-optimal results based on the selected algorithm. The simulation results demonstrate that the method proposed leads to a 69–72% enhancement in state estimation, a 29–33% increase in rate improvement, while simultaneously achieving minimal costs in the utilization of guidance, navigation, and control decision criteria. Real-time optimal (nonlinear) state estimation using the Moore– Penrose pseudoinverse has been found to be the most recommended approach with very highly accurate estimates and mathematically optimal low utilization costs. However, the application of those methods to conditions of high variability of environment has not been fully mentioned.

In this paper, a combination of the new adaptive Kalman algorithm and IMM is presented. Firstly, the paper describes the proposed adaptive interacting multiple model algorithm, which involves continuously adjusting the residual values of sub-filters in the IMM to enhance flexibility and applicability, ultimately improving tracking performance. Secondly, simulation and real data results concerning the performance of the proposed algorithm are given. A general conclusion of the obtained results is presented in the last section.

2. Methodology

The proposed adaptive interacting multiple model (AIMM) algorithm is divided into three parts: model interaction or mixer, individual model filtering, and model combination. Two sub-filters are utilized to capture common motion models of targets. The first sub-filter is a linear Kalman filter for constant velocity segments, while the second is an augmented-state Unscented Kalman filter for horizontal turn segments. In the second part of the AIMM algorithm, an adaptive update is implemented for each sub-filter in response to anomalies in detection measurements. The diagram of the proposed method is illustrated in Figure 1.

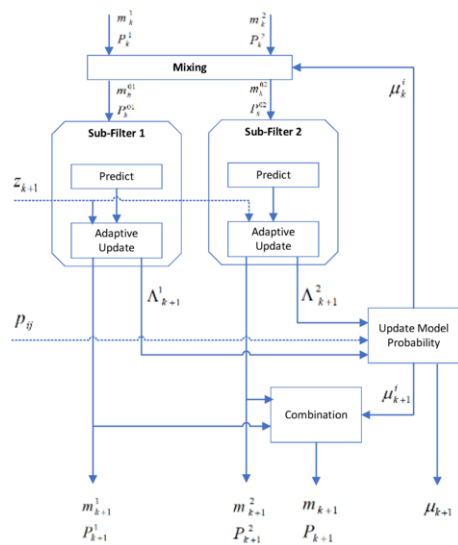


Figure 1. Algorithm of the proposed method

Part 1: Interaction

Assume the probability of each model M^j is μ_k^j at the moment k , we have:

$$\mu_k^j = P\{M_k^j\} \quad (1)$$

The normal factor is defined as:

$$\bar{c}_j = \sum_{i=1}^N p_{ij} \mu_k^i \quad (2)$$

where N represents the total number of the filter models in the model set; p_{ij} is the transition probability.

Then the mixture probability converting from model i to model j is written as:

$$\mu_{k+1}^{ij} = \frac{1}{\bar{c}_j} p_{ij} \mu_k^i \quad (3)$$

Let the state estimation and the covariance matrix of each sub filter in IMM Kalman filter at the moment k be m_k^i and P_k^i respectively. Accordingly, the mixture state estimation of all filters m_k^j and the corresponding mixture covariance matrix P_k^j are shown as follows:

$$m_k^{0j} = \sum_{i=1}^N \mu_{k+1}^{ij} m_k^i \quad (4)$$

$$P_k^{0j} = \sum_{i=1}^N \mu_{k+1}^{ij} * \{P_k^i + [m_k^i - m_k^j][m_k^i - m_k^j]^T\} \quad (5)$$

Part 2: Filter

Perform Kalman filter for each model M respectively:

$$[m_{k+1}^{-i}, P_{k+1}^{-i}] = \text{Filter}_{\text{predict}}(m_k^j, P_k^j, A_k^i, Q_k^i) \quad (6)$$

$$[m_{k+1}^i, P_{k+1}^i] = \text{Filter}_{\text{update}}(m_{k+1}^{-i}, P_{k+1}^{-i}, y_{k+1}, H_{k+1}^i, R_{k+1}^i) \quad (7)$$

The proposed adaptive interacting multiple model (AIMM) method aims to adjust parameters in each sub-filter based on input data to adapt to variability and uncertainty in the environment, optimizing estimation performance in challenging situations. However, the complexity of the problem necessitates a new solution for more effective parameter calculation to reduce errors and increase reliability. One approach in this method is fine-tuning the residual value of each sub-filter in the IMM algorithm. The residual in each sub-filter is typically the difference between the observed value and the predicted value from the system state estimate. Enhancing the residual can enhance filter performance. The ratio between the residual and the square root of the residual covariance matrix is used to create an index measuring the difference between prediction and observation in each sub-filter. The formula for this index can be written as follows:

$$\text{adapThres}(i) = \frac{\text{Res}(i)}{\sqrt{\text{ResCov}(i,i)}} \quad (8)$$

The larger the *adapThres*, the larger *Res* relative to its variation, may indicate that the filter's prediction may not be reliable. On the contrary, if *adapThres* is smaller, it can indicate that the filter's prediction has a higher level of confidence. We utilize the statistical "3-sigma rule" to assess the variability and stability of a system, process, or data [19]. This principle is based on measuring the dispersion or variability of data through the standard deviation and applying a threshold based on multiple standard deviations. In particular, the 3-sigma rule shows that in a normal distribution (Gaussian distribution), about 99.7% of the observations are within ± 3 standard deviations of the

mean. This means that variation usually occurs within this range and only a small fraction (about 0.3%) falls outside this range. Therefore, if the *adapThres* is greater than 3, this may suggest that the difference between prediction and measurement at time k has an uncertainty greater than the threshold of 3 standard deviations. This may indicate that there is a significant or imprecise difference occurring at this time, beyond the estimated level of uncertainty. It is an indication of abnormal or error conditions. Then we need to consider the scale ratio based on the difference between the predicted and measured parameters:

$$scale = \frac{\left(\frac{Res(i)}{adapThres}\right)^2 - R(i,i)}{\tilde{P}(i,i)} \quad (9)$$

Then, we apply the data recalibration by adjusting the *Res* value. If the *scale* exceeds the *maxCovScale* threshold, we will update the *Res* value to smooth the data according to the following formula:

$$Res(i) = adapThres \sqrt{maxCovScale \tilde{P}(i,i) + R(i,i)} \quad (10)$$

The *maxCovScale* value is the cut threshold which is determined based on the distribution of the scale values. Figure 2 shows the histogram with the distribution fit of scale values in the low measurement accuracy case as described in section 3.2. The *maxCovScale* value in that case is approximately equal to 2.25.

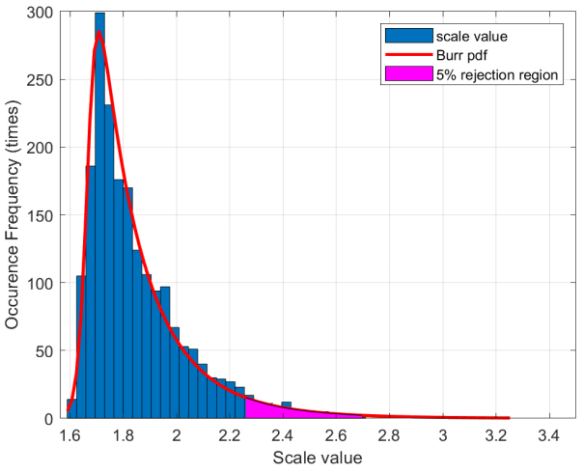


Figure 2. The histogram with the distribution fit of scale value

Calculate the likelihood value of model i :

$$\Lambda_{k+1}^i = \mathcal{N}(v_{k+1}^i; 0; S_{k+1}^i) \quad (11)$$

where $\mathcal{N}(\cdot)$ represents Gaussian distribution function; v_{k+1}^i and S_{k+1}^i represent the observation innovation and its covariance matrix, respectively.

The model probability at the moment $(k+1)$ is:

$$\mu_{k+1}^i = \frac{1}{c} \Lambda_{k+1}^i \bar{c}_i \quad (12)$$

where c is the normalization coefficient:

$$c = \sum_{i=1}^n \Lambda_{k+1}^i \bar{c}_j \quad (13)$$

Part 3: Combination

The estimated output of IMM Kalman filter is:

$$m_{k+1} = \sum_{i=1}^N \mu_{k+1}^i m_{k+1}^i \quad (14)$$

$$P_{k+1} = \sum_{i=1}^N \mu_{k+1}^i \left\{ P_{k+1}^i + [m_{k+1}^i - m_{k+1}][m_{k+1}^i - m_{k+1}]^T \right\} \quad (15)$$

3. Result and discussion

To demonstrate the effectiveness of the proposed adaptive interacting multiple model (AIMM) method, we now consider tracking a target using the models and parameters mentioned above. Initially, the target is positioned at $(x, y, z) = (7000 \text{ m}, 7000 \text{ m}, 800 \text{ m})$ with an initial velocity of 150 m/s . The tracking process unfolds as follows: For the first 100 sampling periods, the target follows the constant velocity (CV) model. From sampling period 101 to 120, the target switches to the constant acceleration (CA) model with an acceleration of 0.1 m/s^2 . Between sampling periods 121 to 200, the target adopts the constant turn (CT) model with a rotation rate of 0.4 deg/s . In sampling periods 201 to 300, another CT model is employed, but with a rotation rate of -0.3 deg/s . Finally, from sampling periods 301 to 400, the target reverts to the CV model. The trajectory of the target is illustrated in Figure 3(a). The radar is located at Cartesian coordinates $(0 \text{ m}, 0 \text{ m}, 0 \text{ m})$ with a sampling interval of $T = 10 \text{ s}$. To simulate different levels of measurement accuracy, we conducted two test cases: test case 1 with high measurement accuracy, and test case 3 with low measurement accuracy.

In these experiments, the conventional interacting multiple model (IMM) [8], IMM Aided by Elman Neural Network (IMM-ENN) [11] and our proposed adaptive IMM (AIMM) are implemented and compared. The position root-mean-square error (RMSE) is utilized to estimate the performance.

3.1. High measurement accuracy case

In the first case, the process noises are assumed to be zero-mean white Gaussian with standard deviations of range, azimuth and elevation measurements are $\sigma_r = 50 \text{ m}$, $\sigma_a = 0.2 \text{ deg}$ and $\sigma_e = 0.2 \text{ deg}$, respectively. In most cases with the high measurement accuracy, all three methods achieve the same track performance, as shown in Figure 3(b). The proposed algorithm and IMM-ENN method give results that are closer to the true path than the traditional IMM method. However, the difference is not too much.

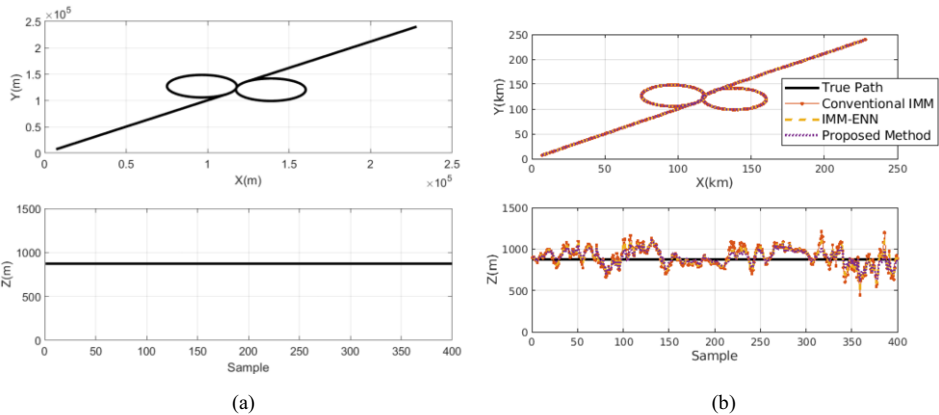


Figure 3. Trajectory of simulated target (a) and Tracking result with the high measurement accuracy (b)

Figure 4(a) illustrates the position error, including range, azimuth, and elevation, when employing three different methods in comparison to the true path. The range and azimuth errors of the proposed method closely align with those of the IMM-ENN and traditional IMM methods. However, there is a noticeable reduction in the elevation error, particularly in the turning section (from sample 121 to sample 300). In Figure 4(b), the velocity RMSE resulting from the use of three different methods is compared to the true path. In terms of numerical values, as indicated in Table 1, it is evident that the range RMSE of the proposed method improves by approximately 6% compared to the IMM-ENN method and roughly 11% compared to the traditional IMM method. The azimuth RMSE of the proposed algorithm closely matches that of IMM-ENN and demonstrates an improvement of approximately 12% compared to the traditional IMM method. Furthermore, the elevation RMSE displays an improvement of approximately 17% compared to IMM-ENN and a substantial 29% improvement in comparison to the traditional IMM method. As for velocity RMSE, it shows an improvement of approximately 10% and 25% compared to IMM-ENN and the traditional IMM method, respectively.

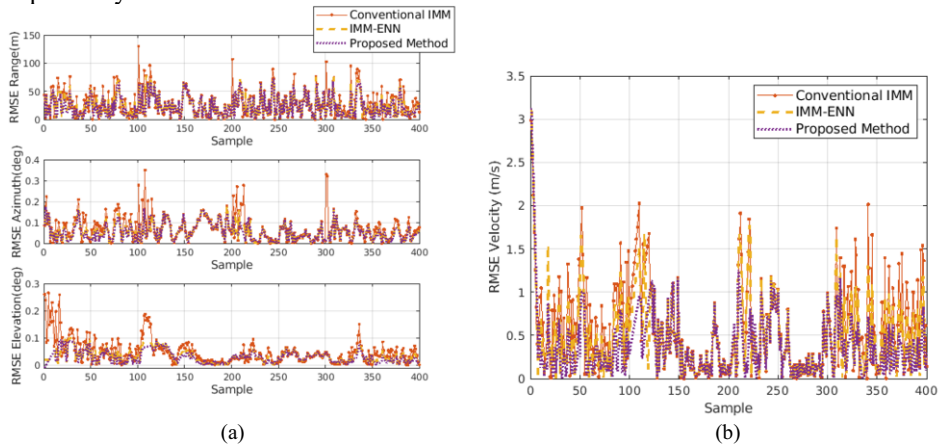


Figure 4. Position RMSE (a) and Velocity RMSE (b)

Table 1. The RMSE of each method

	Conventional IMM	IMM-ENN	Proposed Method
RMSE Range (m)	38	36.3	34.1
RMSE Azimuth (deg)	0.09	0.082	0.08
RMSE Elevation (deg)	0.07	0.06	0.05
RMSE Velocity (m/s)	1.2	1.0	0.9
RMSE of CV Model Mode Probability	0.09	0.08	0.076

Figure 5 shows the mode probability of the constant turn (CV) model with three methods with respect to the true mode. As shown in the figure, the proposed method has the result of updating the CV model probability quite similar to the IMM-ENN and conventional IMM method. In particular, the CV model mode probability RMSE improved approximately 5% compared with IMM-ENN, and approximately 16% compared with the traditional IMM method.

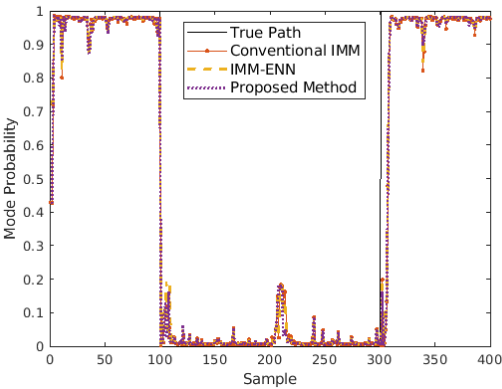


Figure 5. The mode probability of CV model

3.2. Low measurement accuracy case

In the second case, standard deviations of range, azimuth and elevation measurements are $\sigma_r = 250$ m, $\sigma_a = 1.5$ deg, and $\sigma_e = 1.5$ deg, respectively. Figure 6(a) shows the tracking result of three methods. For this case, the proposed method shows significantly better results than the two reference methods.

Figure 7(a) and Figure 7(b) show the position and velocity RMSE of three methods under the condition of high measurement error. It can be seen that the IMM Aided by Elman Neural Network (IMM-ENN) method and the proposed method have lower position error than the traditional IMM method. The proposed method has a much lower elevation RMSE than the IMM-ENN method. Numerically, as shown in Table 2, we can see that the range RMSE of the proposed method improves by approximately 15% compared to the IMM-ENN method, and approximately 25% with respect to that of the traditional IMM method. The azimuth RMSE of the proposed method also improves by approximately 12% and 30% compared with the IMM-ENN method and the traditional

IMM method, respectively. In particular, the elevation RMSE improved approximately 45% compared with IMM-ENN, and approximately 60% compared with the traditional IMM method. The velocity RMSE improved approximately 17% and 28% compared with IMM-ENN and the traditional IMM method, respectively.

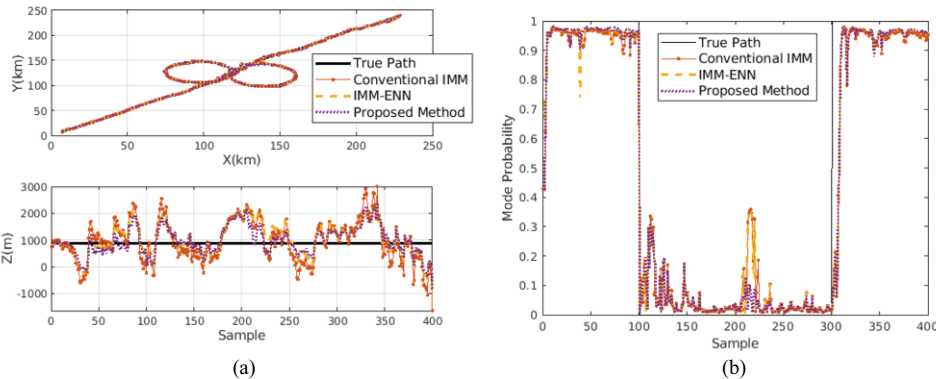


Figure 6. Tracking result with the low measurement accuracy (a) and the mode probability of CV model (b)

Figure 6(b) shows the mode probability of the CV model with the IMM Aided by Elman Neural Network (IMM-ENN), the conventional IMM and proposed adaptive interacting multiple model (AIMM) with respect to the true mode. It is evident that the mode probability of the proposed algorithm closely aligns with the true mode probability in the sample ranges 1-100 and 300-400 when compared to the two reference methods. In particular, the proposed method gives much better results at the maneuvering section (in the sample ranges 200-250). Numerically, the CV model mode probability RMSE improved approximately 13% compared with IMM-ENN, and approximately 17% compared with the traditional IMM method.

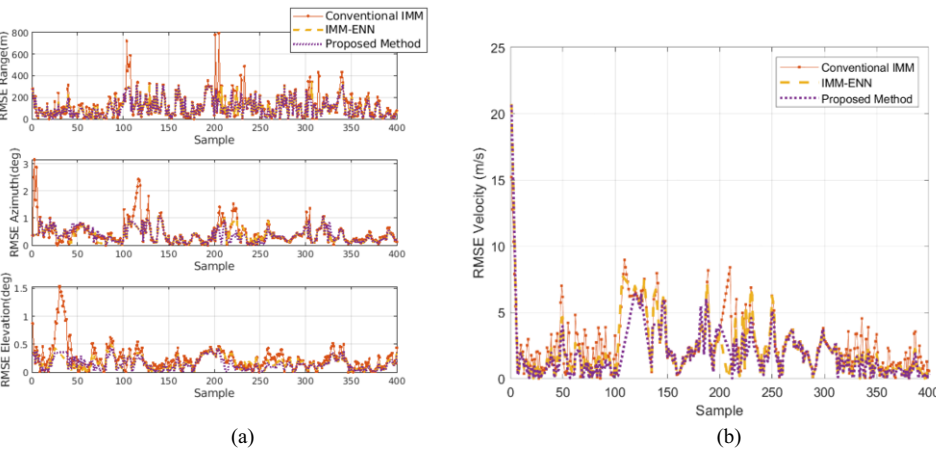


Figure 7. Position RMSE (a) and Velocity RMSE (b)

Table 2. The RMSE of each method

	Conventional IMM	IMM-ENN	Proposed Method
RMSE Range (m)	172	152	129
RMSE Azimuth (deg)	0.58	0.45	0.4
RMSE Elevation (deg)	0.3	0.22	0.12
RMSE Velocity (m/s)	3.6	3.1	2.6
RMSE of CV Model Mode Probability	0.095	0.09	0.079

The proposed method was utilized in testing at an air surveillance radar station. The tracking results of an aircraft target are shown in Figure 8. At some detection points with large measurement errors, the traditional IMM method displayed non-seamless trajectory tracking (left figure), whereas the proposed method showed smooth tracking results (right figure). As a result, the position and velocity errors were reduced by approximately 15% and 18% compared to the traditional IMM method, respectively. It is important to note that both IMM methods utilized the same structure and parameters.

