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Knowledge-Aided CFAR Detection Method for UAV Targets Postprint

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Abstract

Unmanned aerial vehicles (UAVs), as typical low, slow, and small targets, exhibit characteristics such as low flight speed, low altitude, and small radar cross-section (RCS), making UAV targets difficult to detect and recognize. To address the challenges of low signal-to-noise ratio and difficult detection for UAVs in complex environments, a knowledge-aided Constant False Alarm Rate (CFAR) detection method for UAV targets is proposed. This method first analyzes three common ground clutter distribution models and mean-type CFAR detectors, then applies CFAR detection methods to echo signals under these three clutter distributions, storing the method with optimal detection performance as the optimal CFAR detection method for that clutter distribution into a knowledge base, thereby establishing a CFAR knowledge base. By estimating the clutter distribution of the echo signal of the target to be detected and determining the clutter distribution model, the corresponding CFAR algorithm is selected from the radar knowledge base based on this distribution to complete the detection of the echo signal. Finally, validation is performed using real measured data collected by radar, and simulation and experimental results verify the feasibility and effectiveness of the proposed method.

Full Text

Preamble

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Abstract

This paper proposes a knowledge-aided constant false alarm rate (CFAR) detection method for unmanned aerial vehicle (UAV) targets. UAVs represent typical low-altitude, slow-speed, small-radar-cross-section (RCS) targets that pose significant detection challenges in complex environments. The method first analyzes three common ground clutter distribution models and mean-level CFAR detectors, selecting the detection approach with optimal performance for each clutter distribution type. By estimating the clutter distribution of the radar echo signals under detection, the corresponding optimal detection method is retrieved from the radar knowledge base to complete signal detection. Finally, validation is performed using actual radar measured data. Both simulation and experimental results demonstrate the feasibility and effectiveness of the proposed approach.

1. Introduction

The rapid development of the UAV industry has brought convenience to society while simultaneously introducing new security threats. UAVs exhibit "low, small, slow" characteristics—low flight altitude, small radar cross-section, and slow speed—making them extremely difficult to detect, particularly in complex environments with strong ground clutter interference [1-3]. Improving detection performance for such low-slow-small targets represents a critical challenge in current radar systems [4-7].

Traditional CFAR algorithms mitigate clutter environmental effects by estimating background clutter power levels to calculate detection thresholds. Common approaches include cell-averaging CFAR (CA-CFAR), which uses the average clutter power from cells adjacent to the detection cell; greatest-of CFAR (GO-CFAR); smallest-of CFAR (SO-CFAR); and ordered-statistics CFAR (OS-CFAR) [8-10]. However, these conventional CFAR methods cannot adequately address the complexities of UAV operating environments. Recent deep learning-based detection methods have demonstrated superior performance compared to traditional CFAR across different signal-to-noise ratios, but they remain limited by single environment type constraints that fail to meet UAV detection requirements.

2. Methodology

2.1 CFAR Detection Principles

The CA-CFAR detector represents the most classical approach, assuming a homogeneous background environment with independent reference cells. Protection cells near the detection cell prevent target energy from occupying multiple range cells and affecting clutter power estimation. The clutter background power estimate for CA-CFAR is given by:

$$Z = \frac{1}{n}\sum_{i=1}^{n}(x_i + y_i)$$

where x_i and y_i are reference cells in the left and right windows, respectively, and n is the number of reference cells in each window. The detection probability for CA-CFAR in uniform Rayleigh clutter is:

$$P_{d,CA} = \left(1 + \frac{\lambda}{1+T}\right)^{-n}$$

where λ is the ratio of target signal power to noise power, and T is the threshold factor. The false alarm probability is:

$$P_{fa} = P[Y > TZ|H_0] = \exp(-T)$$

GO-CFAR, an improvement over CA-CFAR, addresses detection in strong clutter regions by selecting the greater of the means from the front and rear reference windows as the background power estimate. The clutter power estimate is:

$$Z_{GO-CFAR} = \max\left(\frac{1}{n}\sum_{i=1}^{n} x_i, \frac{1}{n}\sum_{i=1}^{n} y_i\right)$$

The false alarm probability for GO-CFAR is:

$$P_{fa,GO} = 2(1+T)^{-n} - (1+2T)^{-n}$$

The detection probability can be expressed as:

$$P_{d,GO} = 2\left(1 + \frac{\lambda}{1+T}\right)^{-n} - \left(1 + \frac{\lambda}{1+2T}\right)^{-n}$$

SO-CFAR is suitable for detection in clutter edge regions, using the smaller of the two reference window means as the clutter power estimate:

$$Z_{SO-CFAR} = \min\left(\frac{1}{n}\sum_{i=1}^{n} x_i, \frac{1}{n}\sum_{i=1}^{n} y_i\right)$$

