

CFAR Detection of High-Accelerating Targets: A Study of the Probability of False Alarm

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Abstract—Fast accelerating targets feature a nonnegligible time-varying Doppler shift which induces a drop in signal-to-noise ratio (SNR) at the output of a classical range-Doppler radar detector. The optimal detector against fast accelerating targets retrieves the maximum available SNR by a 3-D search to match the target echo to the target range, Doppler, and acceleration. This operation, however, modifies the statistical properties probability density function (p.d.f) and the correlation of background white Gaussian noise at the output of the filter and, ultimately, impacts the receiver probability of false alarm and how this can be robustly controlled. In this article, we study the statistical properties of white Gaussian background noise at the output of the optimal processor and propose a modified one-parametric largest exponential value (LEV) distribution to fit the receiver noise before the detection threshold. Two constant false alarm rate (CFAR) schemes are proposed and developed based on the modified LEV distribution and their performance is characterized analytically and compared with simulated data and experimental data collected at C-band. Results show that the distribution parameter of the modified LEV converges to a fixed value as the number of filters in the acceleration domain increases. This yields detection performance that is independent of the relevant detection parameters. CFAR results demonstrate that the probability of false alarm can be robustly controlled with the proposed solution on simulated and real experimental data.

Index Terms—Accelerating target, constant false alarm rate (CFAR), largest exponential value (LEV) distribution, probability of false alarm, radar detection.

I. INTRODUCTION

THE problem of detecting accelerating targets has been studied from the 1960s, and one of the first works developing the mathematical approach for optimal detection and the properties of the Doppler-acceleration ambiguity function was presented in [1]. An analog radar signal processor for the matched filtering of trains of coherent pulses

from targets displaying significant radial acceleration called coherent acceleration and velocity observation in real time (CAVORT) was introduced in [2]. Strengths and limitations of standard Doppler processing against accelerating targets were investigated in [3]. In [4], a method to detect accelerating targets against sea clutter was proposed which is based on the Wigner Distribution (WD) and relies on the knowledge that the phase of an accelerating target echo is of a quadratic form similar to chirps. Similarly, computationally efficient methods to compensate range and Doppler migrations and estimate the Doppler and acceleration of high speed accelerating targets were presented in [5]. Detection and estimation methods for complex maneuvering targets at high speed and acceleration, with jerk effects, were proposed in [6] which are based on a geometric-auxiliary location rotation transform and a periodic, scaled, generalized, high-order ambiguity function (PSGHAF). The probability of detection against accelerating targets in multiple input multiple output (MIMO) radars using orthogonal waveforms was investigated in [7] by studying the effects of range-Doppler migrations in standard range-Doppler processing. The detection of accelerating targets in a passive bistatic context was studied in [8] as a M-ary hypothesis testing problem. This study also proposes a parameterized expression of the probability of false alarm to control the detection threshold and its performance is investigated with experimental results. Target localization performance by a multistatic radar network in the presence of an accelerating target is presented in [9]. Two computationally efficient methods, that account for the target acceleration, to estimate the target range and target velocity are proposed that attain the Cramer–Rao lower bound (CRLB).

In the past, most research efforts have been dedicated to solutions and computationally efficient algorithms that can retrieve the full target signal-to-noise ratio (SNR) and improve detection performance. However, very little work has been done to understand their implications on the probability of false alarm and how this can be robustly controlled with little loss.

In this article, the statistical properties of the background noise after the range-Doppler-acceleration ambiguity function are studied in detail as a function of the number of acceleration filters employed at the radar receiver. A modified one-parametric largest exponential value (LEV) distribution is proposed to fit the noise probability density function (p.d.f) at the output of the optimal detector. The distribution parameter is shown to describe the equivalent percentage

Received 9 November 2025; revised 21 January 2026 and 24 March 2026; accepted 26 March 2026. Date of publication 30 March 2026; date of current version 3 April 2026. This work was supported in part by the Progetti di Rilevante Interesse Nazionale (PRIN) 2022 Project “Communications and Radar Co-Existence (CIRCE)” funded by European Union–NextGeneration under Grant 202238BJ2R and Grant CUP B53D23002180006. (Corresponding author: Fabiola Colone.)

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Digital Object Identifier 10.1109/TRS.2026.3679015

number of acceleration filters that, in practice, can be considered uncorrelated. The modified LEV distribution is used to develop two constant false alarm rate (CFAR) detection strategies to control the probability of false alarm at the detector. Results are corroborated with simulations and validated through the application against experimental data collected at C-band.