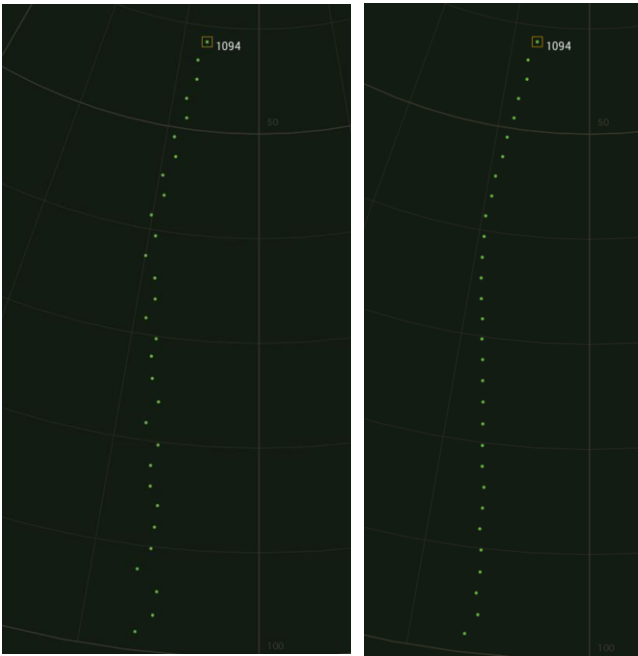


Figure 8. Target tracking result with the traditional IMM (left) and proposed method (right)

4. Conclusion

This paper provides an in-depth exploration of a novel approach for tracking maneuvering targets under conditions of low-accuracy measurement. We investigate an

Adaptive Interacting Multiple Model (AIMM) algorithm, which combines elements of the adapted Kalman algorithm with the IMM algorithm to create a more comprehensive method aimed at enhancing tracking performance. We propose a continuous adjustment of the residual values within each sub-Kalman filter of the IMM algorithm, with the goal of adapting to the high mobility of the target and improving position estimation accuracy. Based on simulated data, our study demonstrates the effectiveness of our proposed method in terms of enhancing the accuracy of target state estimation under conditions of low measurement accuracy. Notably, the proposed method achieves a notable reduction in the Root Mean Square Error (RMSE) for range, approximately 15% compared to the IMM-ENN method, and an even more significant improvement of approximately 25% compared to the traditional IMM method. Similarly, the azimuth RMSE of the proposed method experiences enhancements of approximately 12% and 30% when compared to the IMM-ENN and traditional IMM methods, respectively. Of particular significance is the elevation RMSE, which witnesses a remarkable improvement of approximately 45% compared to IMM-ENN and an impressive 60% improvement relative to the traditional IMM method. Additionally, the velocity RMSE demonstrates substantial enhancements of approximately 17% and 28% when compared to IMM-ENN and the traditional IMM method, respectively.

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Enhanced Multi-Target Tracking with Combination of Position, Power and Ambiguous Doppler Measurements

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Abstract. Multiple Target Tracking (MTT) is one of the most challenging topics in radar target tracking. In addition to conventional position measurements, the integration of target Doppler and power information can offer valuable insights into a target's kinematic state, thereby improving tracking performance. This article discusses a tracking approach that incorporates those components into the measurement enhancement process and assesses the advantages of the proposed strategy. Firstly, we investigated an improved data association scheme that exploits statistical features of position, Doppler and power. The estimated Doppler value calculated from the target range and timestamp will be compared with the measured Doppler to deal with the Doppler ambiguity situation. Secondly, we studied an augmented unscented Kalman filter (UKF) algorithm using position, Doppler measures, and the indirect measure of radial velocity in the linear domain. The experimental results show that the proposed solution has good performance in terms of reduced number of false tracks and improving the accuracy of the target state estimation.

Keywords. MTT, data association, position, power, Doppler ambiguity, UKF

1. Introduction

In the MTT system, sensors generate multiple detections from many targets in a scan. To track these targets, the conventional methods only use the position information of the detections in the data assignment algorithms. However, those methods lead to outstanding problems if the number of targets or detections is large. Especially, when the target moves in the noise area, the noise detections appear around the target detection, so the targets may choose the wrong detections. In a pulse-Doppler radar system, beyond conventional position measurements, Doppler and power measurements can offer additional information about the target state, which would improve tracking performance. Literature [1] discussed an adjusted JPDA (Joint Probabilistic Data Association) algorithm which combines range rate measurements with position measurements to enhance the tracking operation. A better data association scheme, which utilizes range rate measurements to reduce the number of false tracks [2]. Literature [3] recommended an enhanced Doppler data association approach which utilizes target range and target

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velocity measurements for linear multi-target tracking. The target velocity measurements are applied to the observation likelihood estimation, which is an essential part of differentiating true measurements from false targets. Reference [4] recommended the Doppler information of the target based on multiple models generalized labeled multi-Bernoulli (MM-GLMB) in the high clutter environment and the processing of the measurements using the adaptive tracking gate can improve the tracking performance.

Most traditional tracking filters consider only position measurements to estimate the moving state of the target. However, the operation principle of the track filters shows that a filter using both position and Doppler measurements is more efficient than a filter using only position. Reference [2] developed a scheme by using an interacting multiple model estimator containing several extended Kalman filter (EKF) elements to handle Doppler measurements. Various recursive nonlinear filtering approaches are used to process Doppler measurements [5-6]. A linear denoising filter is presented in [7] to reduce the converted Doppler measurement errors is investigated. A sequential converted measurement Kalman filter with Doppler measurements when there is a correlation between Doppler and slant range was proposed in [8]. Motion models in the range-Doppler plane and state estimation technique using Doppler and range measurements were also investigated in [9]. Literature [10] proposed a sequential linear filtering algorithm to process the position-Doppler information. The proposed method was combined with the IMM algorithm to enhance the maneuvering target tracking.

Conversely, the aforementioned methods only integrate the measurement of Doppler without any ambiguity. Because of the spectral aliasing, an elementary problem is Doppler ambiguity, particularly at low pulse repetition frequencies (PRF) [11]. Reference [12] discussed a target tracking method in ambiguous Doppler situations using Gaussian Mixture. A Track-Before-Resolving approach for resolving the ambiguity in Doppler measurements was proposed in [13]. This new method considers the maximum probability computed in the multiple model estimation. Literature [14] proposed a scheme that is based on the modified multiple hypothesis tracking and the probabilistic data association to resolve the ambiguous Doppler problem.

In this study, a new approach for Multi-Target Tracking with a combination of position, ambiguous Doppler and power measurements is presented. Firstly, we investigated an improved data association scheme that exploits statistical features of position, Doppler and power. The estimated Doppler value calculated from the target range and timestamp will be compared with the measured Doppler to deal with the Doppler ambiguity situation. Secondly, we studied an augmented unscented Kalman filter algorithm using position, Doppler measures, and the indirect measure of radial velocity in the linear domain.

2. Methodology

2.1. Data Association

The proposed data association method uses position, Doppler and power measurements to calculate the score value of each detection in the target gate. The radial velocity value is indirectly calculated from the range and the timestamp of the detection. After that it will be converted to the estimated Doppler. If the detection comes from the target, the difference between the measured Doppler and estimated Doppler will be small. This is a new and effective solution when applying information directly in the Doppler ambiguity

situation. Similarly, if a detection belongs to the target, the difference between the measured power value and the average power value of the target will also be small.

Detailed algorithm is done through the following steps:

Step 1: Calculate the radial velocity

Determine the value of the radial velocity using the range and timestamp in the following formula:

$$rr_i = \frac{1}{N} \left(\frac{r_{i-N+1} - r_{i-N+2}}{t_{i-N+2} - t_{i-N+1}} + \frac{r_{i-N+2} - r_{i-N+3}}{t_{i-N+3} - t_{i-N+2}} + \dots + \frac{r_{i-1} - r_i}{t_i - t_{i-1}} \right) \quad (1)$$

where rr_i , r_i and t_i denote the radial velocity, range and timestamp at the scan i , respectively.

N is the integer selected depending on the maneuverability of the target and the data update cycle of the radar. The less maneuver the target or the faster the target data update, the greater N can choose. In common situations, we propose to use N in the range of 2-4. The timestamp is taken directly from the Analog-to-Digital module of the hardware device to increase the accuracy of calculating the value of the radial velocity.

Step 2: Calculate the estimated Doppler from the radial velocity

The estimated Doppler $\widehat{F}_D$ is calculated from the radial velocity according to the following formula:

$$DopplerAbs = \text{mod} \left(\frac{rr}{v_d}, M \right) \quad (2)$$

where $DopplerAbs$ denotes the absolute estimated Doppler value, v_d is the Doppler resolution and M is the total number of Doppler banks processed.

If the Doppler increases clockwise with the original bank F_0 ,

$$\widehat{F}_D = \text{mod}(F_0 + DopplerAbs, M) \quad (3)$$

If the Doppler increases counter-clockwise with the original bank F_0 ,

$$\widehat{F}_D = \begin{cases} F_0 - DopplerAbs & \text{if } F_0 \geq DopplerAbs \\ F_0 + M - DopplerAbs & \text{if } F_0 < DopplerAbs \end{cases} \quad (4)$$

Step 3: Determine Doppler difference and power difference

The main idea of using Doppler information is that assuming y_i is the detection of the target at the time i , the value of the estimated Doppler from the radial velocity will be approximately equal to the measured Doppler at the time i .

The Doppler difference ΔF_D is calculated as follows:

$$\Delta F_D = |F_D - \widehat{F}_D| \quad (5)$$

If $\Delta F_D > M/2$:

$$\Delta F_D = M - \Delta F_D \quad (6)$$

where F_D is the measured Doppler of the detection.

The use of the Doppler difference is completely unwavering by the Doppler ambiguity problem.

Similarly, the main idea of using power information is that assuming y_i is the detection of the target at the time i , the value of the measured power at the time i will be

approximately equal to the mean power of the target. In particular, the power value used to calculate is the normalized value regardless of the range.

The power difference ΔP is described by:

$$\Delta P = |P - \bar{P}| \quad (7)$$

where P is the measured power and $\bar{P}$ is the mean power.

Step 4: Determine Doppler difference distance, power difference distance and position distance

The Doppler difference distance $d_{\Delta F_D}$ is calculated according to the following formula:

$$d_{\Delta F_D} = \sqrt{(\Delta F_D - \mu_{\Delta F_D})(S_{\Delta F_D}^2)^{-1}(\Delta F_D - \mu_{\Delta F_D})^{-1}} \quad (8)$$

where $\mu_{\Delta F_D}$ and $S_{\Delta F_D}^2$ are the mean and variance of Doppler difference values, respectively.

The power difference distance $d_{\Delta P}$ is given by:

$$d_{\Delta P} = \sqrt{(\Delta P - \mu_{\Delta P})(S_{\Delta P}^2)^{-1}(\Delta P - \mu_{\Delta P})^{-1}} \quad (9)$$

where $\mu_{\Delta P}$ and $S_{\Delta P}^2$ are the mean and variance of power difference values, respectively.

The position distance d_p is expressed as following:

$$d_p = \sqrt{(\mathbf{p} - \boldsymbol{\mu}_p)\boldsymbol{\Sigma}^{-1}(\mathbf{p} - \boldsymbol{\mu}_p)^{-1}} \quad (10)$$

where $\mathbf{p}$ is the measured position vector, $\boldsymbol{\mu}_p$ and $\boldsymbol{\Sigma}$ are the predicted position vector and covariance matrix of the tracking filter used, respectively.

Step 5: Calculate the score for each distance value

The score value $score_{\Delta F_D}$ for the Doppler difference distance is calculated using the following form:

$$score_{\Delta F_D} = \begin{cases} (thres_{F_D} - d_{\Delta F_D}) & \text{if } d_{\Delta F_D} < thres_{F_D} \\ 0 & \text{if } d_{\Delta F_D} > thres_{F_D} \end{cases} \quad (11)$$

where $thres_{F_D}$ is the cut threshold of the Doppler difference distance which is determined by:

$$thres_{F_D} = F^{-1}(95\%) \quad (12)$$

where F is the cumulative distribution function of the Doppler difference distance distribution.

The score value $score_{\Delta P}$ for the power difference distance can be derived as:

$$score_{\Delta P} = \begin{cases} (thres_{\Delta P} - d_{\Delta P}) & \text{if } d_{\Delta P} < thres_{\Delta P} \\ 0 & \text{if } d_{\Delta P} > thres_{\Delta P} \end{cases} \quad (13)$$

The score value $score_p$ for the position distance is calculated according to the following formula:

$$score_p = \begin{cases} (thres_p - d_p) & \text{if } d_p < thres_p \\ 0 & \text{if } d_p > thres_p \end{cases} \quad (14)$$

where $thres_{\Delta P}$ and $thres_p$ are the cut thresholds of the power difference distance and position distance, respectively. The method of determining these two values is similar to the way of determining $thres_{F_D}$.

Step 6: Normalize the score

Because Doppler and power are used to complement the position information to enhance the efficiency of the detection score calculation function, the score values must be normalized in the range of $[0 \ q]$, where $q = q_{max}/3$ and q_{max} is the maximum value of the position distance scores.

$$score_{\Delta F_D norm} = \frac{score_{\Delta F_D} * q}{thres_{F_D}} \quad (15)$$

$$score_{\Delta P norm} = \frac{score_{\Delta P} * q}{thres_{\Delta P}} \quad (16)$$

Step 7: Calculate the total score for the detection

The total score value $TScore$ of the detection in the target gate shows the appropriate level of that detection for the target. The higher the value of this score, the more suitable the detection to assign the target.

$$TScore = score_p + W_{Doppler} * score_{\Delta F_D norm} + W_{Power} * score_{\Delta P norm} \quad (17)$$

where $W_{Doppler}$ and W_{Power} are weights of $score_{\Delta F_D norm}$ and $score_{\Delta P norm}$, respectively.

$$W_{Doppler} + W_{Power} = 1 \quad (18)$$

The value of the weights depends on the measurement accuracy of each quantity in the radar system. The total score value of the detection in the gate of all tracks is put into auction algorithm to select the most appropriate track-to-detection.

2.2. Tracking Filter

Firstly, the position measurements, including azimuth, range and elevation in sphere coordinates, will be transformed into linear forms in Cartesian coordinates using the method presented in [15]. The completed UKF algorithm is used as follows [16]. In this study, a linear time-invariant system with constant velocity model is considered for simplicity. Accordingly, the state estimate $\hat{\mathbf{X}}$ and the state covariance matrix $\hat{\mathbf{P}}$ of the proposed augmented-state UKF filter are written as the following equation:

$$\hat{\mathbf{X}} = [x \ v_x \ y \ v_y \ z \ v_z \ v_h \ F_D]^T \quad (19)$$

$$\hat{\mathbf{P}} = \begin{bmatrix} \sigma^{xx} & 0 & \sigma^{xy} & 0 & \sigma^{xz} & 0 & 0 & 0 \\ 0 & \sigma^{v_x v_x} & 0 & 0 & 0 & 0 & 0 & 0 \\ \sigma^{yx} & 0 & \sigma^{yy} & 0 & \sigma^{yz} & 0 & 0 & 0 \\ 0 & 0 & 0 & \sigma^{v_y v_y} & 0 & 0 & 0 & 0 \\ \sigma^{zx} & 0 & \sigma^{zy} & 0 & \sigma^{zz} & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & \sigma^{v_z v_z} & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & \sigma^{v_h v_h} & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & \sigma^{F_D F_D} \end{bmatrix} \quad (20)$$

where x, y, z, v_x, v_y, v_z are the position and velocity components of target in the 3-D Cartesian space, v_h which is the augmented element of the state estimate is the radial velocity or range rate, F_D is the Doppler bank, σ is the standard deviation.

Measurement vector $\mathbf{z}$ can be written as:

$$\mathbf{z} = [z_p \ rr \ F_D]^T \quad (21)$$

where $z_p = [r, a, e]$ is the position measurement of range, azimuth and elevation, respectively; rr is the indirect radial velocity measurement calculated based on equation (1); F_D is the Doppler measurement.

State transition equations of the filter are used:

$$v_x^k = v_x^{k-1} \quad (22)$$

$$v_y^k = v_y^{k-1} \quad (23)$$

$$v_z^k = v_z^{k-1} \quad (24)$$

$$x^k = x^{k-1} + v_x^k * \Delta T \quad (25)$$

$$y^k = y^{k-1} + v_y^k * \Delta T \quad (26)$$

$$z^k = z^{k-1} + v_z^k * \Delta T \quad (27)$$

$$v_h^k = \frac{-(x^k * v_x^k + y^k * v_y^k + z^k * v_z^k)}{\sqrt{x^k * x^k + y^k * y^k + z^k * z^k}} \quad (28)$$

If Doppler increases clockwise:

$$F_D^k = \text{mod} \left(F_0 + \text{mod} \left(\frac{v_h^k}{v_d}, M \right), M \right) \quad (29)$$

Otherwise,

$$F_D^k = F_0 - \text{mod} \left(\frac{v_h^k}{v_d}, M \right) \text{ if } F_0 \geq \text{mod} \left(\frac{v_h^k}{v_d}, M \right) \quad (30)$$

$$F_D^k = F_0 + M - \text{mod} \left(\frac{v_h^k}{v_d}, M \right) \text{ if } F_0 < \text{mod} \left(\frac{v_h^k}{v_d}, M \right) \quad (31)$$

3. Result and discussion

3.1. Single target case

We now consider tracking a single target in a clean environment using the constant velocity model with the following set of parameters. For the target, the initial state is $\hat{X}_0 = \left[950 \text{ m}, 10 \frac{\text{m}}{\text{s}}, 310 \text{ m}, 10 \frac{\text{m}}{\text{s}}, 0 \text{ m}, 0 \frac{\text{m}}{\text{s}}, 0 \frac{\text{m}}{\text{s}}, 0 \right]^T$. The radar is located at Cartesian coordinates (0 km, 0 km, 0 km) and sampling interval of $T = 1 \text{ s}$. The process noises are presumed to be zero-mean white Gaussian with standard deviations of azimuth, range, and Doppler measurements are $\sigma_a = 2 \text{ deg}$, $\sigma_r = 90 \text{ m}$, and $\sigma_D = 1 \text{ bank Doppler}$, respectively. The Doppler resolution is 0.5 m/s and the total number of Doppler banks processed is 24. The tracking result is compared with the traditional method which only used the position measurement and the modified UKF presented in [14] in two different groups of measurements: 1) position and ambiguous Doppler, 2) position and unambiguous Doppler. The position and velocity root-mean-squared error (RMSE) errors are utilized to estimate the tracking performance.

In most cases, both modified UKF in [14] and proposed method can effectively resolve the Doppler ambiguity and obtain the same track performance as with unambiguous Doppler situation as indicated in Figure 1(a). Both methods also present the better tracking result than the position-only method. However, in some instances, the modified UKF [14] uses an inaccurate estimate of mean and covariance or an erroneous innovation, which would lead to divergence as illustrated in Figure 1(b). On the other hand, the proposed method shows the same result as the unambiguous Doppler case.