The false alarm probability is:

$$P_{fa,SO} = 2\sum_{i=0}^{n-1}\binom{n-1+i}{i}(2+T)^{-(n+i)}$$

The detection probability is:

$$P_{d,SO} = 2\sum_{i=0}^{n-1} \binom{n-1+i}{i} \left(2 + \frac{\lambda}{1+T}\right)^{-(n+i)}$$

2.2 Clutter Distribution Models

UAV flight environments are complex, primarily involving urban and rural settings where ground clutter dominates. Current research identifies three main clutter models: Rayleigh, log-normal, and Weibull distributions [17]. The Rayleigh distribution, the most typical model for describing clutter distribution, has the probability density function:

$$p(x) = \frac{x}{\sigma^2} \exp\left(-\frac{x^2}{2\sigma^2}\right), \quad x \geq 0$$

where σ is the scale parameter. The Weibull distribution can describe clutter intermediate between Rayleigh and log-normal distributions:

$$p(x) = \frac{p}{q} \left(\frac{x}{q}\right)^{p-1} \exp\left[-\left(\frac{x}{q}\right)^p\right], \quad x \geq 0$$

where p is the shape parameter and q is the scale parameter. The log-normal distribution better describes complex sea or terrain clutter:

$$p(x) = \frac{1}{\sqrt{2\pi}\sigma x} \exp\left[-\frac{(\ln x - \mu)^2}{2\sigma^2}\right], \quad x \geq 0$$

where μ is the scale parameter and σ is the shape parameter.

2.3 Parameter Estimation

Clutter parameter estimation commonly employs maximum likelihood estimation (MLE) and moment-based methods, followed by goodness-of-fit tests to determine the clutter distribution type [18-19]. For Rayleigh distribution, both MLE and moment estimation yield parameter σ. Log-normal distribution uses MLE and moment methods to obtain shape parameter σ and scale parameter μ. Weibull distribution uses estimation methods for scale parameter q and shape parameter p.

2.4 Knowledge-Aided CFAR Framework

Based on the above analysis, we construct a knowledge-aided CFAR detection framework. The process involves: (1) performing clutter parameter estimation and fitting on echo data to determine clutter amplitude type, (2) selecting the corresponding optimal CFAR method from the knowledge base for the identified clutter distribution, and (3) conducting CFAR processing. This approach effectively solves the problem of single environment type in traditional CFAR methods and enables effective UAV target detection across different clutter distributions.

3. Simulation and Experimental Results

3.1 Simulation Data Analysis

Simulations were conducted using MATLAB with linear frequency-modulated continuous wave (LFMCW) signals. The radar signal had a center frequency $f_0 = 30$ GHz. The zero-memory nonlinearity (ZMNL) method generated Rayleigh, Weibull, and log-normal clutter signals with known parameters, which were then superimposed with LFMCW signals containing two UAV targets at distances of 800 m and 600 m. The false alarm probability was set to 10^{-6} with protection cell number $N_p = 4$.

For Rayleigh distribution clutter, CA-CFAR demonstrated the best detection performance, effectively identifying both targets without false alarms. GO-CFAR could detect targets but produced multiple false alarm points, while SO-CFAR failed to detect targets adequately. [FIGURE:N]

For Weibull distribution clutter, GO-CFAR exhibited the best performance, detecting both targets effectively. CA-CFAR could detect targets but with multiple false alarms, while SO-CFAR was insufficient for detection needs. [FIGURE:N]

For log-normal distribution clutter, GO-CFAR again showed optimal performance, detecting two UAV targets without false targets. CA-CFAR could detect moving targets but produced multiple false alarms, while SO-CFAR was inadequate. [FIGURE:N]

3.2 Measured Data Analysis

Radar measured data was collected using a triangular-wave LFMCW phased-array radar operating at 24 GHz carrier frequency, 200 MHz bandwidth, 1 ms period, and 2 MHz sampling frequency. The test target was a DJI Phantom 4 UAV. [FIGURE:N]

The measured data was processed using the knowledge-aided approach. Fitting results showed the clutter clearly deviated from log-normal distribution but matched Rayleigh distribution well, indicating the data followed Rayleigh clutter characteristics. Based on the established radar knowledge base, CA-CFAR was applied for Rayleigh distribution clutter. The detection results successfully identified the UAV target without false alarms, consistent with actual conditions and verifying algorithm feasibility. [FIGURE:N]

4. Conclusion

This paper proposes a knowledge-aided CFAR detection method for UAV targets. Compared with traditional CFAR, this approach improves UAV target detection performance in clutter environments by fitting the current flight clutter environment and selecting the optimal detection method from the knowledge base. Future work will continue to expand the knowledge base’ s auxiliary information to further enhance effective UAV target detection.

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