The rest of the article is organized as follows. Section II introduces the signal model and the optimal detector. It also contains the derivation of the noise statistics with respect to the acceleration and correlation properties. Section III presents the noise statistical characterization and contains the results of the simulations to find the parameters to fit the noise distribution and control the probability of false alarm. Section IV presents the mathematical development of two CFAR detection strategies and the demonstration that they both have CFAR properties with respect to the receiver noise mean power. The results of the simulations are then corroborated with experimental trials in Section V. Finally, conclusion and recommendations for further work are given in Section VI.

II. SIGNAL MODEL

Let us consider the binary detection model in equation (1) consisting of a noisy target return under the hypothesis H_1 and a noise only signal under hypothesis H_0 . The radar measures signals with complex envelopes

$$z(t) = \begin{cases} \tilde{b} \sqrt{E_s} s(t; \theta) + n(t), & H_1 \\ n(t), & H_0 \end{cases} \quad (1)$$

where E_s is a scaling factor representing the transmitted energy, $s(t; \theta)$ is the target echo complex signal with unit energy and target parameters θ , $n(t)$ is white noise with power spectral density (PSD) N_0 , and $\tilde{b}$ is commonly modeled as a target constant complex scaling factor, or as a zero-mean complex Gaussian random variable with $E\{|\tilde{b}|^2\} = 2\sigma_b^2$, to account for the target radar cross section (RCS) as well as multipath and propagation channel fluctuations [10].

The optimal solution to the detection problem in (1), when the target parameters θ are perfectly known, is well known [10]. The optimal detector to maximize the SNR for a Gaussian $\tilde{b}$ is of the form

$$\left| \int z(t) s^*(t; \theta) dt \right|^2 \leq \gamma \quad (2)$$

with threshold $\gamma = N_0(N_0 + 2\sigma_b^2 E_s / 2\sigma_b^2 E_s) \log \eta$, where η is a constant deriving from the log-likelihood ratio test. The results for the case of a constant complex $\tilde{b}$ are similar and can be found in [11] and [12].

When the vector of parameters is unknown, the generalized likelihood criterion is typically used, namely the parameters are estimated by finding θ that maximizes the square amplitude of the integral in (2) as follows:

$$\max_{\theta} \left| \int z(t) s^*(t; \theta) dt \right|^2 \leq \gamma \quad (3)$$

and the decision rules becomes suboptimal.

To investigate the suboptimal detector performance in terms of probability of false alarm, we study the properties of the complex noise process

$$x(\theta) = \int n(t) s^*(t; \theta) dt \quad (4)$$

under the hypothesis H_0 . The study of the cross correlation of $x(\theta)$ is important because it helps understand the expected statistics of the random variable

$$y = \max_{\theta} \left(|x(\theta_1)|^2, |x(\theta_2)|^2, \dots, |x(\theta_N)|^2 \right) \quad (5)$$

when the search for the maximum is obtained over a discrete finite number of target parameter samples θ_i , for $i = 1, \dots, N$. The number of samples of θ (that is N) is also commonly referred to as the number of filters at the receiver, to indicate filters were traditionally used to extract the values $x(\theta_i)$. The cross correlation $R(\delta\theta)$ of $x(\theta)$ is calculated as follows:

$$\begin{aligned} R(\delta\theta) &= E\{x(\theta) x^*(\theta + \delta\theta)\} \\ &= E\left\{ \int z(t_1) s^*(t_1; \theta) dt_1 \int z^*(t) s(t; \theta + \delta\theta) dt \right\} \\ &= \int \int N_0 \delta(t - t_1) s^*(t_1; \theta) s(t; \theta + \delta\theta) dt dt_1 \\ &= N_0 \int \int \delta(t - t_1) s^*(t_1; \theta) s(t_1; \theta + \delta\theta) dt dt_1 \\ &= N_0 \int s^*(t_1; \theta) s(t_1; \theta + \delta\theta) dt_1. \end{aligned} \quad (6)$$

We also observe that $x(\theta)$ is a zero-mean stationary random process with variance $E\{|x(\theta)|^2\} = N_0$. Finally, for a zero-mean Gaussian process the correlation of the process squared amplitude can be expressed as [13, pp. 562]

$$E\{|x(\theta)|^2 |x^*(\theta + \delta\theta)|^2\} = E\{|x(\theta)|^2\}^2 + |R(\delta\theta)|^2. \quad (7)$$

As a result, the covariance of the process $|x(\theta)|^2$ is $|R(\delta\theta)|^2$. This property can be easily demonstrated with the use of the characteristic function of a joint Gaussian vector and leads to the expression of the correlation coefficient

$$\rho(\delta\theta) = \left| \int s^*(t; \theta) s(t; \theta + \delta\theta) dt \right|^2. \quad (8)$$