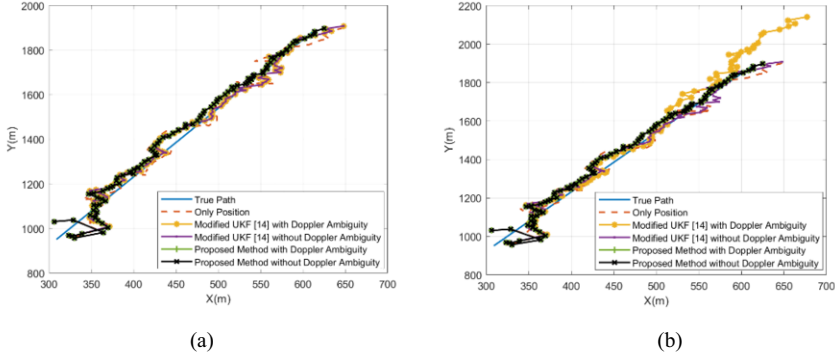


Figure 1. Tracking results in convergent case (a) and divergent case of modified UKF [14] (b)

As can be seen from Figure 2, the proposed method obtains the velocity and position RMSE values of the Doppler ambiguity situation almost overlies with those of the unambiguous situation. Moreover, the enhancements in position and velocity RMSEs are approximately 18% and 55%, respectively, compared with RMSE when using the position-only method, about 8% and 10% compared with RMSE when using the modified UKF [14] method.

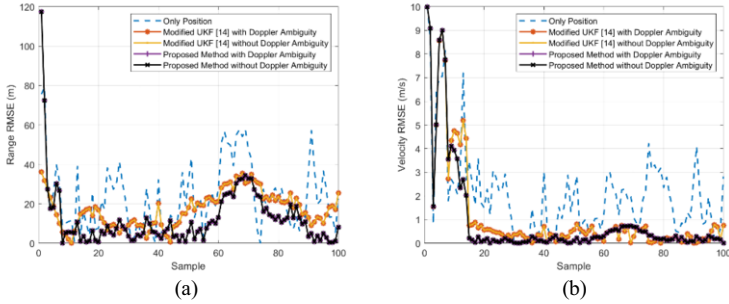


Figure 2. RMSE for modified UKF [14] and Proposed method, (a) Range RMSE, (b) Velocity RMSE

3.2. Multitarget case

A multi-target tracking scenario with three targets using the constant velocity model is illustrated. The starting time for each target is zero seconds. The radar is located at Cartesian coordinates (0 km, 0 km, 0 km) and sampling interval of $T = 1$ s. The process noises are assumed to be zero-mean white Gaussian with standard deviations of range, azimuth, Doppler and power measurements are $\sigma_r = 15$ m, $\sigma_a = 0.3$ deg, $\sigma_D = 1$ bank Doppler, and $\sigma_p = 15$ dB, respectively. The Doppler resolution is 0.5 m/s and the total number of Doppler banks processed is 24. The trajectory of each target is shown in

Figure 4(a). The high clutter region is generated around the target. The Doppler and power measurements for clutter points have uniform distributions over the regions (0, 12) and (0, 100), respectively.

Figure 3 shows the distributions of three parameters: position distance, power difference distance and Doppler difference distance. The cut threshold value for each of those parameters is determined based on the corresponding distribution. Accordingly, the cut thresholds of position distance, power difference distance and Doppler difference distance are 5.3, 2.8 and 8, respectively.

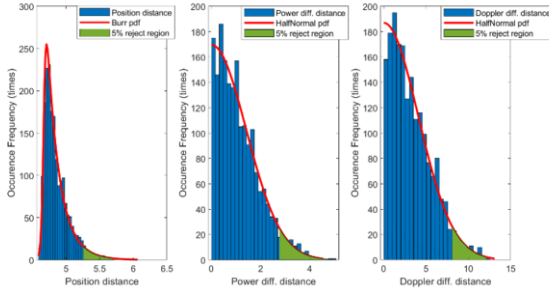


Figure 3. Histogram with distribution fit of position, power difference and Doppler difference distance

Figure 4(b) presents the tracking results with three methods: 1) Position only, 2) joint integrated probabilistic data association (JIPDA) method [14] and 3) the proposed method. The performances are compared in terms of RMSE and false detection rate. The false detection rate is defined as the number of false detections per time scan, determined by

$$R_f = \frac{1}{T_{sim}} \sum_{i=1}^{T_{sim}} N_f(i)$$

where T_{sim} is the total simulation time and $N_f(i)$ is the total number of false detections at the time i .

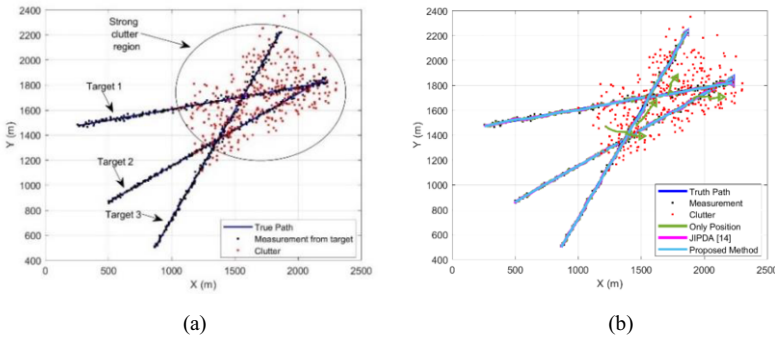


Figure 4. Simulated targets and surrounded clutter (left) and Estimated tracks (right)

It can be seen that the relative position RMSE of the proposed method becomes smaller than those of the position-only method and JIPDA [14] method (shown in Figure 4b). It means the estimated tracks are close to the true paths. Meanwhile, the position-only method generates a lot of false tracks. Numerically, from Table 1, the improvements in the position and velocity RMSEs are about 21% and 40% with respect to those of the

JIPDA [14] method. With the presence of power measurement, the proposed method also obtains the lower false detection rate than the JIPDA [14] method in the high clutter situation. Specifically, the false detection rate has decreased up to 95% compared with the JIPDA [14] method.

Table 1. The performance comparison of the proposed method and the peer method JIPDA

	Position Only	JIPDA [14]	Proposed Method
RMSE Position (m)	11.5	8.8	6.9
RMSE Velocity (m/s)	0.63	0.41	0.25
False detection rate	35	5.6	0.3

The proposed method is also applied to a coastal surveillance radar station for our test. We are interested in “Track 1” area (inside the blue circle) in which there are usually sea and weather clutters. The results are shown in Figure 5. The position-only method which only used position in MTT system leading the target chose wrong detection from clutter and move incorrect direction (left figure). The proposed method shows that the target choose correct detection and move right direction (right figure).

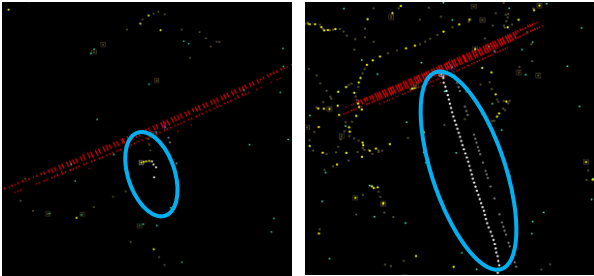


Figure 5. Target tracking result with position-only method (left) and proposed method (right)

4. Conclusion

In this paper, a new approach for Multi-Target Tracking with combination of position, power and ambiguous Doppler measurements is presented. Firstly, we investigated an improved data association scheme that utilizes statistical features of position, Doppler and power. The estimated Doppler value calculated from the target range and timestamp will be compared with the measured Doppler to deal with the Doppler ambiguity situation. Secondly, we studied an augmented UKF algorithm using position, Doppler measures, and the indirect measure of radial velocity in the linear domain. Based on the simulated and real data, it was shown that our proposed method has good performance in terms of reduced number of false track-to-detection association and improving the accuracy of the target state estimation. The improvements in the position and velocity RMSEs are about 21% and 40% with respect to the JIPDA [14] method. The false detection rate has decreased up to 95% compared with the reference method.

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Ambiguity Resolution for Ground-based Pulse-Doppler Radars Using Multiple Medium PRF

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ABSTRACT

In this paper, we propose an adaptive method to resolve ambiguities and a ghost target removal process to extract targets detected by a ground-based pulse-Doppler radar using medium pulse repetition frequency waveforms. The ambiguity resolution method is an adaptive implementation of the coincidence algorithm, which is implemented on a two-dimensional (2D) range-velocity matrix to resolve range and velocity ambiguities simultaneously, with a proposed clustering filter to enhance the anti-error ability of the system. Here we consider the scenario of multiple target environments. The ghost target removal process, which is based on the power after Doppler processing, is proposed to mitigate ghosting detections to enhance the performance of ground-based radars using a short PRF schedule in multiple target environments. Simulation results on a ground-based pulsed Doppler radar model will be presented to show the effectiveness of the proposed approach.

Keywords: Ambiguity resolution, Coincidence algorithm, Medium PRF, Ghost target removal

1. INTRODUCTION

Pulse-Doppler radar detects a target by transmitting pulses of radio frequency energy and receiving the energy reflected towards the radar by the target. Depending on the pulse repetition frequency (PRF) and its ambiguity characteristics, pulse-Doppler radar operation is commonly divided into low PRF, medium PRF and high PRF mode. In low PRF mode, the PRF is sufficiently low to be unambiguous in range of interest but is ambiguous in velocity, that is, ambiguous in Doppler frequency. In high PRF mode, the ambiguity characteristics are the opposite, the radar is ambiguous in range and unambiguous in Doppler frequency. In medium PRF mode, the radar is ambiguous in both range and Doppler frequency. However, the ambiguity can be resolved by transmitting a set of multiple medium PRFs, each PRF corresponds to a coherent processing interval (CPI), to produce different ambiguous measurements. Then, the true range and velocity of targets can be decoded by combining these data.

Chinese Remainder Theorem (CRT) [1], [3] is one of the mainstreams in resolving ambiguity in a pulse-Doppler radar. It offers an analytic procedure for calculating the unambiguous range from the measured range on different PRFs. However, CRT approach is too sensitive to measurement errors. It also requires the PRFs to be co-prime which may make it harder to find a PRFs set satisfying both resolving range and velocity ambiguity. In [4], [5], clustering algorithm was proposed to gain better anti-error ability. It rearranges all possible ambiguous range corresponding to different PRFs in ascending order and calculate the cluster variation in order. The best clutter occurs at the value when the variation is minimum. Clustering algorithm is found to be superior to CRT, but it requires heavy computation and can only resolve range or velocity ambiguity at a time.

The coincidence algorithm [2] is an essentially graphical implementation of the CRT. The algorithm unfolds all possible ambiguous ranges and velocities over the space of interest. It then combines ambiguous data over the several CPIs to detect true target. The coincidence algorithm can provide a good ambiguity resolution with high precision and less computation complexity. However, in multiple targets condition, coincidence algorithm may report ghost targets. To deal with the ghosting problem, the author in [6] proposed a target extraction algorithm that is based on the concept that true targets are detected in a large number of CPIs, whereas ghost targets are more likely to be observed in fewer CPIs. The method was shown to be good with a long PRF schedule, but with a short PRF schedule, it may not clearly distinguishable between true and ghost targets based on the number of detections.

In this paper, we aim to address the ambiguity in the ground-based pulse-Doppler radar operating in multiple medium PRF mode. We present an adaptive implementation of the coincidence algorithm which is implemented on a 2D range-

velocity matrix to resolve range and velocity ambiguities simultaneously and propose the implementation of a clustering filter to enhance the anti-error ability of the system. To combat ghost targets, we propose a ghost removal process that addresses the case of a short PRF schedule being used in the system. The ghost removal process is based on the power after Doppler processing to distinguish true and ghost targets. This case is essentially necessary in desire of the short illumination time of rapidly scanned narrow beam in a ground-based pulse-Doppler radar in a multiple target environment.

The paper is organized as follows: we briefly describe medium PRF radar in section 2. In section 3 and section 4, the proposed ambiguity resolution approach and the ghost removal process are presented, respectively. The simulation results are given in section 5. The last section is dedicated to summary of this paper.

2. MEDIUM PRF RADAR DESCRIPTION

The radar under consideration in this paper is a ground-based air surveillance pulse-Doppler radar that employs medium PRF waveforms to detect targets. Each PRF has a maximum unambiguous range and velocity of a target that can be detected by the radar as:

$$r_{ua} = \frac{c}{2 \times PRF} = \frac{c \times PRI}{2} \quad (1)$$

$$v_{ua} = \pm \frac{c \times PRF}{4 \times f_0} \quad (2)$$

where c is the speed of electromagnetic wave in space, PRI is the pulse repetition interval ($PRI = 1/PRF$) and f_0 is the carrier frequency of the radar signal. When a target range exceeds r_{ua} , the measured range is ambiguous and can be expressed as:

$$r_t = r_x + m \times r_{ua} \quad (3)$$

where r_t is the true target range, r_x is the range measured by the radar, $m=0,1,2,\dots$ is the order of the range ambiguity. The same principle is true for velocity ambiguity when a target velocity exceeds v_{ua} . The ambiguity in velocity can be expressed in Doppler frequency shift measured by the radar as:

$$f_{dt} = f_d \pm n \times f_r \quad (4)$$

where f_{dt} is the true Doppler shift, f_d is the Doppler frequency shift which is determined by the radar, f_r is equal to the PRF, $n=0,1,2,\dots$ is the order of Doppler ambiguity.

In the pulse-Doppler radar, the signal processing utilizes range gating and pulse compression in range domain to get a fine range resolution, ΔR , which depends on the bandwidth of the modulated pulse [9]. In Doppler frequency domain, Discrete Fourier Transform (DFT) is used to processing the spectrum of the echo signal. The DFT quantities frequency domain into Doppler frequency bins with the frequency resolution can be calculated as:

$$\Delta f = \frac{PRF}{N_{pulse}} \quad (5)$$

where N_{pulse} is the number of pulse during a CPI.

The ambiguous range can be expressed in term of range bin which is an integer multiplier of range resolution as:

$$R_t = R_x + m \times R_{ua} \quad (6)$$

where R_t , R_x , R_{ua} are the true range bin, the measured ambiguous range bin and the maximum unambiguous range bin. The ambiguous frequency can be expressed by Doppler filter bank and frequency resolution as:

$$f_{dt} = (n_d \pm n \times N_{pulse}) \times \Delta f \quad (7)$$

where n_d is the Doppler filter bank corresponding to the Doppler frequency shift determined by the radar.

The range ambiguity and velocity ambiguity, or that is, Doppler frequency ambiguity, can be resolved by using multiple medium PRFs. Considering a set of N PRFs, the radar radiates N CPIs, with each corresponding to a PRF. Each CPI

consists of a number of transmission pulses with identical characteristics. The measurements carried out over N CPIs are used to resolve the ambiguities. The criterion M/N is used for target detection, that is, a target presence is declared at a certain range and Doppler frequency if there are at least M out of N CPIs in which the target is detected.

3. THE PROPOSED APPROACH TO RESOLVE AMBIGUITES

3.1 Coincidence algorithm

The coincidence algorithm resolves ambiguities by unfolding and combining ambiguous measurements. For each PRF in which a target is detected, all possible ambiguous ranges and velocities are computed to the maximum range and velocity of interest. The ambiguities are then resolved by combining the ambiguous data over N CPIs at every range and Doppler bin. A detection at a specific range bin and Doppler bin is declared if this bin is in at least M out of N CPIs.

Consider range ambiguity resolution. Assuming that three PRFs are used and the criterion $2/3$ is used for target detection. The maximum unambiguous range bins corresponding to the three PRFs are $R_{ua1} = 6$, $R_{ua2} = 8$, $R_{ua3} = 11$. Further, suppose a target appears at the range bin of $R_t = 15$, therefore the measured ambiguous range bin by the three PRFs are 3, 7, 4 respectively, and the ambiguous range equations are:

$$\begin{aligned} R_{tPRF1} &= 3 + m_1 \times R_{ua1} = 3, 9, \underline{15}, 21, \dots \\ R_{tPRF2} &= 7 + m_2 \times R_{ua2} = 7, \underline{15}, 23, \dots \\ R_{tPRF3} &= 4 + m_3 \times R_{ua3} = 4, \underline{15}, 26, \dots \end{aligned} \quad (8)$$

The coincidence algorithm calculates possible ambiguous ranges for each PRF and combine the data over 3 PRFs. The algorithm then searches for a range bin that exhibits detection in at least $2/3$ PRFs to declare the detection. As calculated in equation (8), the algorithm correctly detects the true target range bin at 15.

In case of Doppler frequency ambiguity resolution, care must be taken that canonical coincidence algorithm requires Doppler frequency resolution to be the same among CPIs so that data is combined at the same Doppler frequency. Equation (5) indicates that the frequency resolution is dependent on PRF and N_{pulse} which means it can be different between CPIs. To overcome this limitation, an adaptation of the coincidence algorithm which chooses a fixed reference Doppler frequency resolution, Δf_{ref} , to rescale ambiguous Doppler frequency measurements to the same base as follows:

$$\frac{f_{dt}}{\Delta f_{ref}} = (n_d \pm n \times N_{pulse}) \times \frac{\Delta f}{\Delta f_{ref}} \quad (9)$$

Equation (9) can be written in terms of integer frequency bin after rescaling as:

$$F_{dt} = (n_d \pm n \times N_{pulse}) \times \frac{\Delta f}{\Delta f_{ref}} \quad (10)$$

where F_{dt} is the true frequency bin after rescaling. The Doppler frequency ambiguity is identical to that of range ambiguity, the same principle of range resolution can be applied to resolve Doppler frequency ambiguity.

3.2 2-D matrix implementation of Coincidence algorithm

Figure 1 illustrates the signal processing procedure to resolve ambiguities for a pulsed-Doppler medium PRF radar.

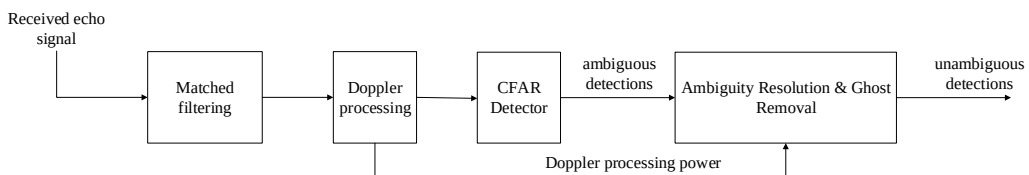


Figure 1. Signal processing procedure

In the pulse-Doppler radar, the signal processing divides range and Doppler frequency into multiple range bins and Doppler frequency bins. After the CFAR detector of each CPI, a 2-D binary range-Doppler matrix presents the information of detected points. A value of 1 means a detection at that range-Doppler bin. For each 1's value in the matrix, all possible ambiguities corresponding to that detected point are computed to maximum range and rescaling Doppler bin, which results in a new 2-D binary range-Doppler matrix of full range and Doppler bins of interest as illustrated in Figure 2. The results of N CPIs are combined by summing the result matrix of each CPI to get a combined result matrix. During the process of unfolding detected points, the power after Doppler processing of each range-Doppler bin is also unfolded in each CPI. The true target is then extracted from the combined matrix and the unfolded power after Doppler processing.

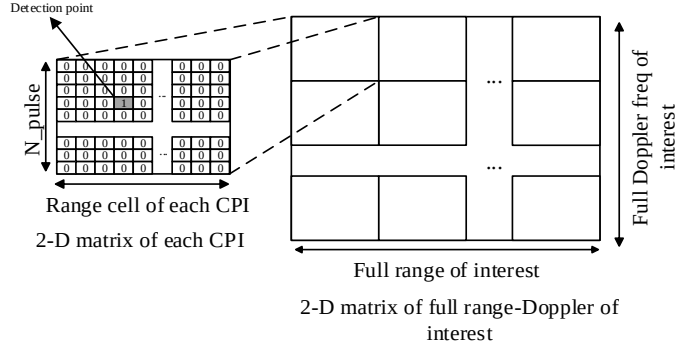


Figure 2. 2-D unfolding matrix

3.3 Clustering filter

The M/N criterion requires M out of N detections at a range-Doppler bin to declare a target detection. However, detected points of a true target at different CPI may not be aligned due to:

- Range error measurements may happen in the system.
- Error resulting from integer rounding and misalignment when rescaling Doppler frequency.