A. Accelerating Target

Let us now assume that the signal $s(t; \bar{\theta})$ is the echo from a target that is moving radially with a constant acceleration $\bar{a}$, with the dynamic law

$$R(t) = \bar{R}_0 + \bar{v} \left(t - \frac{\bar{t}_0}{2} \right) + \frac{1}{2} \bar{a} \left(t - \frac{\bar{t}_0}{2} \right)^2 \quad (9)$$

where $\bar{R}_0$ and $\bar{v}$ are the range and speed at the instant $t = \bar{t}_0/2$. The received signal is delayed of a time delay

$$\tau(t) = \frac{2}{c} R \left(t - \frac{\tau(t)}{2} \right) \quad (10)$$

which can be approximated with a second-order polynomial

$$\tau(t) = \bar{t}_0 + \bar{\alpha}(t - \bar{t}_0) + \bar{\beta}(t - \bar{t}_0)^2 \quad (11)$$

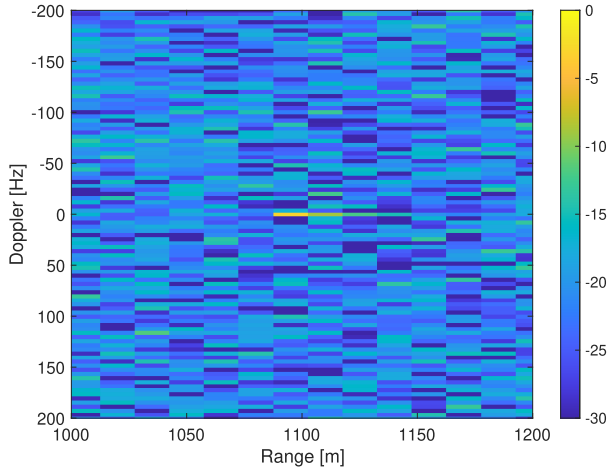


Fig. 1. Range Doppler map for a target with no acceleration obtained with standard Doppler processing.

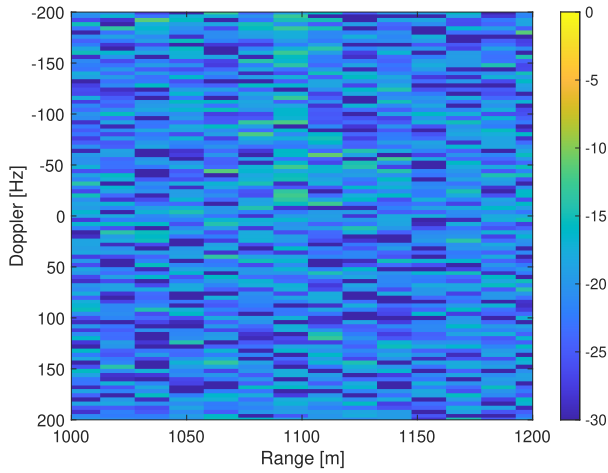


Fig. 2. Range Doppler map for a target moving with $a = 3g$ obtained with standard Doppler processing (no acceleration compensation).

to indicate that the time delay at $t = \bar{t}_0$ is $\bar{t}_0 = 2\bar{R}_0/c$, where c is the speed of light.

With some simple algebra [1], it is straightforward to determine that, because $\bar{v} \ll c$, the parameters $\bar{\alpha} \approx 2\bar{v}/c$ and $\bar{\beta} \approx \bar{a}/c$ and show that, under the narrowband approximation, the complex envelope of the noise-free received signal can be expressed as function of the complex envelope of the transmitted signal $s_T(t)$ as follows:

$$s(t; \bar{\theta}) = s_T(t - \bar{t}_0) e^{j2\pi \bar{f}_D t} e^{-j2\pi \frac{\bar{a}}{\lambda} (t - \bar{t}_0)^2} \quad (12)$$

with $\bar{f}_D = -2\bar{v}/\lambda$, where λ indicates the wavelength at the operating carrier frequency of the radar and $\bar{\theta} = [\bar{t}_0 \ \bar{f}_D \ \bar{a}]^T$ is the vector that contains the true target parameters.