These errors can result in several misaligned bins between CPIs at a target's detected point. A clustering filter is proposed to enhance error tolerance of the system. Figure 3 illustrates the process of clustering filter:

Step 1: In each range-Doppler point, open a window of size $(x \times y)$ and calculate sum of the values in this window.

Step 2: If the sum is greater than or equal to M and the value of the current point is greater than or equal to 1, declare a detected point at that range-Doppler bin.

Step 3: Scan the window all over the combined result matrix to detect all possible point.

Step 4: Implement ghost removal process to detect the true target and update the combined result matrix.

Step 5: Repeat the process on the newly updated combined result matrix until there is no more target detection.

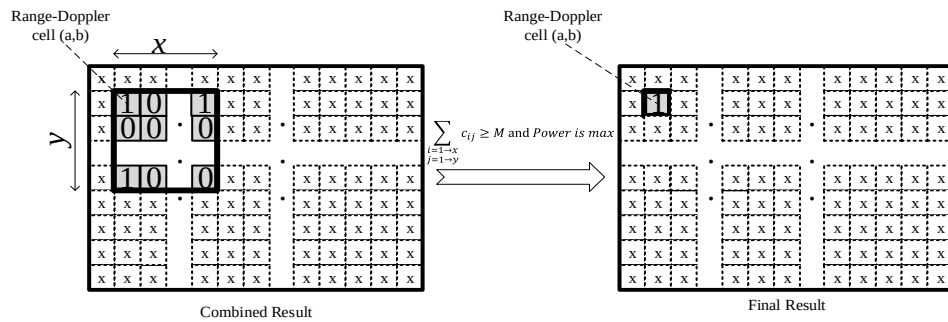


Figure 3. Clustering filter

4. GHOSTING REMOVAL PROCESS

Combining ambiguous data from several CPIs may result in false target detections or ghost targets. This happens because:

- Multiple targets correlate with each other, that is an ambiguous range and Doppler bin of one target may be in coincidence with ambiguous range and Doppler bins of other targets and exceed M coincidence requirements. The more targets there are in the beam, the greater possibility that ghost targets are detected.
- Noise spike may correlate with an ambiguous target.

In [6], the authors deal with ghost targets based on the number of detections over N CPIs. After combining the results of N CPIs, the target that appears the most over N CPIs will be declared as a genuine target. The detected points relating to this genuine target are then removed. The process keeps going until there are no more reported targets. However, if a short PRF schedule is used, the number of detections may not be clearly different among targets in order to distinguish true targets and ghost targets. In this paper, we propose a process to mitigate ghosting detections by using the power after Doppler processing, as follows:

Step 1: After the clustering filter process, find the detected point that has maximum power and mark this detection as a genuine target. The power is the sum of maximum power after Doppler processing over a window of size $(x \times y)$ of each CPI at the considered point.

Step 2: From the genuine target in step 1, find all the ambiguous range-Doppler bins corresponding to this target.

Step 3: At each range-Doppler bin in step 2, open a window of size $(x \times y)$ on the combined result matrix, decrease the values in the window by 1.

Step 4: Repeat the process to extract new targets.

5. RESULT

We evaluate the proposed approach by simulation on a model of a ground-based to air surveillance pulse-Doppler radar. The parameters of the radar are given in Table 1.

Table 1. Radar model parameters

Parameter	Value	Parameter	Value
Carrier frequency	3 GHz	Transmitted pulse width	30 μ S
Antenna 3 dB beam-width	3.5°	Duty cycle	Variable (max 10%)
Stacked beams	3 beams	PRIs	[500; 425; 358] μ S
Antenna scan rate	6 rpm	PRFs	[2000; 2352; 2793] Hz
Beam Dwell-time	97.2 ms	N_{pulse}	20
Pulse compression	Linear Frequency Modulation	Range resolution	75 m
Signal bandwidth	2 MHz	Reference Doppler resolution	100 Hz (5 m/s velocity resolution)
Maximum range of interest	160 km	Ambiguity resolution	2/3 criterion, adaptive coincidence algorithm
Maximum velocity of interest	± 300 m/s (± 12 kHz)	Clustering filter window size	3x3

5.1 Medium PRF processing parameters selection

The selection of processing parameters is to select a set of optimum parameters that gives the best medium PRF algorithm detection. The selected parameters include the medium PRFs set and the fixed reference Doppler frequency used in coincidence algorithm in this paper. The flow of selection is that the medium PRFs set is firstly selected to give an optimum or near optimum detection performance in range domain. The fixed reference Doppler frequency is then selected in combining with a number of reasonable good PRFs sets to select the optimum PRFs set and fixed reference Doppler frequency.

In consideration of the PRFs set selection, the goal is to find PRFs sets that have minimum blind zone while maintains the decodable and operational constraints of the radar [7], [8]. In this paper we consider the case of a short PRFs set is used. This case is essentially necessary in desire of the short illumination time of rapidly scanned narrow beam in a ground-based pulse-Doppler radar in a multiple target environment. Note that in Table 1, the transmitted pulse width is 30 μ S and the duty cycle is limited by 10%, so the minimum value of PRI is 300 μ S. For the chosen PRFs, stacked beams and N_{pulse} , the total illuminating time is 76.98 μ S (79% of beam dwell-time). If a longer PRFs schedule is desired, that is more than 3 PRFs are used, there will be a trade-off by reducing the transmitted pulse width or by reducing N_{pulse} , which reduces the coherent processing gain, otherwise the longer PRFs schedule may exceed beam dwell-time which is not acceptable. Figure 4 illustrates the detection performance of the selected PRIs set on range domain. The value of 0 indicates the blind zone, the other value indicates the detectable zone. The result show that, the PRIs gives no blind zone over the maximum range of interest except for the undesirable blind zone due to the first transmitted waveform length.

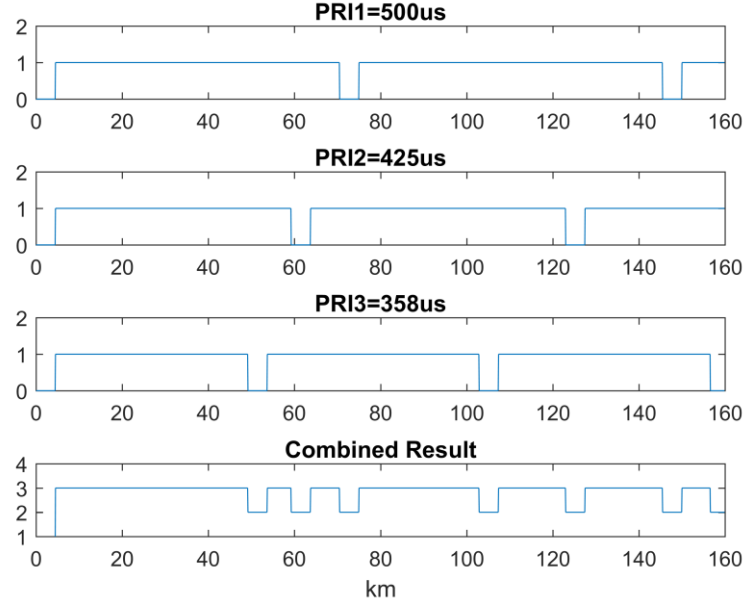


Figure 4. Detection performance on range domain of the selected PRFs set

In consideration of the fixed reference Doppler frequency (Δf_{ref}) selection, there are multiple factors that affect the selection value of Δf_{ref} :

- The maximum value of Δf_{ref} is less than or equal to the minimum frequency resolution of the PRFs set
- The value of Δf_{ref} should be the divisible number of the maximum speed of interest
- The higher Δf_{ref} requires less computation because the 2D range-Doppler matrix of interest has smaller size
- The lower Δf_{ref} has better Doppler frequency accuracy estimation, or that is the velocity accuracy estimation

After determining the constraints to select Δf_{ref} , numerical simulation can be conducted to select the optimum Δf_{ref} value. For the PRFs set and N_{pulse} in Table 1, the frequency resolution is $\Delta f = [100; 117.6; 139.65]$ Hz. The corresponding velocity resolution is $\Delta v = [5; 5.88; 6.9825]$ m/s. The possible value of $\Delta v_{ref} = [1; 2; 3; 4; 5]$ m/s, which results in equivalent possible $\Delta f_{ref} = [20; 40; 60; 80; 100]$ Hz. The simulation of the PRFs set in combining with the Δf_{ref} gives the results of blind zone ratio over maximum range and velocity of interest in Table 2. From the simulation results, it can be seen that $\Delta f_{ref} = 100$ Hz or $\Delta v_{ref} = 5$ m/s gives the best medium PRF detection. Figure 5 shows the overall detection performance of the selected PRIs and Δf_{ref} . The value of 1 gives the detectable zone, while the value of 0 gives the blind zone. It can be seen that on the range domain, the selected parameters have blind zone due to the first transmitted waveform length. On the velocity domain, the blind zone is the result of removing Doppler bank filter which is near zero frequency to suppress ground clutter effect.

Table 2. Detection performance with different Δf_{ref}

Δf_{ref} (Hz)	Blind zone ratio (%)
20	29.28
40	10.65
60	4.15
80	3.8
100	3

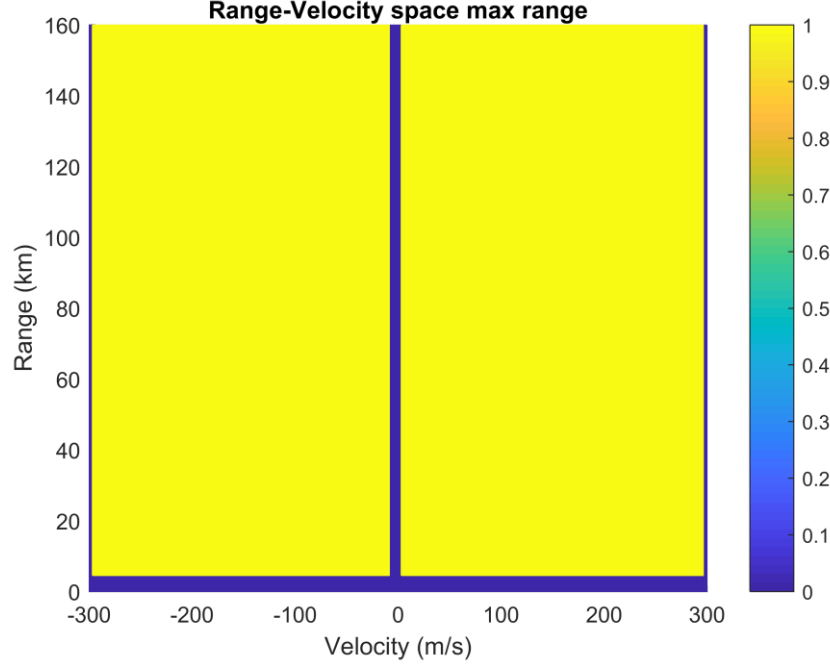


Figure 5. Detection performance over the maximum range and velocity of interest of the selected PRFs set and Δf_{ref}

5.2 Performance of the proposed approach in simulation

We test the proposed approach in four cases with different numbers of targets: 1, 5, 10, 15. For each case, we run 200 tests with the targets randomly selected in the space of range and velocity of interest. The results of detection are given in Table 3 below.

Table 3. Result of target detection of the proposed scheme

Number of targets	Total targets	Number of corrected detections
1	200	200
5	1000	958
10	2000	1858
15	3000	2731

The results show that the best detection performance is in the case of a single target with 100% detection. The case of five targets gives 95.8%, the case of 10 targets gives 92.9%, and the case of 15 targets gives 91.03% of correctly detected targets.

In order to make a comparison on the number of ghost target detections, we also run the test with the proposed ghost removal approach in [6]. The results are given in Table 4 below.

Table 4. Result of ghosting in the two schemes

Number of targets	Number of ghost targets	
	Approach in this paper	Approach in [6]
1	0	0

5	6	18
10	22	63
15	41	130

As shown in Table 4, in the case of a single target, the two proposed approaches do not detect any ghost target. However, as the number of targets increases, the number of ghost detections also increases. The results show that the proposed approach in this paper detects fewer ghost targets, about 3 times fewer, than the approach proposed in [6]. This is an improvement of the approach in this paper over the one in [6].

Figure 6 to Figure 9 show an example of the ambiguity resolution process in the case where the number of targets is 10. The information of 10 targets in range-velocity space is given in Table 5.

Table 5. Target's information in the example

Target	Range (km)	Velocity (m/s)
1 st	19	-53
2 nd	14	-228
3 rd	130	113
4 th	15	115
5 th	50	126
6 th	126	99
7 th	75	-125
8 th	145	-255
9 th	89	-78
10 th	71	206

Figure 6 shows the 2-D full range and velocity matrix over the space of interest after unfolding all possible ambiguous points of each PRF. Figure 7 shows the combined result matrix after the first clustering filter. At this stage, there are 13 range-velocity points having a cluster window value of 2 and there are three range-velocity points having a cluster window value of 3.

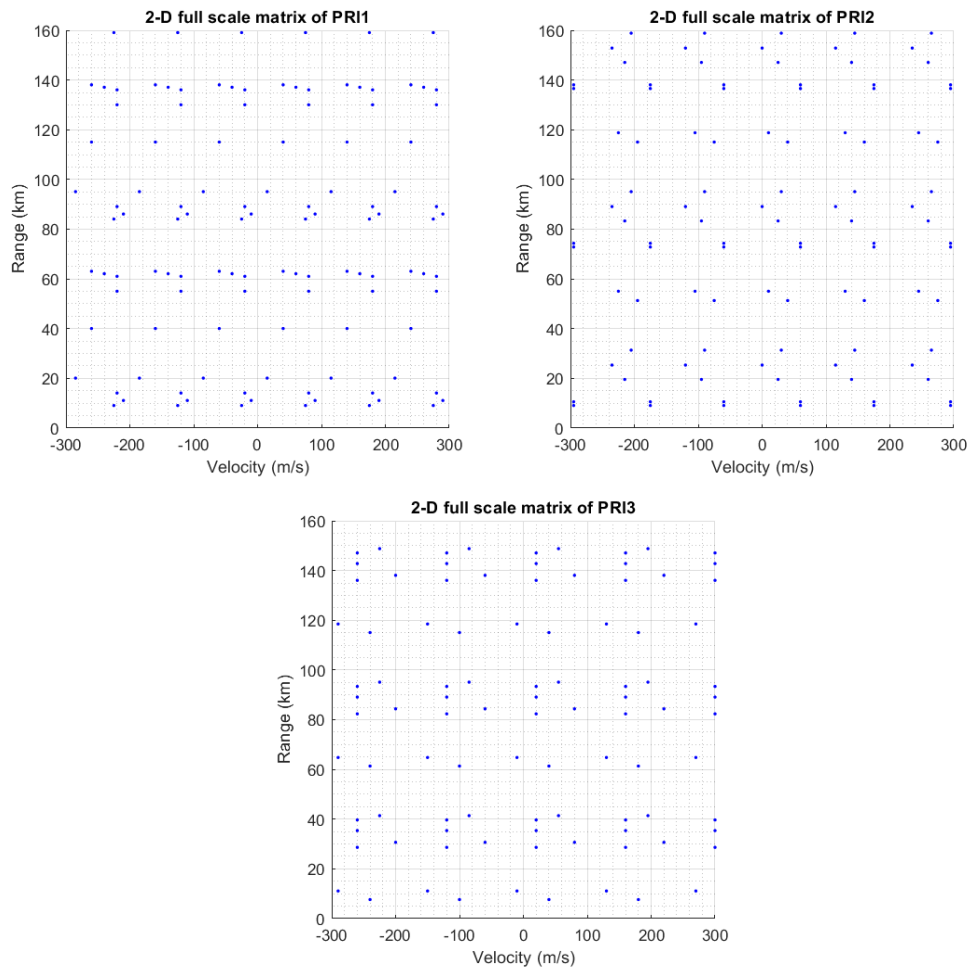


Figure 6. 2-D full range and velocity matrix of 3 PRFs

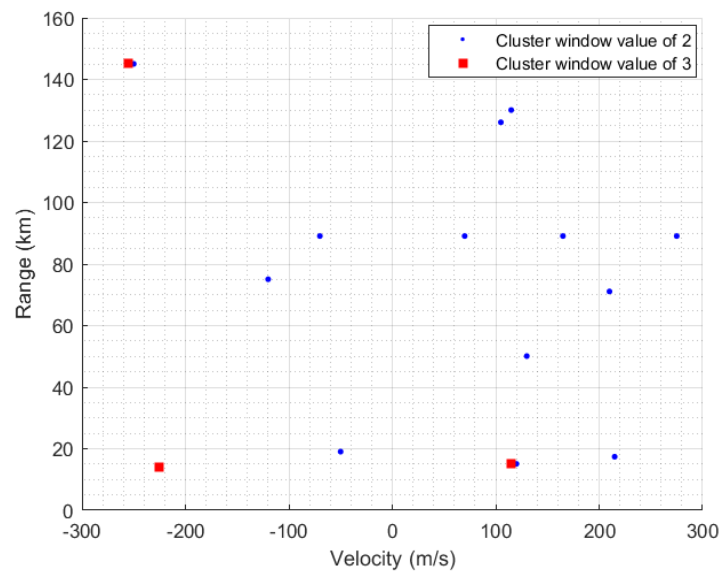


Figure 7. Combined result matrix after the first clustering filter

Without the ghost removal process, there would be 16 targets to be declared, that means six false alarm detections. By applying the ghost removal process proposed in this paper and the one in [6], the detection results are better. Figure 8 shows the detection results by the proposed approach in this paper. All 10 targets are detected correctly. Figure 9 shows the detection results by the proposed process in [6]. There are 11 targets to be declared, including 10 genuine targets and one ghost target. Note that 13 values of 2 and three values of 3 may be not clear enough to distinguish a genuine target and a ghost target based on the number of detections over N CPIs, so that the performance by the process in [6] still reports a ghost target.

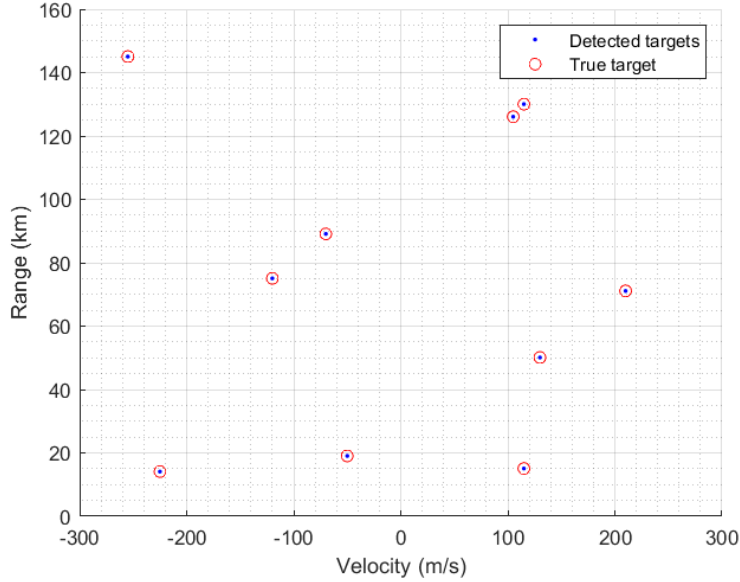


Figure 8. Detection results of the proposed scheme in this paper

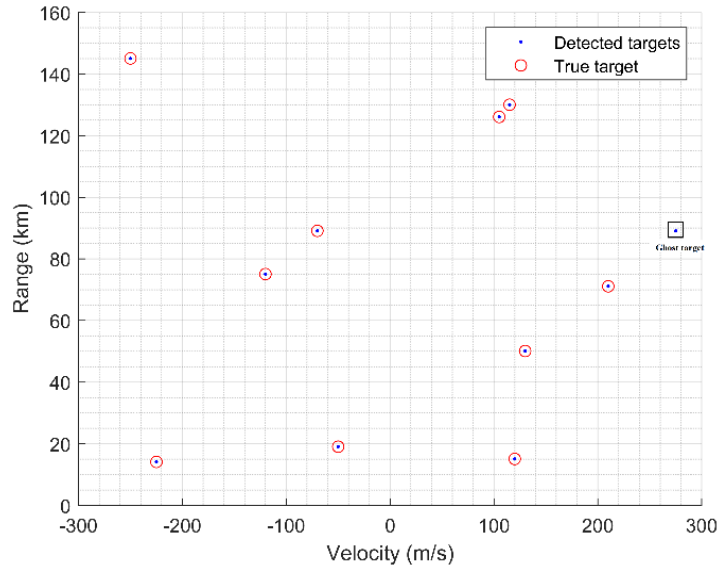


Figure 9. Detection results of the proposed scheme in [6]

In order to make a comparison of computation complexity, we record the computation time of the two method in different cases of number of targets. The simulations are conducted on MATLAB 2017a with Core i3-10100. Table 6 shows the computation time. The results show that, there is no significant difference in computation complexity between the two approaches. That is because the two approach is calculated only by addition and subtraction. The only difference

in processing is that the proposed approach in this paper uses power after Doppler processing to extract true target which requires processing in float data type, while the approach in [6] uses integer data type to be processed.