The instantaneous frequency due to the phase terms of the signal in (12) is the following equation:

$$f_i(t) = \bar{f}_D - \frac{2\bar{a}}{\lambda} (t - \bar{t}_0). \quad (13)$$

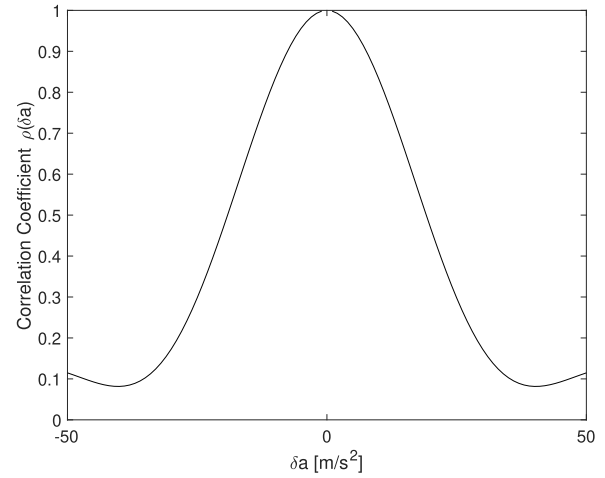


Fig. 3. Correlation coefficient for an unmodulated signal of duration $T = 40$ ms at 4.255 GHz. The plot is obtained as a direct implementation of (22).

With standard range-Doppler processing and a number of pulses N_p , a Doppler migration occurs when the frequency straddle within the integration time $N_p PRI$ is larger than the Doppler resolution $1/(N_p PRI)$ as follows:

$$\frac{2\bar{a}}{\lambda} N_p PRI > \frac{1}{N_p PRI} \quad (14)$$

and Doppler migration occurs when

$$\bar{a} > \frac{\lambda}{2} \left(\frac{PRF}{N_p} \right)^2. \quad (15)$$

An example of the effects of Doppler migration due to acceleration is presented in Figs. 1 and 2. The figures are related to a radar operating at 4.255 GHz that transmits a $10 \mu\text{s}$ long linear chirp of 10 MHz bandwidth with a PRF of 4 KHz. A target is simulated with an RCS that results in an SNR of -10 dB after pulse compression in the fast time slow time diagram and the radar integrates 1000 pulses (i.e., the final optimal SNR is 20 dB). If standard Doppler processing is applied, the target can be detected if it is not accelerating (Fig. 1) but falls under the noise floor for an acceleration of $3g$ with g being gravitational acceleration (Fig. 2).

In general, the vector of the unknown target parameters $\theta = [t_0 \ f_D \ a]^T$ consists of the target time delay, Doppler shift and acceleration. Here, we consider the detector that tests the presence of a target in any range-Doppler bin. The detector operates on a delay-Doppler grid by fixing the target time delay $t_0 = \bar{t}_i$ and the target Doppler $f_D = \bar{f}_j$ and for this delay-Doppler pair it only maximizes with respect to the target acceleration, i.e., $\theta = a$ is a scalar variable.¹ This operation is repeated for all available delay-Doppler pairs. With this

¹The analysis of the probability of false alarm is independent of the true target parameters. The probability of detection is a function of SNR and is maximized if the bin in the grid corresponds to the true target parameters. For the case of the train of pulses described in Section II-B, when the output of the detector is obtained in a slow time-fast time implementation, any range migrations should be compensated to maximize SNR.

detector and the signal model in (12), the cross correlation function of $x(a)$ becomes

$$\begin{aligned} R(\delta a) &= E \{x(a) x^*(a + \delta a)\} \\ &= N_0 \int |s_T(t - \bar{t}_i)|^2 e^{-j2\pi \frac{a(t-\bar{t}_i)^2}{\lambda}} e^{j2\pi \frac{(a+\delta a)(t-\bar{t}_i)^2}{\lambda}} dt \\ &= N_0 \int |s_T(t)|^2 e^{j\pi \frac{2\delta a}{\lambda} t^2} dt. \end{aligned} \quad (16)$$

We note that for a continuous signal with no amplitude modulation

$$s_T(t) = \begin{cases} \frac{1}{\sqrt{T}}, & 0 < t < T \\ 0, & \text{elsewhere} \end{cases} \quad (17)$$

observed for a dwell time T , the cross correlation function is proportional to the Fourier Transform in $f = 0$ of a linear chirp of duration T and chirp rate $\gamma = (2\delta a/\lambda)$. However, the corresponding time-bandwidth product of this chirp is $(2\delta a/\lambda)T^2$, which for common accelerations is a small number. We cannot therefore use standard stationary phase approximations to solve the integral as the time-bandwidth product is not large. In this case, we can express the integral as follows:

$$R(\delta a) = \frac{N_0}{T} \quad (18)$$

$$\begin{aligned} &\times \left[\int_0^T \cos\left(\frac{2\pi\delta a}{\lambda} t^2\right) dt \right. \\ &\left. + j \int_0^T \sin\left(\frac{2\pi\delta a}{\lambda} t^2\right) dt \right] \end{aligned} \quad (19)$$