Table 6. Computation time in the two schemes

Number of targets	Computation time (s)	
	Approach in this paper	Approach in [6]
1	2.29	2.18
5	6.05	5.86
10	10.86	10.5
15	14.91	14.07

6. CONCLUSION

In this paper, we have presented an approach to resolve ambiguity based on an adaptive implementation of the coincidence algorithm with a proposed clustering filter. The proposed approach can handle both range and velocity ambiguities simultaneously. In the case of a multiple target scenario, a ghost removal process that utilizes the power after Doppler processing is proposed. The simulation shows the effectiveness of the proposed target extraction when a short PRF schedule is used in the system. Future work will focus on further evaluation and optimization of the computation complexity of the proposed approach.

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A Discrete Clutter Reduction Method for Drone Detection with High Resolution Radars

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Abstract. The paper deals with a problem of noise reduction for drone detection with high range resolution radars. The considered discrete clutter includes land vehicles, birds, etc. This clutter involves in the radar echo signals and could not be rejected by using classical methods, for example moving target indicator (MTI) and moving target detection (MTD). As a result, this clutter forms the false alarms on the radar screen. To reduce clutter we propose a new method which is based on the target's Doppler dispersion and moving characteristic. The study is integrated on a drone detection radar and is tested with a variety of drones in different moving scenarios. The test results show that the proposed method achieves a better performance than that one recently published.

Keywords. Radar signal processing, clutter reduction, drone detection radar, high resolution radar

1. Introduction

A radar is a complicated system that uses the radio waves to detect objects (targets). In the radar signal echoes, beside the signals from considered objects there are signals from unwanted objects, for example, for a drone detection radar with a high range resolution (HRR) (see [1, ch. 9]) unwanted objects are land (or surface) clutter (grasses, trees, ground), volume clutter (precipitation and chaff) and discrete (or point) clutter (birds, insects, land vehicles, wind turbines, buildings, water tanks). These clutters form false alarms on the radar screen and degrade the system performance (see Figure 1).

Two most popular methods for radar clutter reduction are the MTI and MTD. The MTI was firstly discussed by Ridenour (see [2]) and Grisetti et al. (see [3]) and it contains a delay line and a subtraction circuit which takes the difference between consecutive pulses (see Figure 2). For a moving target, the Doppler shift of the carrier frequency will change the phase of the received pulse whereas a ground or building echo will leave it essentially unchanged. Therefore, the clutter will be cancelled in the output pulse.

The subsequent studies are extended to the case of digital MTI (see [4]), MTI with the staggered pulse repetition frequency (see [5], [6]). However, there are many causes such as small movements of trees on the ground, rotation of the radar antenna that lead to inefficiency of the MTI.

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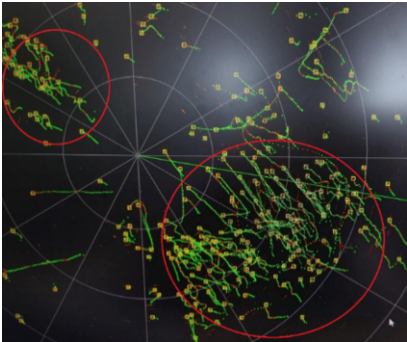


Figure 1. Illustration of false alarms (in the circles) from volume clutter on a high range resolution radar

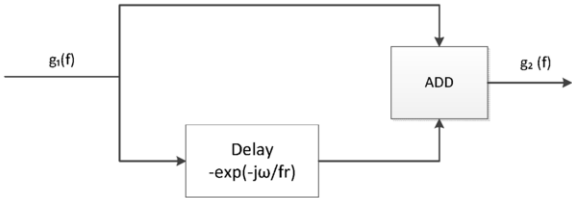


Figure 2. Block diagram of an MTI system [3]

The MTD is the newer approach for detection of moving targets than the MTI (see [7], [8]). One of the main blocks of the MTD system (see Figure 3) is the block “Doppler Filter Bank” that separates objects into different velocity levels (or equivalent, different Doppler banks) in order to reduce clutter (see Figure 4).

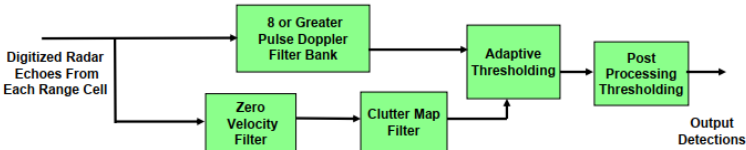


Figure 3. Block diagram of an MTD system [8]

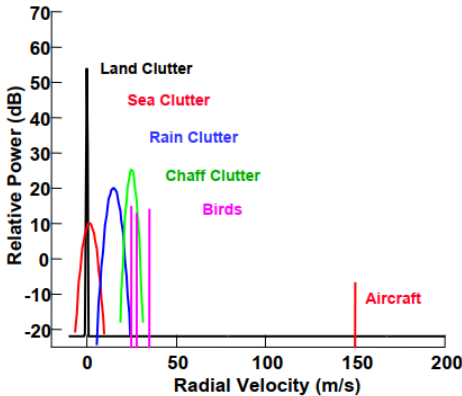


Figure 4. Example of clutter spectra [8]

For 2D (or even 3D) drone detection radars, it is hard to reduce discrete clutter (such as land vehicles and birds) because its Doppler is similar to that one of drones which fly slowly or at a low altitude. In this situation the use of MTI and MTD cannot help. Therefore, there is a need to explore new methods to avoid these difficulties.

Among a large number of works concerning to radar discrete clutter suppression, let us recall the work of Martin and Shapiro (see [9]) with a method for discrimination of birds and insects for high resolution weather radars using a combination of estimated radar cross section and density of targets, the work of Zaugg et al. (see [10]) studied a problem of automatic identification of bird targets from insects and ground clutters for radars using wing flapping patterns and support vector classifiers, the work of He et al. (see [11]) investigated a problem of wind farm discrete clutter suppression for air surveillance radar based on clutter map and a generalizing algorithm of K-means clustering process, the work of Jatau et al. (see [12]) for detecting birds and insects in the atmosphere using machine learning on pattern of bird and insect echoes based on dual polarization variables. The reduction methods for another type of radar discrete clutters reflected from buildings was studied in [13-16].

In this paper, we propose a new method to recognize drones from discrete clutter. The method is based on the target's Doppler diversion and the moving characteristic. The paper is organized in the following way. In the next section, we take a statistical analysis on target's Doppler and moving properties. In section 3, the proposed design and algorithms are described. Then, the test results show the efficiency of the study. The last section deals with the conclusion and future works.

2. Analysis

In this section by using a HRR radar (see Figure 5 and Table 1) we analyze the characteristics of drone (Inspire 2, Phantom 4, Mavic 3) and discrete clutter (such as land vehicles, birds) based on their radar signal echoes.

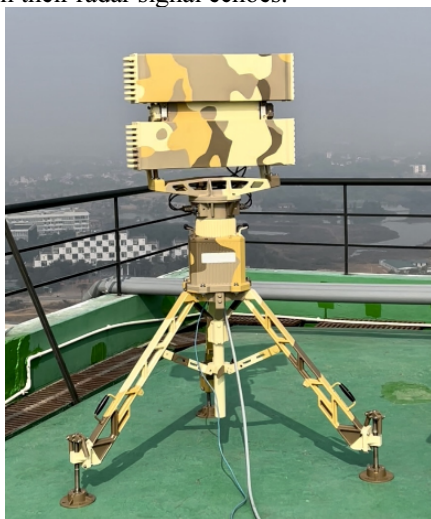


Figure 5. The radar used for the study

Table 1. Radar parameters

Parameter	Value
Radar type	FMCW, 2 dimensions
Frequency	X-band
Instrumented range	12km
Range resolution	1.5m
Scan rate	01Hz

2.1. Doppler characteristic

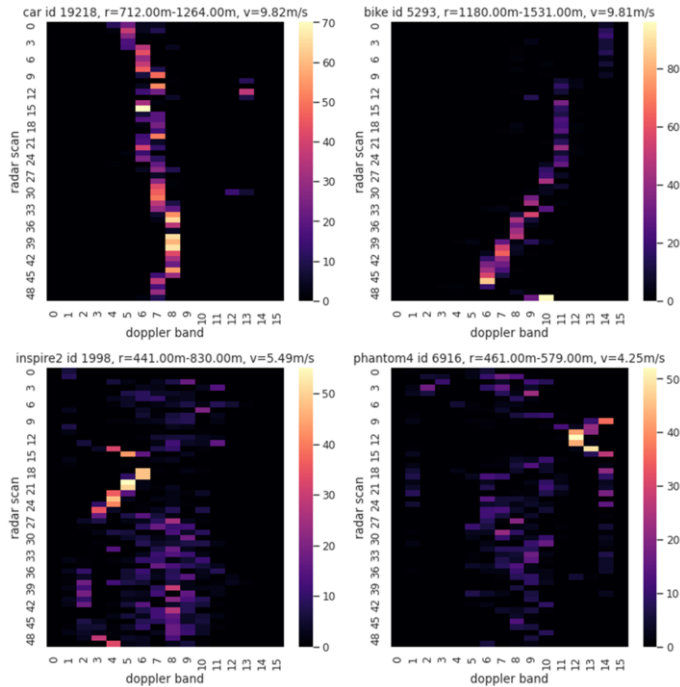


Figure 6. Doppler characteristic of different targets

There are 16 Doppler bands using for coherent integration in this study. The number “16” of Doppler bands is followed from the radar parameters (see Table 1). At each radar scan, a target will be detected as a group of plots. Each plot characterizes an echo pulse from a part of the target and has its own Doppler. Counting the plots which have the same Doppler and displaying the results with consecutive scans we obtain the target’s Doppler characteristic picture (see Figure 6).

The target’s Doppler dispersion is featured by $(\overline{\Delta f_D}, \sigma_{\Delta f_D})$:

$$\overline{\Delta f_D} = \text{mean}\{\Delta f_{D1}, \Delta f_{D2}, \dots, \Delta f_{DM}\} \tag{1}$$

$$\sigma_{\Delta f_D} = \text{std}\{\Delta f_{D1}, \Delta f_{D2}, \dots, \Delta f_{DM}\} \tag{2}$$

where Δf_{Di} is the target’s Doppler spread at i -th scan and mean and std denote the mean and standard deviation, M is number of scans and the target’s Doppler spread on the Doppler banks.

Analyzing data from radar targets with range less than 1,7km we obtain the following statistic of targets Doppler dispersion (see Figure 7 and 8)

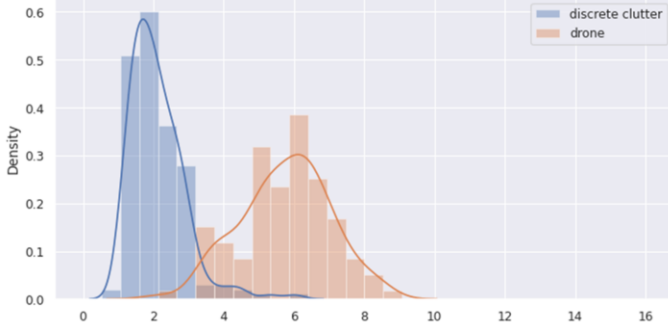


Figure 7. Distribution of $\overline{\Delta f_D}$ of discrete clutters and drones

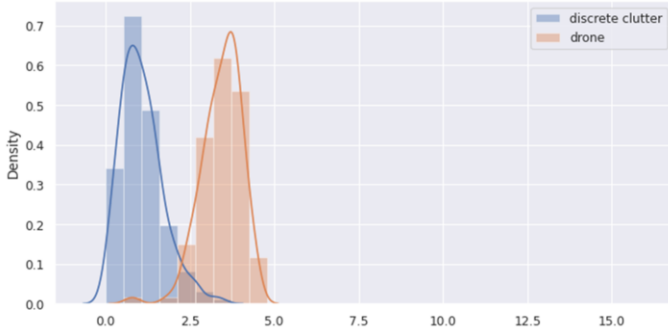


Figure 8. Distribution of $\sigma_{\Delta f_D}$ of discrete clutters and drones

2.2. Moving characteristic

As given in the previous section, the targets Doppler dispersion feature is not enough to reduce the discrete clutters because of its dependence on the range from the radar to the targets. For a small drone moving far from the radar, its Doppler dispersion feature is the same as discrete clutter. Therefore, in this section we introduce a street data which is used to extract targets moving characteristic for clutter reduction.

A street data is taken from www.openstreetmap.org and it contains a list of elements (or equivalent streets). Each element (or street) is constructed by connecting adjacent nodes (or points) together. For illustration, Figure 9 shows an element in a street data.

To perform a street map, we need the well-known following converting formula.

For a point A with range d (m) and azimuth α (rad), its latitude and longitude are defined as:

$$lon_A = lon_{root} + \frac{d \times hs \times \sin \alpha}{\cos \frac{lat_{root} \times \pi}{180}} \quad (3)$$

$$lat_A = lat_{root} + d \times hs \times \cos \alpha \quad (4)$$

where (lat_{root}, lon_{root}) is the latitude and longitude of the radar position and

$$hs = \frac{1}{\frac{2\pi}{360} \times R}, R = 6378.137 \text{ (°/m)} \quad (5)$$

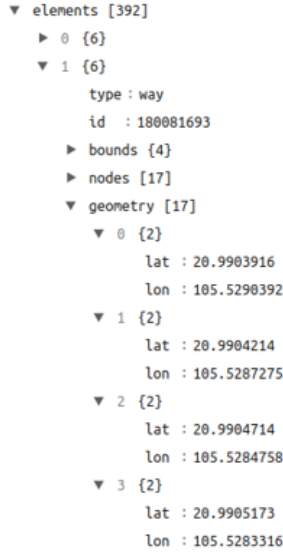


Figure 9. An element with its first three nodes

For a point A (lat_A, lon_A), its coordinates (x_A, y_A) in the Cartesian coordinate are

$$x_A = \left(\frac{lat_A - lat_{root}}{hs} \right) / scale \quad (6)$$

$$y_A = \left(\frac{lon_{root} - lon_A}{hs} \right) / scale \quad (7)$$

where $scale$ (pixel/m) is a parameter.

Now let us present the method to construct a street map with (approximately) the same range resolution with the radar. In fact, the radar used in this study has the range resolution 1,5m (see Table 1), hence we can use the value $scale = 1,5/\sqrt{2} \approx 1(\frac{pixel}{m})$, i.e. the street map has resolution 1,0m in the Cartesian coordinate (see Figure 10).

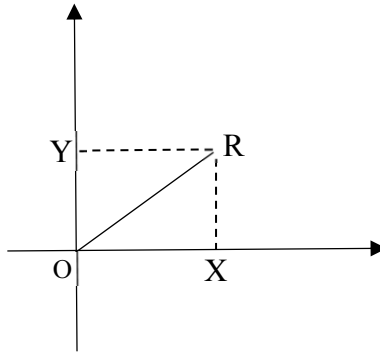


Figure 10. Illustration of different resolutions: range resolution OR and resolution in Cartesian coordinate OX, OY

The process is as following.

Step 1. From www.openstreetmap.org load the street data where the radar set up. The street data is determined by a square shape with length $2R_{ins}$ (m) and center in the radar position (see Figure 11), where R_{ins} is the radar instrumented range.



Figure 11. Illustration of the radar position and the loaded street data (the square shape)

Step 2. Using formulas (2) and (3) calculate the latitude and longitude of Point A (see Figure 12) with (lat_{root}, lon_{root}) is the latitude and longitude of the radar.

Step 3. For each street in the loaded data, convert coordinates of all nodes into Cartesian coordinate using formulas (5), (6), the latitude and longitude of Point A as (lat_{root}, lon_{root}) .

Step 4. Connect consecutive nodes of a street and interpolate values (coordinates) for other points in the street (in order of resolution 1m of the street map). Repeat for all other streets we obtain the street map with (approximately) the same range resolution with the radar (see Figure 12).



Figure 12. A street map (red color) displayed on the radar screen

For analyzing of moving characteristic of radar discrete clutters with respect to the street map we collect 10676 distance samples and 9311 moving direction samples from 380 discrete clutter (cars, motorbikes, birds) and take the statistic of the distance and moving direction of targets to the nearest street on the street map. The statistic results are given in Figure 13.

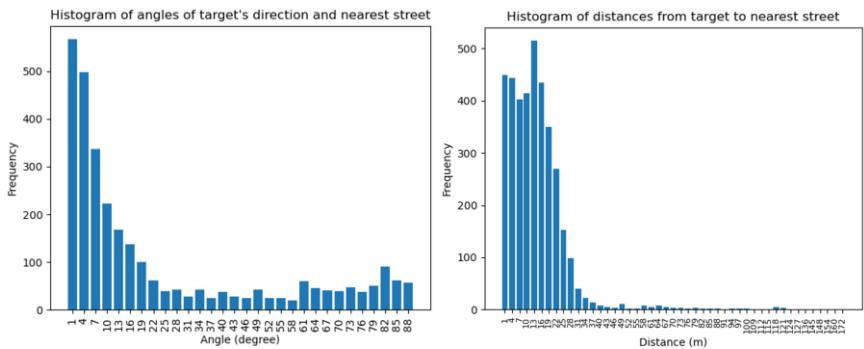


Figure 13. Statistic results of radar target trajectories

3. Proposed method and test results

3.1. Proposed method

We propose a system design and algorithms for module “Discrete clutter reduction”. The principle of the module is included in the classification of discrete clutters and drones. The design of the module is represented in Figure 14.

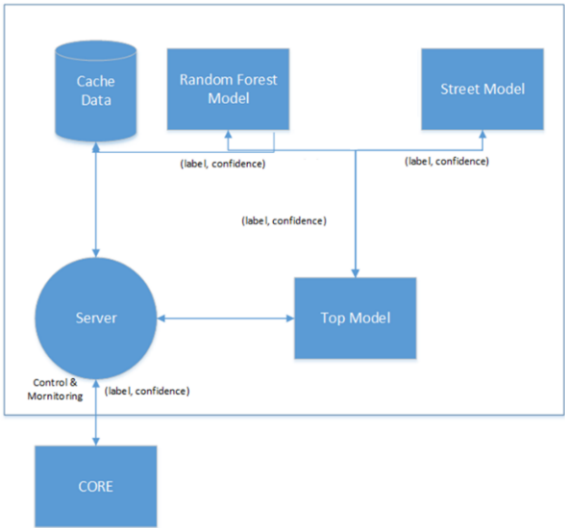


Figure 14. System design of module “Discrete clutter reduction”

The data flow is as follows.

Step 1: From “Core” the target parameters (such as ranges, azimuths, moving direction) is transferred into “Random Forest Model” and “Street Model” via “Server” and “Top Model”.