and use the Fresnel functions

$$C(z) = \int_0^z \cos\left(\frac{\pi}{2} t^2\right) dt \quad (20)$$

and

$$S(z) = \int_0^z \sin\left(\frac{\pi}{2} t^2\right) dt. \quad (21)$$

The solution to the integrals, for $\delta a \geq 0$, can be written as a function of the Fresnel integrals after the change of variable $x = ((4\delta a/\lambda))^{1/2} t$ which leads to

$$\begin{aligned} R(\delta a) &= \frac{N_0}{T} \sqrt{\frac{\lambda}{4\delta a}} \\ &\times \left[\int_0^{\sqrt{\frac{4\delta a}{\lambda}} T} \cos\left(\frac{\pi}{2} x^2\right) dx + j \int_0^{\sqrt{\frac{4\delta a}{\lambda}} T} \sin\left(\frac{\pi}{2} x^2\right) dx \right] \\ &= \frac{N_0}{T} \sqrt{\frac{\lambda}{4\delta a}} \left[C\left(\sqrt{\frac{4\delta a}{\lambda}} T\right) + jS\left(\sqrt{\frac{4\delta a}{\lambda}} T\right) \right] \end{aligned} \quad (22)$$

and the covariance coefficient becomes

$$\rho(\delta a) = \left| \frac{1}{T} \sqrt{\frac{\lambda}{4\delta a}} \left[C\left(\sqrt{\frac{4\delta a}{\lambda}} T\right) + jS\left(\sqrt{\frac{4\delta a}{\lambda}} T\right) \right] \right|^2. \quad (23)$$

It is straightforward to observe that, as expected, $R(-\delta a) = R(\delta a)^*$ and that therefore $\rho(\delta a) = \rho(-\delta a)$. Fig. 3 shows the result of the direct implementation of (22) for an unmodulated signal of duration 40 ms at 4.255 GHz ($\lambda = 7.05$ cm). Results clearly show that the correlation coefficient never equals zero over the entire time interval, indicating that it is not possible to

obtain a sequence $|x(a_i)|^2$ of statistically independent samples (i.e., it is impossible to use processing filters whose outputs are statistically independent).

B. Pulsed Waveform

For a transmitted signal consisting of a train of pulses, the Fourier Transform of the received signal in (12) in the presence of the target acceleration is no longer a frequency shifted version of the Fourier Transform of a periodical signal of period equal to the pulse repetition interval (PRI). In addition, the cross correlation function with respect to a is also not periodical of the PRF.

Let us consider the case when the spacing δa is kept uniform and equal to a fraction of a reference spacing $\Delta a = (\lambda/2)((PRF/N_p))^2$ as follows:

$$\delta a = \frac{1}{2^m} \Delta a \quad (24)$$

for m integer and $m \geq 0$ and study (22). It can be observed that, for these values of δa , the term

$$\sqrt{\frac{\lambda}{T^2 4\delta a}} = \sqrt{\frac{\lambda}{N_p^2 \text{PRI}^2 4} 2^m \frac{N_p^2}{\lambda \text{PRF}^2}} = \sqrt{2^{m-1}} \quad (25)$$

and therefore

$$\begin{aligned} R_m(k) &= R(k\delta a) = N_0 \frac{\sqrt{2^{m-1}}}{\sqrt{k}} \\ &\times \left[C\left(\frac{\sqrt{k}}{\sqrt{2^{m-1}}}\right) + jS\left(\frac{\sqrt{k}}{\sqrt{2^{m-1}}}\right) \right] \end{aligned} \quad (26)$$

for $k = 1, \dots, N$. As a result, with this filtering scheme, the covariance coefficient

$$\rho_m(k) = \rho(k\delta a) = \frac{2^{m-1}}{k} \left| C\left(\frac{\sqrt{k}}{\sqrt{2^{m-1}}}\right) + jS\left(\frac{\sqrt{k}}{\sqrt{2^{m-1}}}\right) \right|^2 \quad (27)$$

does not depend on the radar parameters and on the background noise mean power. This is an interesting result because if we found that the probability distribution of y only depends on the correlation coefficients $\rho_m(k)$, we would be able to control the probability of false alarm for all radars equally.

Fig. 4 shows the plots relative to $\rho_m(k)$ for $m = 4, 5$ and 6.

C. Statistical Properties

We can now study the statistical properties of the random variable

$$y = \max(|x(a_1)|^2, |x(a_2)|^2, \dots, |x(a_N)|^2) \quad (28)$$

as a function of the number of filters N (i.e., the number of samples of $|x(a_i)|^2$ for $i = 1, \dots, N$). For $N = 1$, y is exponentially distributed with mean value N_0 . For $N > 1$, the distribution of y is known only when the N samples $x(a_i)$ are not correlated. In this case, the distribution is a LEV [14] with a cumulative distribution of the form

$$F_y(y) = (1 - e^{-y/N_0})^N \quad (29)$$

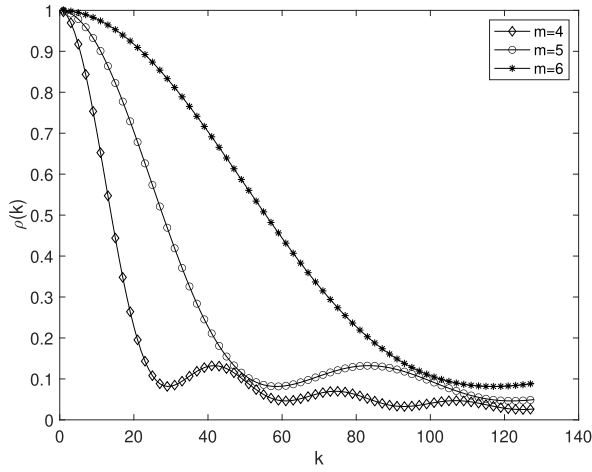


Fig. 4. Covariance coefficient as a function of the filter separation step k for different values of m .

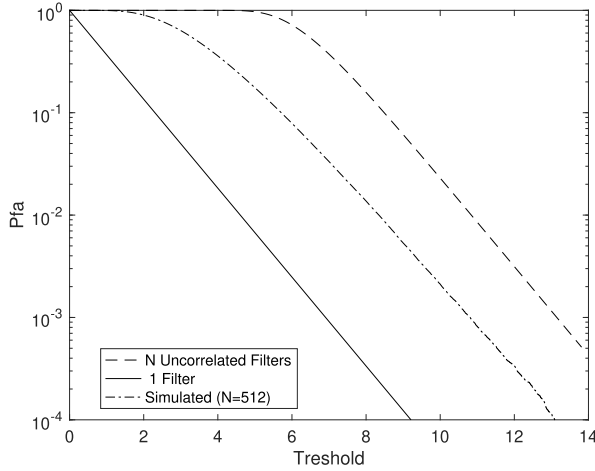


Fig. 5. Plots of the distribution for $N = 512$, $m = 4$, and $N_p = 10$. Simulated with 10^6 Monte Carlo Simulations.

and p.d.f.

$$f_y(y) = \frac{N}{N_0} (1 - e^{-y/N_0})^{N-1} e^{-y/N_0}. \quad (30)$$

When the N samples $x(\theta_i)$ are correlated the distribution of y is unknown. Fig. 5 shows a comparison of the probability of false alarm plots for $N = 1$ filter and $N = 512$ filters arranged with a spacing δ_a at 4.255 GHz and for $N_p = 10$. For comparison, the plot also shows the curve of the probability of false alarm corresponding to the case of $N = 512$ uncorrelated samples. The plot clearly shows that the simulated curve is between the other two curves. Neglecting the correlation between samples would therefore lead to significant errors in terms of P_{fa} .

III. STATISTICAL CHARACTERIZATION AND P_{Fa} CONTROL

In this article, we look for a suitable approximation of the cdf of y that could be conveniently used to guarantee the control of the false alarm rate (FAR). To this purpose, we propose to fit the simulated P_{fa} curves with those corresponding to a

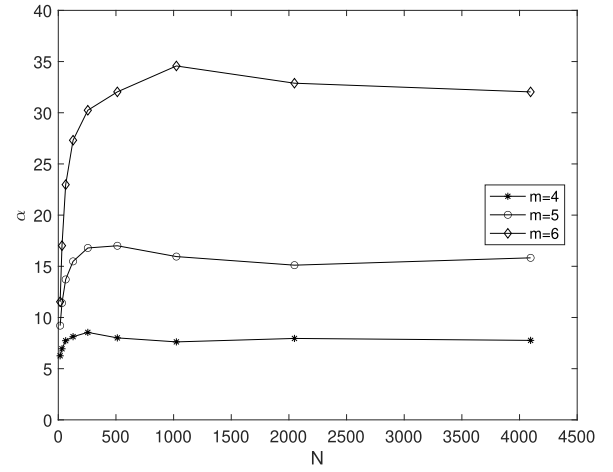


Fig. 6. Value of the parameter α obtained from the simulation as a function of the number of filters N for $m = 4, 5, 6$ and obtained for $P_{fa} = 10^{-5}$ and $N_p = 20$ pulses. Curves have been simulated with 10^8 Monte Carlo simulations.