Step 2: Each of submodules “Random Forest Model” and “Street Model” will predict the targets as “drone” or “discrete clutter” and sends the label with confidence score (probability of classification) back to the “Top Model”.

Step 3: At the “Top Model” a decision for each target is confirmed and the results are back in “Core” to display on the radar monitor.

The algorithms for “Random Forest Model”, “Street Model” and “Top Model” are described in Algorithm 1, Algorithm 2 and Algorithm 3 respectively.

Algorithm 1 (Random forest model).

Input: Doppler dispersion of targets;

Output: targets label (“drone” or “discrete clutter”);

Model: random forest with 20 trees;

Dataset for training: we collect 20.000 samples with 10.000 samples of drones and 10.000 samples of discrete clutter.

The structure of a decision tree is given in Figure 15.

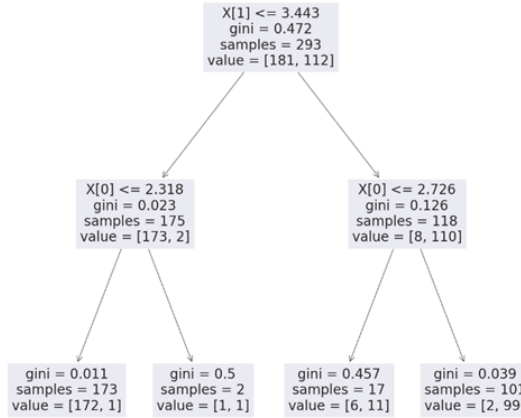


Figure 15. Structure of a decision tree ($X[1]$ is $\overline{\Delta f_D}$ and $X[0]$ is $\sigma_{\Delta f_D}$)

Algorithm 2 (Street model).

Input: target’s trajectory from radar;

Output: target’s label (“drone” or “undefined”).

Step 1: For a radar target, convert its ranges and azimuths to latitude and longitude coordinates using formulas (2) and (3). Then using formulas (5) and (6) with the root at Point A (Figure 12) we obtain target’s positions in the street map (see Figure 16).

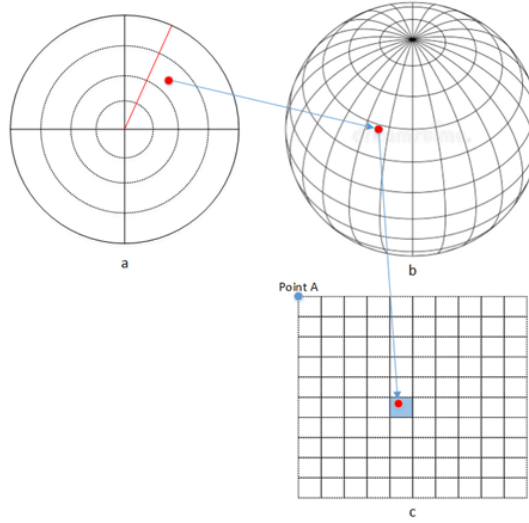


Figure 16. Illustration of the coordinate conversions in Step 1: target's position on radar screen (a), geographic coordinate (b) and street map (c)

Step 2: From the target's current position (in the street map) open a square gate with center at target's position and radius r (see Figure 17). If there is a node (point) in the gate which belongs to a street, then target's current position is considered as "near street".

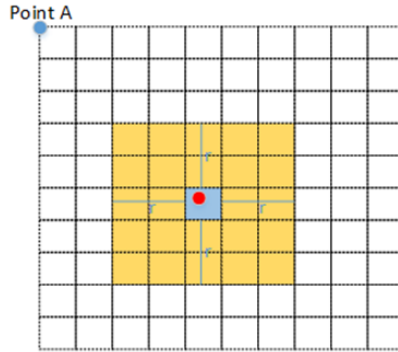


Figure 17. An example of a square gate on the street map

Step 3. Repeat Step 2 for N consecutive radar scans, if there are at least M scans at which target's position is near street and $M \geq N \times \text{nearStreetRate}$, then we decide that the target is near street.

Step 4. For a near street target, consider N last radar scan ($n-N+1, n-N+2, \dots, n$) where n is the current radar scan. A window with length k ($k < N$) is used to calculate $N-k+1$ angles $\{angle_1, angle_2, \dots, angle_{N-k+1}\}$ between target's moving direction and the nearest street. If $\text{median}\{angle_1, angle_2, \dots, angle_{N-k+1}\} < \text{angleMax}$, then we conclude that the target is moving along the street.

Step 5. If a target is moving along the street we classify it as "undefined", else classify as "drone".

The parameters used in this study for algorithm 2 are given in Table 2.

Table 2. Parameter values for Algorithm 2

Parameter	Value
r (radius of square gate)	30m
N (number of consecutive scans)	15
$nearStreetRate$	0.5
k (window size)	5.0
$angleMax$	30degree

Algorithm 3 (Top model).

The top model uses rule-based method to confirm a target as “drone” or “discrete clutter”.

Input: target’s labels from submodules “Random Forest Model” (for short: RFM) and “Street model” (for short: StM); active ranges of models (1,7km for random forest model and 12km for street model as given in section 2);

Output: target’s confirmed label (“drone”, “discrete clutter” or “undefined”).

The main logic rules of the top model are as follows (see Figure 18 for more details).

If RFM is inactive, i.e. the target’s range is greater than 1,7km, then StM is used.

If target’s predicted label (PRED) is different with “UNDEFINED”, then use MN logic (in this study $M = 6$, $N = 10$) to confirm target as “drone” or “discrete clutter”.

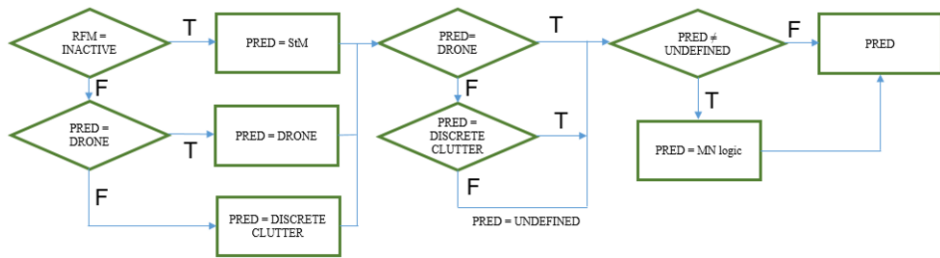


Figure 18. Diagram of Top model

3.2. Test results

The module was integrated in the radar system and tested with different drones (inspire 2, phantom 4, mavic 3) in different moving scenarios (such as radial flight, tangent flight). For the performance evaluation we use the following metrics:

$$\text{True Rate of Clutter Reduction (TRCR)} = \frac{\text{number of true clutters classified}}{\text{number of all discrete clutters}} \quad (8)$$

$$\text{True Rate of Drone Recognition (TRDR)} = \frac{\text{number of true drone classified}}{\text{number of all drones}} \quad (9)$$

$$\text{MRDR} = \text{Maximum Range for Drone Recognition} \quad (10)$$

The results are given in Table 3 and Figure 19-21.

Table 3. Test results	
Parameter	Value
TRCP	0.95
TRDR	1.0
MRDR for drones moving across the streets	3.0km
MRDR for drones moving along the streets	1.7km

For comparison, Table 4 shows the results of our study and of Robin [17].

Table 4. Comparison with the same module on Robin drone detection radar

Parameter	Robin radar	Proposed module
TRCP	-	0.95
TRDR	-	1.0
MRDR	2.2km	3.0km



Figure 19. “Discrete clutter” and “Drone” on radar screen (recognize a drone from 3km)



Figure 20. Test results with different moving scenarios: drone moves in a sinusoidal trajectory (above) and along the street (below)



Figure 21. Three drones (inspire 2, phantom 4 and mavic 3) and a bird (inside the circle) in a test

4. Conclusion and future works

The paper presented the new approach for discrete clutter reduction with drone detection radars. A machine learning and a street model is combined to reduce discrete clutter and recognize a drone based on Doppler diversion moving trajectories. The tests show that 95% discrete clutter was rejected while 100% drones were exactly recognized.

In future works we will extend the study to recognize more different types of targets such as drones, helicopter, UAV from discrete clutter.

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BỘ KHOA HỌC VÀ CÔNG NGHỆ
CỤC SỞ HỮU TRÍ TUỆ

CỘNG HÒA XÃ HỘI CHỦ NGHĨA VIỆT NAM
Độc lập – Tự do – Hạnh phúc

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Chủ Bảng độc quyền:

TẬP ĐOÀN CÔNG NGHIỆP - VIỆN THÔNG QUẢN ĐỘI (VN)
Lô D26 Khu đô thị mới Cầu Giấy, phường Yên Hoà, quận Cầu Giấy,
thành phố Hà Nội.

Tác giả:

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2. (Danh sách kèm theo)

Số đơn:

1-2023-06876

Ngày nộp đơn:

03/10/2023

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VN 1-005



Lê Huy Anh

BẢNG ĐỘC QUYỀN SÁNG CHẾ SỐ: 52696

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(12) BẢN MÔ TẢ SÁNG CHẾ THUỘC BẰNG ĐỘC QUYỀN SÁNG CHẾ

(19) Cộng hòa xã hội chủ nghĩa Việt Nam (VN)
CỤC SỞ HỮU TRÍ TUỆ

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(43) 25/01/2024 430A

(73) TẬP ĐOÀN CÔNG NGHIỆP - VIỆN THÔNG QUÂN ĐỘI (VN)

Lô D26 Khu đô thị mới Cầu Giấy, phường Yên Hoà, quận Cầu Giấy, thành phố Hà Nội.

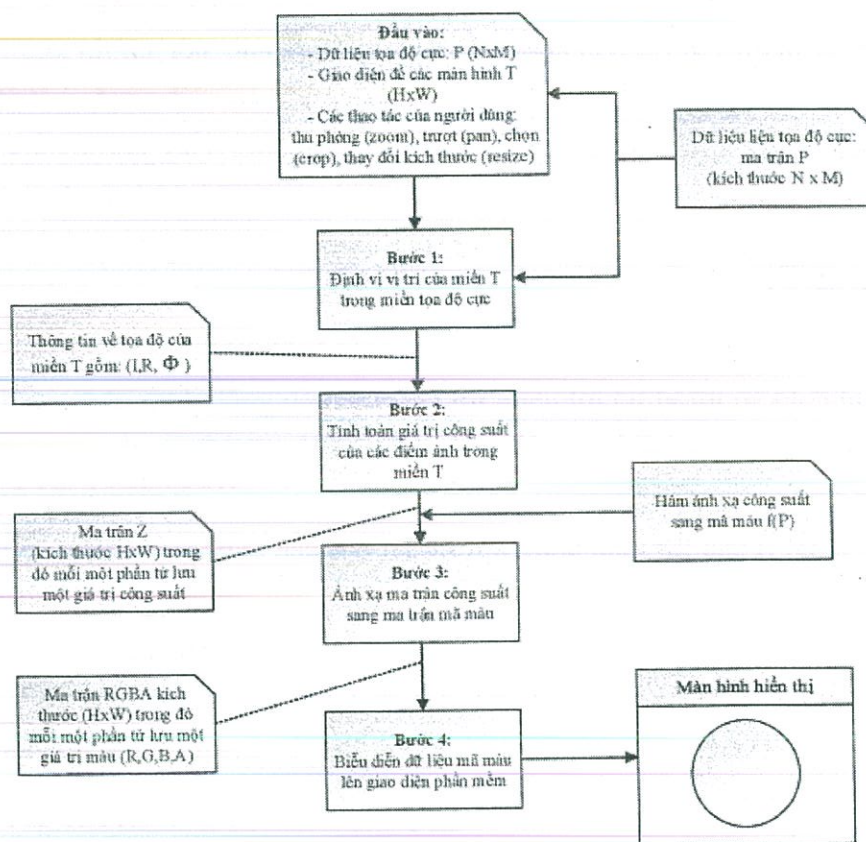
(72) TRẦN TRUNG KIÊN (VN); VŨ TRUNG NGHĨA (VN); NGUYỄN VĂN KHƯƠNG (VN); TRẦN VŨ HỢP (VN); TRẦN QUỐC TUÂN (VN).

(74) Công ty TNHH NACILAW (NACILAW)

(54) PHƯƠNG PHÁP CHUYỂN ĐỔI VÀ HIỆN THỊ DỮ LIỆU QUÉT RA-ĐA ĐỘ
PHÂN GIẢI CAO

(21) 1-2023-06876

(57) Sáng chế đề xuất phương pháp chuyển đổi và hiển thị dữ liệu quét với các đài ra-đa độ phân giải cao, dựa trên ý tưởng cho phép máy tính chỉ cần xử lý tính toán trên không gian dữ liệu của số giao diện trên miền đề-các thường rất nhỏ so với không gian dữ liệu tọa độ cực chứa dữ liệu quét ra-đa. Phương pháp đề xuất giúp tăng hiệu năng của chương trình về cả số lượng khung hình trên giây (FPS) cũng như chất lượng hình ảnh biểu diễn dữ liệu quét ra-đa trên tọa độ đề-các, ngoài ra độ chi tiết của hình ảnh hiển thị tự động thay đổi phù hợp với miền quan sát hiện tại của mắt người, tùy theo kích thước khung hình và mức độ thu phóng mà không phụ thuộc vào lưới tọa độ cực rất lớn ban đầu.



Hình 1

52696

SỬA ĐỔI



(12) BẢN MÔ TẢ SÁNG CHẾ THUỘC BẰNG ĐỘC QUYỀN SÁNG CHẾ

(19) Cộng hòa xã hội chủ nghĩa Việt Nam (VN)
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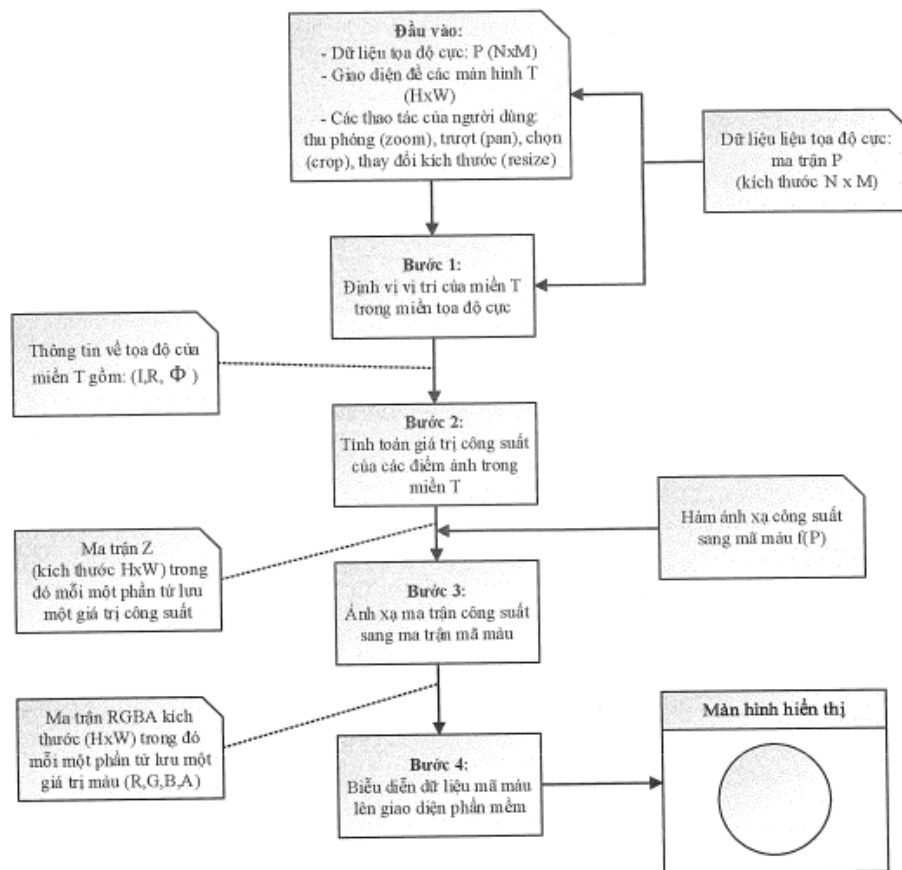
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Hình 1

Lĩnh vực kỹ thuật của sáng chế

Sáng chế đề cập tới phương pháp chuyển đổi và hiển thị dữ liệu quét ra-đa độ phân giải cao. Cụ thể, các đài ra-đa phát sóng điện từ ra ngoài không gian và nhận về tín hiệu phản xạ dưới dạng công suất, tín hiệu phản xạ này được số hóa và hiển thị trên phần mềm vận hành ra-đa; sáng chế sau đây đề xuất một phương pháp chuyển đổi dữ liệu, tối ưu chất lượng hiển thị và tốc độ hiển thị dữ liệu quét của các đài ra-đa có độ phân giải tín hiệu cao.

Tình trạng kỹ thuật của sáng chế

Một trong những đặc điểm quan trọng của ra-đa là cho phép quan sát mục tiêu theo thời gian thực, để làm được điều này là sự kết hợp của rất nhiều chuyên ngành khác nhau như: cơ khí, điện tử viễn thông, điều khiển tự động, công nghệ thông tin,.... Phạm vi của sáng chế này xét đến khía cạnh xử lý thông tin và hiển thị dữ liệu quét lên phần mềm hiển thị giao diện cho các đài ra-đa có độ phân giải tín hiệu cao. Cụ thể, các đài ra-đa phát sóng điện từ ra ngoài không gian và nhận về tín hiệu phản xạ, tín hiệu phản xạ này được số hóa và hiển thị trên phần mềm vận hành ra-đa, dữ liệu này đến theo từng tia phương vị theo thời gian thực; thể hiện công suất phản xạ tại các giá trị cự ly tăng dần từ cự ly tối thiểu tới cự ly tối đa phát hiện được; tùy theo loại ra-đa, cự ly tối đa có thể từ vài kilomet đến vài trăm kilomet, khi nhận được dữ liệu này, phần mềm xử lý và hiển thị lên giao diện tọa độ đề-các (Cartesian). Dữ liệu địa vật này thường được biểu diễn dưới dạng màu sắc thể hiện mức công suất tại các ô cự ly – phương vị theo miền tọa độ cực. Trong khi đó, cần phải thể hiện dữ liệu đó trên màn hình đồ họa với miền tọa độ đề-các với đơn vị là điểm ảnh (pixel). Từ đây xuất hiện bài toán biểu diễn tọa độ cực (Polar Data - tập các tia phương vị) trên miền đề-các của giao diện cửa sổ máy tính, trong lĩnh vực ra-đa bài toán này có tên là chuyển đổi dữ liệu quét ra-đa (Radar Scan Conversion - RSC).

Đầu vào của RSC là một ma trận $P_{N \times M}$ trong đó:

- N là số tia phương vị trên một vòng quét ra-đa 360 độ, tương ứng với độ phân giải phương vị của đài ra-đa.
- M là số ô cự ly trên một tia phương vị, tương ứng với độ phân giải cự ly của đài ra-đa.
- $P_{i \times j}$ là giá trị công suất của tia phương vị thứ i tại cự ly j

$$P_{N \times M} = \begin{bmatrix} P_{00} & P_{01} & \dots & P_{0M} \\ P_{10} & P_{11} & \dots & P_{1M} \\ \dots & \dots & \dots & \dots \\ P_{N0} & P_{N1} & \dots & P_{NM} \end{bmatrix}$$

Ánh xạ góc phương vị (0-360 độ) sang số tia phương vị, và cự ly sang số ô cự ly, tùy vào độ chính xác của đài ra-đa thì sẽ có số tia phương vị và số ô cự ly khác nhau. Như vậy với một đài ra-đa có độ phân giải N tia phương vị và M ô cự ly trên mỗi tia phương vị thì độ lớn của ma trận là N x M (phần tử). Giả sử với một đài ra-đa độ phân giải cao, có độ phân giải phương vị là 14 bit, cự ly tối đa là 360 km và độ phân giải 2,5 mét trên một ô cự ly thì sẽ có N = 16383 và M = 144000 => Độ lớn của ma trận P rất lớn là ~ 2,4 tỷ điểm.