TABLE I

VALUES OF $\hat{\alpha}$ FOR $P_{fa} = 10^{-3}$, $P_{fa} = 10^{-4}$ AND $P_{fa} = 10^{-5}$. THE VALUES IN THE TABLE HAVE BEEN ESTIMATED WITH $N = 1024$

m	$\hat{\alpha} (P_{fa} = 10^{-3})$	$\hat{\alpha} (P_{fa} = 10^{-4})$	$\hat{\alpha} (P_{fa} = 10^{-5})$
4	9.42	8.39	7.61
5	19.16	17.25	15.94
6	38.94	34.72	34.57

LEV distribution with a properly selected exponent which can be written as a function of a parameter α as follows:

$$F_y(y) \approx (1 - e^{-y/N_0})^{\frac{N}{\alpha}}. \quad (31)$$

If we determine α empirically as a function of the number of filters N and the position of the samples of $x(a_i)$, we can control the probability of false alarm. Given a threshold γ , the probability of false alarm P_{fa} is

$$P_{fa} = 1 - F_y(\gamma) = 1 - (1 - e^{-\gamma/N_0})^{\frac{N}{\alpha}} \quad (32)$$

and by a simple inversion

$$\gamma = -N_0 \ln \left(1 - (1 - P_{fa})^{\alpha/N} \right) \quad (33)$$

under the assumption that N_0 is perfectly known. Simulations are run as a function of the number of filters N with a spacing δ_a between filters as in (24). For the simulations, we consider a radar signal transmitting $N_p = 20$ pulses at a carrier frequency of 4.255 GHz and additive complex Gaussian noise with variance $N_0 = 1$. The probability of false is alarm is fixed to 10^{-5} to find the corresponding value of the threshold with a grid-search algorithm and predetermined interval step. For each threshold- P_{fa} pair, the value of the parameter α is obtained by inverting (32). This operation is repeated for N varying from 1 to 4096 and m varying from 4 to 6. Fig. 6 shows the results obtained for each m as a function of the number of filters N . Results show that for each m the parameter α converges to a limit $\hat{\alpha}$ as the number of filters increases. For a probability of false alarm equal to 10^{-5} , it takes about 1024 filters for the parameter α to converge for all values of m . Table I shows the values obtained for $\hat{\alpha}$ for a

TABLE II
VALUES OF $\hat{\alpha}$ WITH ASSOCIATED COVARIANCE COEFFICIENT

m	$\hat{\alpha}$	$\rho_m(\hat{\alpha})$	$\rho_m(\frac{\hat{\alpha}}{2})$
4	7.61	0.8177	0.9514
5	15.94	0.80	0.95
6	34.57	0.7706	0.9377

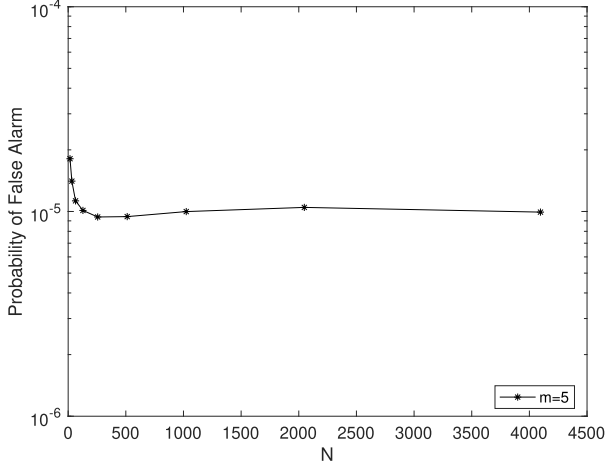


Fig. 7. Value of the Pfa obtained from the simulation as a function of the number of filters N for $m = 5$ obtained for $\alpha = 15.94$ and $N_p = 20$ pulses. Curves have been simulated with 10^8 Monte Carlo simulations.

probability of false alarm equal to $P_{fa} = 10^{-3}$, $P_{fa} = 10^{-4}$ and $P_{fa} = 10^{-5}$. Similar results are obtained for different values of N_p . However, the number of filters required for α to converge to $\hat{\alpha}$ reduces as the desired probability of false alarm increases. Table II reports the values of $\hat{\alpha}$ for a probability of false alarm of 10^{-5} and the corresponding values of the correlation coefficient calculated in $\hat{\alpha}$ and $(\hat{\alpha}/2)$ using (22). Results show that the values of $\rho(\hat{\alpha})$ and $\rho((\hat{\alpha}/2))$ remain about constant with respect to m . This is another interesting result as it allows a calculation of $\hat{\alpha}$ directly by inverting (22).