Đầu ra là hiển thị được dữ liệu tọa độ cực trên lên một giao diện tọa độ đề-các có kích thước $T_{H \times W}$, trong đó:

- W là chiều rộng của cửa sổ giao diện, đơn vị điểm ảnh.
- H là chiều cao của cửa sổ giao diện, đơn vị điểm ảnh.
- T_{ixj} là giá trị màu của điểm ảnh ở hàng i và cột j; giá trị màu thể hiện mức công suất phản xạ tại ô cự ly – phương vị đó; có hai loại thể hiện giá trị màu: đơn sắc (cùng một kênh màu, công suất lớn sẽ hiển thị màu đậm hơn), đa sắc (nhiều kênh màu dựa theo sắc độ).

Ngoài việc thể hiện lượng dữ liệu rất lớn lên màn hình, để thuận tiện trong việc quan sát dữ liệu quét ra-đa, còn phải hỗ trợ một số các thao tác để thuận tiện cho người sử dụng bao gồm: phóng to (zoom in), phóng nhỏ (zoom out), trượt (pan), chọn xem một vùng bất kì (crop) mà vẫn phải đảm bảo hiệu năng hiển thị.

Có nhiều phương án khác nhau để giải quyết bài toán RSC, tuy nhiên một đặc điểm chung của các phương pháp này là sử dụng các biện pháp xấp xỉ biên dạng địa vật tại các ô cự ly - phương vị theo hình thang và tận dụng khả năng tính toán song song của đồ họa GPU. Các phương pháp này thường chia miền đề-các thành các miền tứ giác với số lượng các miền này càng nhiều thì sự xấp xỉ càng chính xác, sau đó tìm ra các điểm ảnh ứng với các đỉnh, tính tọa độ cực của các đỉnh này và lấy ra giá trị công suất tương ứng, giá trị công suất của các điểm ảnh trong miền tứ giác sau đó được tính thông qua các đỉnh nhờ vào một phép nội suy tuyến tính (linear interpolation, bilinear interpolation, ...) hoặc không tuyến tính (cubic interpolation, bicubic interpolation, ...). Điều này làm giảm độ chính xác của dữ liệu trên miền tọa độ đề-các.

Một điểm quan trọng khác của các phương pháp kể trên là miền đề-các là miền vô cùng lớn và luôn chứa đủ dữ liệu tọa độ cực, điều này có nghĩa là các phương pháp này phải xử lý trên toàn bộ dữ liệu của tọa độ cực trong khi thực tế chỉ cần xử lý trên tổng số điểm ảnh của cửa sổ giao diện, con số này là một hằng số và thường bé hơn rất nhiều so với kích thước của dữ liệu tọa độ cực, thường độ phân giải màn hình hiện tại là 1920x1080, tương đương với 2073600 điểm ảnh. Việc phải xử lý trên toàn bộ dữ liệu như vậy khiến cho chương trình chạy chậm, giập khung hình và tốn hiệu năng của máy tính và không đảm bảo hiển thị dữ liệu theo thời gian thực.

Để giải quyết vấn đề trên, sáng chế đề xuất một phương pháp mới cho phép máy tính chỉ cần xử lý trên miền dữ liệu quét địa vật đề-các bằng với kích thước của cửa sổ giao diện và nhỏ hơn rất nhiều so với dữ liệu quét trong miền tọa độ cực ban đầu, phương pháp cũng cho phép xác định chính xác giá trị công suất của từng điểm ảnh hiển thị mà không cần phải thông qua các phép xấp xỉ, từ đó giúp cho hình ảnh biểu diễn chính xác hơn cũng như biểu diễn được biên dạng địa vật dạng hình thang cong chính xác đến từng điểm ảnh và từng ô phân giải ra-đa khi thao tác thu phóng, ngoài ra độ chi tiết của hình ảnh hiển thị tự động thay đổi phù hợp với miền quan sát hiện tại của mắt người, tùy theo kích thước khung hình và mức độ thu phóng mà không phụ thuộc vào lưới tọa độ cực rất lớn ban đầu.

Bản chất kĩ thuật của sáng chế

Mục đích của sáng chế là đề xuất một phương pháp biểu diễn dữ liệu tọa độ cực trên miền đề-các để tối ưu hiển thị dữ liệu quét ra-đa trong các hệ thống ra-đa độ phân giải cao, sáng chế có hai cải tiến như sau:

- Phương pháp đề xuất chỉ cần xử lý hiển thị dữ liệu trên miền đề-các có kích thước $H \times W$ (H: độ cao khung hình, đơn vị điểm ảnh; W: độ rộng khung hình, đơn vị điểm ảnh; khoảng một triệu điểm ảnh (pixels) với màn hình độ phân giải HD) trong khi các phương pháp trước xử lý toàn miền tọa độ cực có kích thước $N \times M$ (N: số ô cực ly, M: số ô phương vị).
- Độ chi tiết của hình ảnh dữ liệu công suất tự động thay đổi phù hợp với miền quan sát hiện tại của mắt người (tùy theo kích thước khung hình và mức độ thu phóng) mà không phụ thuộc vào lưới tọa độ cực rất lớn ban đầu.

Để đạt được mục đích nêu trên, sáng chế đề xuất bao gồm: khối định vị dữ liệu, khối tính toán giá trị công suất, khối ánh xạ công suất sang mã màu và khối hiển thị. Trong đó:

Khởi định vị: thực hiện định vị vị trí của miền đề-các $T_{H \times W}$ trong miền tọa độ cực dữ liệu ra-đa, nhận đầu vào là dữ liệu tọa độ cực dữ liệu quét ra-đa ma trận $P_{N \times M}$, khung giao diện màn hình $T_{H \times W}$ và các thao tác của người dùng, đầu ra là bộ tham số định vị vị trí của $T_{H \times W}$;

Khởi tính toán giá trị công suất: thực hiện tính toán giá trị công suất của các điểm ảnh trong miền $T_{H \times W}$, nhận đầu vào là thông tin vị trí của $T_{H \times W}$ trong tọa độ cực và dữ liệu tọa độ cực từ khởi định vị, đầu ra là một ma trận kích thước HxW trong đó mỗi điểm ảnh lưu một giá trị công suất tương ứng;

Khởi ánh xạ công suất sang mã màu: thực hiện ánh xạ công suất sang mã màu, nhận đầu vào là ma trận công suất từ khởi tính toán giá trị công suất, kèm theo hàm ánh xạ màu từ giá trị công suất sang mã màu, đầu ra là một ma trận hai chiều trong đó mỗi phần tử lưu bốn giá trị (R, G, B, A) thể hiện mã màu tương ứng;

Khởi hiển thị: thực hiện biểu diễn ma trận mã màu lên giao diện.

Để đạt được mục đích nêu trên, sáng chế thực hiện theo bốn bước sau, bao gồm: bước 1: định vị vị trí của khung hình đề-các $T_{H \times W}$ trên miền tọa độ cực; bước 2: tính toán giá trị công suất của từng điểm ảnh trong miền $T_{H \times W}$ dựa trên vị trí của khung hình trong tọa độ cực ra-đa; bước 3: ánh xạ ma trận công suất sang ma trận mã màu; bước 4: biểu diễn dữ liệu mã màu lên giao diện.

Trong sáng chế này tại bước 1, vị trí của khung hình $T_{H \times W}$ được định vị trên tọa độ cực là một khung hình chữ nhật, tỷ lệ giữa chiều rộng và chiều dài của $T_{H \times W}$ là không đổi, tuy nhiên tùy theo mức độ thu phóng và trượt của người dùng mà vị trí cũng như kích thước của khung hình $T_{H \times W}$ trên tọa độ cũng thay đổi theo, bước này sẽ mô tả cách định vị vị trí của $T_{H \times W}$ theo thao tác của người dùng. Ở bước thứ 2, sau khi đã định vị được chính xác vị trí của $T_{H \times W}$, lần lượt từng điểm ảnh trong $T_{H \times W}$ được tính toán ra giá trị công suất tương ứng, việc tính toán này là một phép tính hình học dựa trên các đỉnh và tâm của $T_{H \times W}$. Tại bước 3 và bước 4, các dữ liệu công suất được ánh xạ sang mã màu để vẽ lên giao diện, việc ánh xạ màu như nào là tùy người dùng sau này quyết định giúp tăng tính linh hoạt cũng như phù hợp với từng hàm ánh xạ màu cho từng loại ra-đa khác nhau.

Mô tả vắn tắt các hình vẽ

Hình 1: là sơ đồ phương pháp chuyển đổi và hiển thị dữ liệu quét ra-đa độ phân giải cao được đề cập trong sáng chế;

Hình 2: là hình vẽ định vị vị trí của miền đề-các màn hình trong hệ tọa độ cực ra-đa;

Hình 3: là hình vẽ ánh xạ miền tọa độ cực ra-đa vào hệ tọa độ màn hình ở tỉ lệ gốc;

Hình 4: là hình vẽ một số kịch bản sử dụng và sự thay đổi tương ứng của miền T trong tọa độ cực;

Hình 5: là hình vẽ xác định tọa độ cực của đỉnh A, B, C, D của miền T;

Hình 6: là hình vẽ xác định tọa độ cực của một điểm ảnh bất kỳ trên một đoạn thẳng khi biết tọa độ cực của 2 đầu mút;

Hình 7: là hình vẽ xác định tọa độ cực của toàn bộ điểm ảnh trên miền T.

Mô tả chi tiết sáng chế

Phần sau đây mô tả chi tiết về phương pháp tối ưu hiển thị dữ liệu địa vật trên các đài ra-đa dựa trên hình vẽ (Hình 1 là sơ đồ tổng thể của phương pháp), kèm theo diễn giải.

Hệ tọa độ được sử dụng: hệ tọa độ được sử dụng để biểu diễn dữ liệu quét ra-đa là hệ tọa độ cực, có tâm là vị trí đài ra-đa, góc 0 độ theo phương thẳng đứng, chiều quay theo chiều thuận kim đồng hồ. Trong thực tế, chiều quay của ra-đa là thuận chiều kim đồng hồ do đó việc chọn hệ tọa độ như trên giúp thuận tiện hơn trong quá trình tính toán và lập trình sau này.

Hệ tọa độ đề-các màn hình: hệ tọa độ được sử dụng trên phần mềm máy tính, có gốc tọa độ là góc trên bên trái, chiều x sang phải, chiều y xuống dưới.

Bước 1: định vị vị trí của khung hình đề-các $T_{H \times W}$ trên miền tọa độ cực ra-đa;

Xét trong hệ tọa độ đề-các, T là một hình chữ nhật có kích thước $H \times W$ và số lượng điểm ảnh mà D biểu diễn là $S_T = H \times W$ là hằng số không đổi khi không có các thao tác thay đổi khung hình hiển thị (Hình 2). Xét trong tọa độ cực thì dữ liệu ra-đa gửi về là một hình tròn có bán kính là $R_0 = M$ (M là cự ly phát hiện tối đa của đài ra-đa đó), lúc này T là một hình chữ nhật có tỷ lệ chiều dài và chiều rộng không đổi và có thể phóng to/thu nhỏ cũng như dịch chuyển tự do trên toàn miền. Như vậy vấn đề là làm sao để ánh xạ được các điểm ảnh trong T với các ô phân giải trong tọa độ cực ra-đa của P, để làm được điều đó cần một cách để xác định vị trí chính xác của T trong tọa độ cực. Vị trí của T được biểu thị thông qua ba tham số (I, R, Φ) với:

- I: tâm của T trên miền tọa độ cực là (r_I, φ_I) với r_I là cự ly từ tâm đặt đài O tới tâm I (đơn vị mét) và φ_I là góc phương vị từ tâm đặt đài O tới tâm I thuận chiều kim đồng hồ (đơn vị radian).
- R: độ dài 1/2 đường chéo của T xét trong miền tọa độ cực ra-đa.
- Φ : góc của T, góc này chỉ thay đổi khi người dùng thực hiện thao tác khung hình hiển thị.
- Các thông tin về góc và khoảng cách của các đỉnh (A, B, C, D) có thể được suy ra từ ba thông số (I, R, Φ) .

Dựa trên cách biểu diễn trên, tại thời điểm ban đầu hệ tọa độ cực toàn miền ra-đa được ánh xạ nên màn hình hiển thị trên miền T với tỉ lệ góc (Hình 3) thì tâm I của T có tọa độ $(0, 0)$;

$$\Phi = \arctan\left(\frac{H}{W}\right) \text{ và } R = \frac{R_0}{\sin(\Phi)}.$$

Khi người dùng thực hiện thao tác thu phóng khung hình hiển thị (zoom in/zoom out) thì cần tính toán lại tham số R; khi thực hiện trượt màn hình (pan) thì cần tính toán lại tâm I; khi chọn (crop) một vùng trên màn hình thì cần tính toán lại I và R; khi thực hiện thay đổi khung hình hiển thị (resize) thì cần tính toán lại cả ba tham số (I, R, Φ) .

Hình 4 mô tả sự thay đổi của T trong tọa độ cực theo một số thao tác thực hiện của người dùng. Có thể thấy tại thời điểm ban đầu, tỷ lệ phóng to/thu nhỏ là tỉ lệ góc (1.0), sau khi người dùng thực hiện thao tác phóng to, lúc này miền $T_{H \times W}$ thu nhỏ lại trên miền P làm phóng to vùng cần theo dõi lên. Điều này xảy ra là bởi dù có thực hiện bất kì thao tác nào đi nữa thì số lượng điểm ảnh biểu diễn trên màn hình trong miền T vẫn là $S_T = H \times W$ và không đổi, do đó khi miền T thu nhỏ trên miền P thì số lượng điểm ảnh biểu diễn cho một vùng dữ liệu của P được tăng lên, điều này không chỉ làm phóng to lên mà còn đảm bảo là khi người dùng phóng to một vùng nào đó càng nhiều thì biểu diễn trên T của vùng đó càng chính xác, đồng thời thời gian xử lý được giảm đi rất nhiều vì chỉ cần ánh xạ dữ liệu trong miền T chứa trong miền P, không phải ánh xạ dữ liệu trên toàn miền dữ liệu quét.

Ngược lại khi người dùng thực hiện thao tác thu nhỏ, khi đó số lượng điểm ảnh trên T là không đổi nhưng số lượng ô phân giải ra-đa cần được biểu diễn lại tăng lên dẫn đến giảm độ chính xác của dữ liệu cần biểu diễn. Tuy nhiên dù trong bất kì trường hợp nào thì chương trình chỉ cần tính ra được các ánh xạ tương ứng của $S_T = H \times W$ điểm ảnh trong miền T và không cần

tính toán trên toàn miền dữ liệu P, điều này giúp cho tăng hiệu năng của chương trình, giúp cho tốc độ biểu diễn dữ liệu tăng lên.

Như vậy độ chi tiết của dữ liệu quét ra-đa tự động thay đổi phù hợp với miền quan sát của mắt người (tùy theo kích thước khung hình và mức độ thu phóng) mà không phụ thuộc vào lưới tọa độ cực ra-đa rất lớn ban đầu, đồng thời giảm thời gian tính toán và hiển thị, đáp ứng thời gian thực.

Bước 2: tính toán giá trị công suất của từng điểm ảnh trong miền T dựa trên vị trí của khung hình trong tọa độ cực ra-đa;

Trong bước trước đã trình bày cách để định vị vị trí của miền T trong tọa độ cực ra-đa, bước này mô tả chi tiết cách để ánh xạ từ các điểm ảnh trong T sang các ô phân giải trong P từ đó lấy ra các giá trị công suất tương ứng. Quá trình ánh xạ gồm ba bước chính:

Bước 2.1: tính toán tọa độ của bốn đỉnh của miền T (A, B, C, D) trên hệ tọa độ cực ra-đa từ ba tham số (I, R, Φ) thông qua phép tính hình học trong tọa độ cực.

Như đã trình bày, để xác định tọa độ cực của các điểm ảnh (pixels) trước tiên cần xác định tọa độ cực của bốn đỉnh (A, B, C, D). Một tọa độ cần xác định hai tham số chính là (r, φ) , xét trường hợp xác định cho đỉnh A (Hình 5), dựa theo các công thức tính toán hình học được tạo ra trong sáng chế này, cách xác định như sau:

$$\begin{aligned}\bar{\angle}OE &= \varphi_I - \pi \\ \bar{\angle}IE &= \frac{\pi}{2} - \bar{\angle}OE = \frac{3\pi}{2} - \varphi_I \\ \bar{\angle}IO &= \pi - \Phi - \bar{\angle}IE = \varphi_I - \Phi - \frac{\pi}{2} \\ \Rightarrow \begin{cases} r_A = AO = \sqrt{R^2 + r_I^2 - 2r_I R \cos(\bar{\angle}IO)} \\ \varphi_A = \varphi_I + \arccos\left(\frac{r_I^2 + r_A^2 - R^2}{2r_I r_A}\right) \end{cases}\end{aligned}$$

Các đỉnh (B, C, D) được làm hoàn toàn tương tự như cách tính toán trên

Bước 2.2: tiến hành tính toán tọa độ của toàn bộ điểm ảnh trên miền T trên hệ tọa độ cực ra-đa dựa trên tọa độ điểm A và điểm D được tính từ bước 2.1.

Việc tính tọa độ của các điểm ảnh trong miền T có thể được quy về như trường hợp xác định tọa độ cực của một điểm ảnh X bất kỳ nằm trên đoạn thẳng AD khi biết trước tọa độ cực

của A và D (Hình 6). Đầu vào là tọa độ cực các điểm A, D, vị trí tương đối của điểm X trên đoạn thẳng là $p = \frac{AX}{AD}$, đầu ra cần tính được tọa độ cực của điểm ảnh X trên miền T, dựa theo các công thức tính toán hình học được tạo ra trong sáng chế này, cách xác định như sau:

$$\begin{aligned}\varphi_{DA} &= \varphi_D - \varphi_A \\ L_{AD} &= \sqrt{r_A^2 + r_D^2 - 2r_A r_D \cos(\varphi_{DA})} \\ L_{AX} &= p \cdot L_{AD} \\ \delta &= \arccos\left(\frac{r_A^2 + L_{AD}^2 - r_D^2}{2r_A L_{AD}}\right) \\ \Rightarrow \begin{cases} r_X = \sqrt{r_A^2 + L_{AX}^2 - 2r_A L_{AX} \cos(\delta)} \\ \varphi_X = \arccos\left(\frac{r_A^2 + r_X^2 - L_{AX}^2}{2r_A r_X}\right) \end{cases}\end{aligned}$$

Khi đã biết tọa độ cực của 4 đỉnh (A, B, C, D) trên miền T, lần lượt từ trái sang phải xác định cặp tọa độ biên trên và dưới của hình chữ nhật là X (r_X, φ_X), Y (r_Y, φ_Y) trên miền T (Hình 7) theo công thức tính toán trên. Từ tọa độ cực của 2 điểm biên trên và dưới X, Y, lần lượt xác định tọa độ cực của các điểm ảnh trên đoạn XY từ trên xuống dưới cũng theo công thức tính toán trên. Sau khi tính toán tọa độ cực của toàn bộ điểm ảnh trên toàn miền T, khi đó sẽ có kết quả là ma trận tọa độ cực của miền T như sau:

$$C = \begin{bmatrix} C_{00} & C_{01} & \dots & C_{0W} \\ C_{10} & C_{11} & \dots & C_{1W} \\ \dots & \dots & \dots & \dots \\ C_{H0} & C_{H1} & \dots & C_{HW} \end{bmatrix} \text{ với } C_{ij} = (r_{ij}, \varphi_{ij})$$

Bước 2.3: tiến hành ánh xạ dữ liệu tọa độ cực sang tọa độ trong miền P dưới dạng ô phân giải (cell) theo phương pháp lấy ô phân giải gần nhất.

Với N là số ô phân giải phương vị và M là số ô phân giải cự ly của đài ra-đa; λ là độ phân giải ô cự ly (đơn vị mét), N_{ij} và M_{ij} lần lượt là số ô phân giải phương vị và cự ly tại ô điểm ảnh (i, j), thực hiện tiến hành ánh xạ về miền $P_{N \times M}$ như sau:

$$N_{ij} = \text{round}\left(\frac{2\pi N}{\varphi_{ij}}\right); M_{ij} = \text{round}\left(\frac{r_{ij}}{\lambda}\right)$$

Do N_{ij} và M_{ij} phải là số nguyên, việc làm tròn thực hiện bằng cách làm tròn gần nhất (lấy ô phân giải gần nhất). Sau khi tìm được N_{ij} và M_{ij} tại từng ô điểm ảnh, thực hiện truy vấn giá trị công suất tại ma trận $P_{N \times M}$ là P_{ij} , thực hiện với tất cả các điểm ảnh trong miền T ta được ma trận công suất tương ứng như sau:

$$Z_{H \times W} = \begin{bmatrix} P_{00} & P_{01} & \dots & P_{0W} \\ P_{10} & P_{11} & \dots & P_{1W} \\ \dots & \dots & \dots & \dots \\ P_{H0} & P_{H1} & \dots & P_{HW} \end{bmatrix}$$

Bước 3: ánh xạ ma trận công suất sang ma trận mã màu;

Sau khi xử lý qua hai bước trên, lúc này thu được ma trận $Z_{H \times W}$ chứa các giá trị công suất của từng điểm ảnh, tiếp theo cần ánh xạ các giá trị công suất này sang mã màu để biểu diễn lên giao diện phần mềm. Mã màu được sử dụng bốn kênh màu (RGBA), xây dựng hàm mã màu $RGBA_{ij} = f(P_{ij})$ để ánh xạ từ dữ liệu công suất sang mã màu.

Có nhiều cách để ánh xạ sang mã màu, trong phạm vi sáng chế này trình bày phương pháp sử dụng mã màu đơn sắc để thể hiện công suất. Lựa chọn một kênh màu để thể hiện, mã màu của một kênh thể hiện bằng giá trị từ 0 tới 255. Với điểm ảnh (pixel) có giá trị công suất lớn thì giá trị mã màu lớn và ngược lại. Trong phạm vi sáng chế này, hàm $f(P_{ij})$ sẽ có dạng như sau:

$$\begin{cases} R(red), B(blue) = 0 \\ G(green) = P_{ij} / 255 \\ A(alpha) = 255 \end{cases}$$

Thực hiện ánh xạ tất cả giá trị công suất của ma trận $Z_{H \times M}$ sẽ thu được ma trận mã màu của từng điểm ảnh cần hiển thị.

$$RGBA_{H \times W} = \begin{bmatrix} f(P_{00}) & f(P_{01}) & \dots & f(P_{0W}) \\ f(P_{10}) & f(P_{11}) & \dots & f(P_{1W}) \\ \dots & \dots & \dots & \dots \\ f(P_{H0}) & f(P_{H1}) & \dots & f(P_{HW}) \end{bmatrix}$$

Bước 4: biểu diễn dữ liệu mã màu lên giao diện;

Qua bước này đã thu được giá trị màu của tất cả các điểm ảnh cần hiển thị, sau đó sử dụng thư viện đồ họa OpenGL để biểu diễn lên giao diện phần mềm. Với thư viện OpenGL sẽ dùng hàm `glDrawPixel()` để hiển thị lên phần mềm.

Yêu cầu bảo hộ

1. Phương pháp chuyển đổi và hiển thị dữ liệu quét ra-đa độ phân giải cao, bao gồm các bước:

bước 1: định vị vị trí của khung hình đề-các $T_{H \times W}$ trên miền tọa độ cực ra-đa:

với T là một hình chữ nhật có kích thước $H \times W$ và số lượng điểm ảnh mà T biểu diễn là $S_T = H \times W$ không đổi, $P_{N \times M}$ là ma trận chứa dữ liệu quét ra-đa (với N là số tia phương vị trên một vòng quét ra-đa, tương ứng với độ phân giải phương vị của đài ra-đa và M là số ô cự ly trên một tia phương vị, tương ứng với độ phân giải cự ly của đài ra-đa; vị trí của T trên miền tọa độ cực ra-đa được biểu thị thông qua ba tham số (I, R, Φ) với:

I : tâm của T trên miền tọa độ cực là (r_I, φ_I) với r_I là cự ly từ tâm đặt đài O tới tâm I (đơn vị mét) và φ_I là góc phương vị từ tâm đặt đài O tới tâm I thuận chiều kim đồng hồ (đơn vị radian);

R : độ dài 1/2 đường chéo của T xét trong miền tọa độ cực ra-đa;

Φ : góc của T , góc này chỉ thay đổi khi người dùng thực hiện thao tác khung hình hiển thị;

tại thời điểm ban đầu hệ tọa độ cực toàn miền ra-đa được ánh xạ nên màn hình hiển thị trên miền T với tỉ lệ góc thì tâm I của T có tọa độ $(0, 0)$; $\Phi = \arctan\left(\frac{H}{W}\right)$ và $R = \frac{R_0}{\sin(\Phi)}$;

khi người dùng thực hiện thao tác thu phóng khung hình hiển thị (zoom in/zoom out) thì cần tính toán lại tham số R ; khi thực hiện trượt màn hình (pan) thì cần tính toán lại tâm I ; khi chọn (crop) một vùng trên màn hình thì cần tính toán lại I và R ; khi thực hiện thay đổi khung hình hiển thị (resize) thì cần tính toán lại cả ba tham số (I, R, Φ) ;

bước 2: tính toán giá trị công suất của từng điểm ảnh trong miền T dựa trên vị trí của khung hình trong tọa độ cực ra-đa.

bước này mô tả chi tiết cách để ánh xạ từ các điểm ảnh trong T sang các ô phân giải trong P từ đó lấy ra các giá trị công suất tương ứng; quá trình ánh xạ gồm ba bước chính:

bước 2.1: tính toán tọa độ của bốn đỉnh của miền T (A, B, C, D) trên hệ tọa độ cực ra-đa từ ba tham số (I, R, Φ) thông qua phép tính hình học trong tọa độ cực; để xác định tọa độ cực của

các điểm ảnh trước tiên cần xác định tọa độ cực của bốn đỉnh (A, B, C, D); một tọa độ cần xác định hai tham số chính là (r, φ) , xét trường hợp xác định cho đỉnh A, cách xác định như sau:

$$\begin{aligned}\bar{\angle}OE &= \varphi_I - \pi \\ \bar{\angle}IE &= \frac{\pi}{2} - \bar{\angle}OE = \frac{3\pi}{2} - \varphi_I \\ \bar{\angle}IO &= \pi - \Phi - \bar{\angle}IE = \varphi_I - \Phi - \frac{\pi}{2} \\ \Rightarrow \begin{cases} r_A = AO = \sqrt{R^2 + r_I^2 - 2r_I R \cos(\bar{\angle}IO)} \\ \varphi_A = \varphi_I + \arccos\left(\frac{r_I^2 + r_A^2 - R^2}{2r_I r_A}\right) \end{cases}\end{aligned}$$

bước 2.2: tiến hành tính toán tọa độ của toàn bộ điểm ảnh trên miền T trên hệ tọa độ cực ra-đa dựa trên tọa độ điểm A và điểm D được tính từ bước 2.1.

việc tính tọa độ của các điểm ảnh trong miền T có thể được quy về như trường hợp xác định tọa độ cực của một điểm ảnh X bất kỳ nằm trên đoạn thẳng AD khi biết trước tọa độ cực của A và D; đầu vào là tọa độ cực các điểm A, D, vị trí tương đối của điểm X trên đoạn thẳng là $p = \frac{AX}{AD}$, đầu ra cần tính được tọa độ cực của điểm X trên miền T, cách xác định như sau:

$$\begin{aligned}\varphi_{DA} &= \varphi_D - \varphi_A \\ L_{AD} &= \sqrt{r_A^2 + r_D^2 - 2r_A r_D \cos(\varphi_{DA})} \\ L_{AX} &= p \cdot L_{AD} \\ \delta &= \arccos\left(\frac{r_A^2 + L_{AD}^2 - r_D^2}{2r_A L_{AD}}\right) \\ \Rightarrow \begin{cases} r_X = \sqrt{r_A^2 + L_{AX}^2 - 2r_A L_{AX} \cos(\delta)} \\ \varphi_X = \arccos\left(\frac{r_A^2 + r_X^2 - L_{AX}^2}{2r_A r_X}\right) \end{cases}\end{aligned}$$

khi đã biết tọa độ cực của 4 đỉnh (A, B, C, D) trên miền T, lần lượt từ trái sang phải xác định cặp tọa độ biên trên và dưới của hình chữ nhật là X (r_X, φ_X) , Y (r_Y, φ_Y) trên miền T trong hình 7 theo công thức tính toán trên. Từ tọa độ cực của 2 điểm biên trên và dưới X, Y, lần lượt xác định tọa độ cực của các điểm ảnh trên đoạn XY từ trên xuống dưới theo công thức tính toán trên. Sau khi tính toán tọa độ cực của toàn bộ điểm ảnh trên toàn miền T, , khi đó sẽ có kết quả là ma trận tọa độ cực của miền T như sau:

$$C = \begin{bmatrix} C_{00} & C_{01} & \dots & C_{0W} \\ C_{10} & C_{11} & \dots & C_{1W} \\ \dots & \dots & \dots & \dots \\ C_{H0} & C_{H1} & \dots & C_{HW} \end{bmatrix} \text{ với } C_{ij} = (r_{ij}, \varphi_{ij})$$

bước 2.3: tiến hành ánh xạ dữ liệu tọa độ cực sang tọa độ trong miền P dưới dạng ô phân giải (cell) theo phương pháp lấy ô phân giải gần nhất;

với N là số ô phân giải phương vị và M là số ô phân giải cự ly của đài ra-đa; λ là độ phân giải ô cự ly (đơn vị mét), N_{ij} và M_{ij} lần lượt là số ô phân giải phương vị và cự ly tại ô điểm ảnh (i, j) , thực hiện tiến hành ánh xạ về miền $P_{N \times M}$ như sau:

$$N_{ij} = \text{round}\left(\frac{2\pi N}{\varphi_{ij}}\right); M_{ij} = \text{round}\left(\frac{r_{ij}}{\lambda}\right)$$

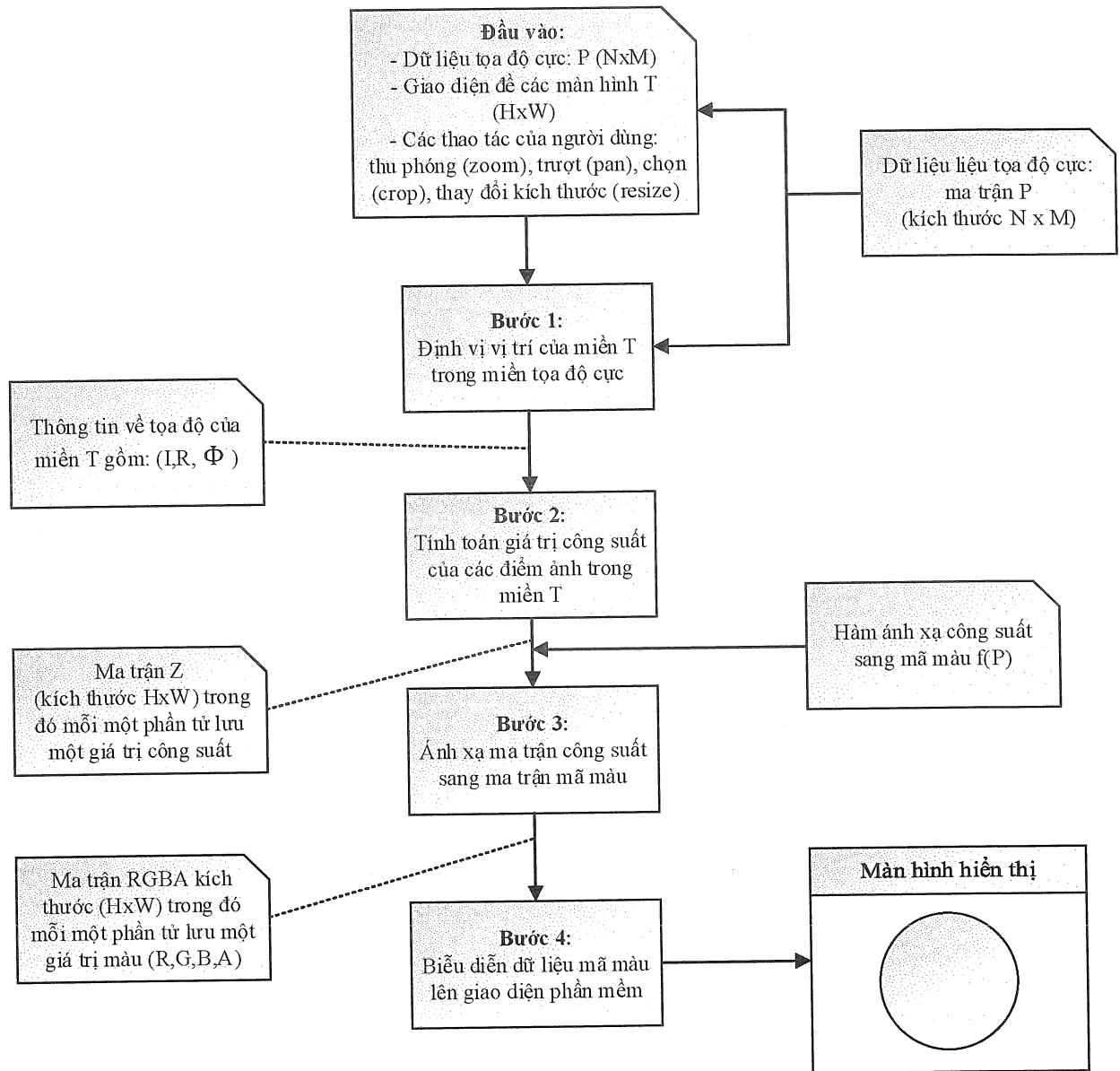
do N_{ij} và M_{ij} phải là số nguyên, việc làm tròn thực hiện bằng cách làm tròn gần nhất (lấy ô phân giải gần nhất); sau khi tìm được N_{ij} và M_{ij} tại từng ô điểm ảnh, thực hiện truy vấn giá trị công suất tại ma trận $P_{N \times M}$ là P_{ij} , thực hiện với tất cả các điểm ảnh trong miền T ta được ma trận công suất tương ứng như sau:

$$Z_{H \times W} = \begin{bmatrix} P_{00} & P_{01} & \dots & P_{0W} \\ P_{10} & P_{11} & \dots & P_{1W} \\ \dots & \dots & \dots & \dots \\ P_{H0} & P_{H1} & \dots & P_{HW} \end{bmatrix}$$

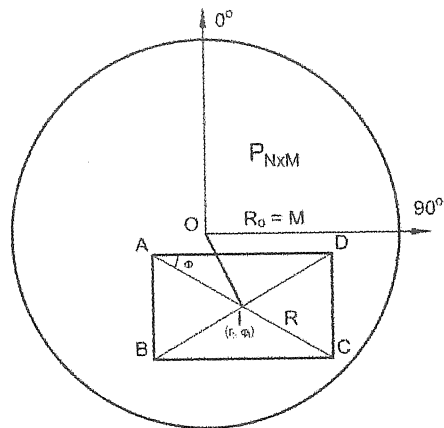
bước 3: ánh xạ ma trận công suất sang ma trận mã màu; lúc này thu được ma trận $Z_{H \times M}$ chứa các giá trị công suất của từng điểm ảnh, tiếp theo cần ánh xạ các giá trị công suất này sang mã màu để biểu diễn lên giao diện phần mềm; mã màu được sử dụng bốn kênh màu (RGBA), xây dựng hàm mã mẫu $RGBA_{ij} = f(P_{ij})$ để ánh xạ từ dữ liệu công suất sang mã màu; có nhiều cách để ánh xạ sang mã màu, trong phạm vi sáng chế này trình bày phương pháp sử dụng mã màu đơn sắc để thể hiện công suất; lựa chọn một kênh màu để thể hiện, mã màu của một kênh thể hiện bằng giá trị từ 0 tới 255; với điểm ảnh (pixel) có giá trị công suất lớn thì giá trị mã màu lớn và ngược lại; thực hiện ánh xạ tất cả giá trị công suất của ma trận $Z_{H \times M}$ sẽ thu được ma trận mã màu của từng điểm ảnh cần hiển thị;

$$RGBA_{H \times W} = \begin{bmatrix} f(P_{00}) & f(P_{01}) & \dots & f(P_{0W}) \\ f(P_{10}) & f(P_{11}) & \dots & f(P_{1W}) \\ \dots & \dots & \dots & \dots \\ f(P_{H0}) & f(P_{H1}) & \dots & f(P_{HW}) \end{bmatrix}$$

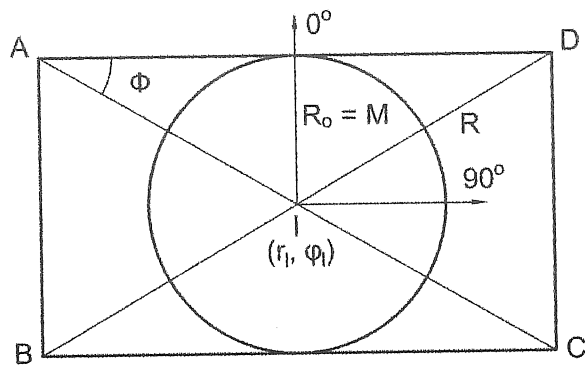
buớc 4: biểu diễn dữ liệu mã màu lên giao diện; tại bước này sử dụng thư viện đồ họa OpenGL để biểu diễn lên giao diện phần mềm; với thư viện OpenGL sẽ dùng hàm `glDrawPixel()` để hiển thị.



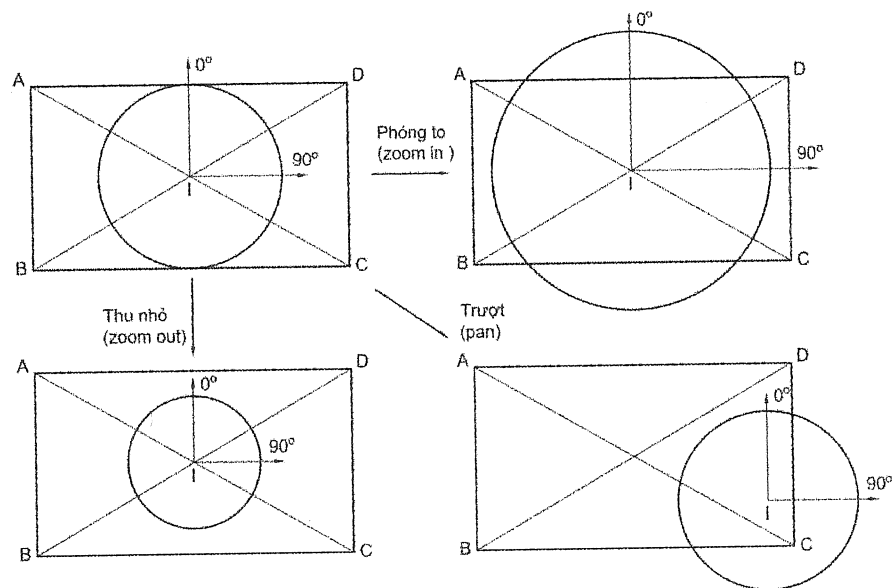
Hình 1



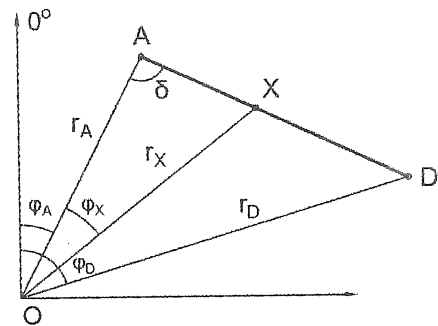
Hình 2



Hình 3



Hình 4



Hình 6



Hình 7