An interpretation of the hypothesis in (31) is that the ratio N/α represents the resulting number of equivalent acceleration filters that can be assumed independent and the parameter α the separation between these resulting equivalent filters. Clearly changing the step between filters will change the value of the number α in a directly proportional fashion.

To study the robustness of the model with respect to the number of filters N , the probability of false alarm is plotted as a function of N for $\alpha = 15.94$ (which was obtained experimentally for $P_{fa} = 10^{-5}$) in Fig. 7. The results show that the probability of false alarm remains largely constant as a function of N with the main deviation occurring for $N < 256$. Similarly, Fig. 8 shows FAR loss, calculated as the ratio between the obtained FAR and the desired probability of false alarm, as a function of a desired P_{fa} when the threshold is calculated with (33) with $\alpha = 15.94$. The results in the figure show that once $\hat{\alpha}$ is found at $P_{fa} = 10^{-5}$, the FAR loss resulting from calculating the threshold relative to other desired probability of false alarms remains within the interval (0.8,1.1) between $P_{fa} = 10^{-4}$ and $P_{fa} = 10^{-6}$. For completeness, Fig. 9 shows the probability of detection as a function of the SNR

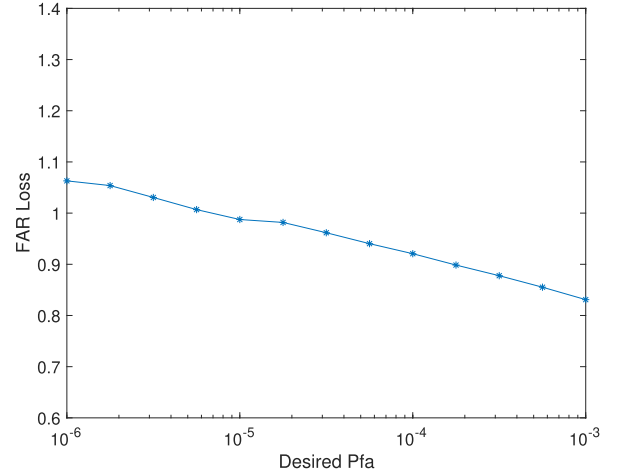


Fig. 8. FAR loss simulated for $\alpha = 15.94$ (obtained for $P_{fa} = 10^{-5}$) for $N = 512$ for $m = 5$ and $N_p = 20$ pulses. Curves have been simulated with 10^9 Monte Carlo simulations.

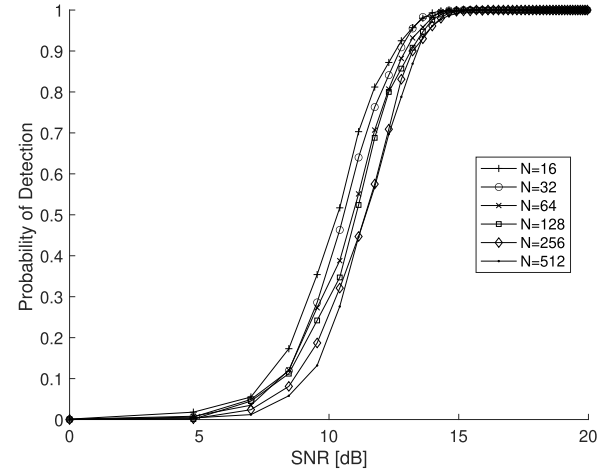


Fig. 9. Probability of detection versus SNR for $P_{fa} = 10^{-5}$ ($m = 5$ and $\alpha = 15.94$).

for multiple values of N , obtained by simulating a steady stationary target. The results have been obtained assuming the power of noise is known with the threshold calculated from (33) for a $P_{fa} = 10^{-5}$ ($\alpha = 15.94$) and $m = 5$. Results show that, because a large N is required, maintaining the probability of false alarm requires a higher threshold [see (33)] and this results in a small loss in probability of detection.

IV. CFAR DETECTION IN UNKNOWN BACKGROUND NOISE

In this section, two detection strategies are proposed and developed analytically for the case of unknown background noise. The theoretical analysis and simulations presented in this section demonstrate the CFAR property of the proposed algorithms with respect to the mean power of the background noise N_0 .

A. Fast-Time/Slow-Time Map CFAR

The first CFAR detection strategy proposed in this article evaluates the detection threshold on the fast-time/slow-time

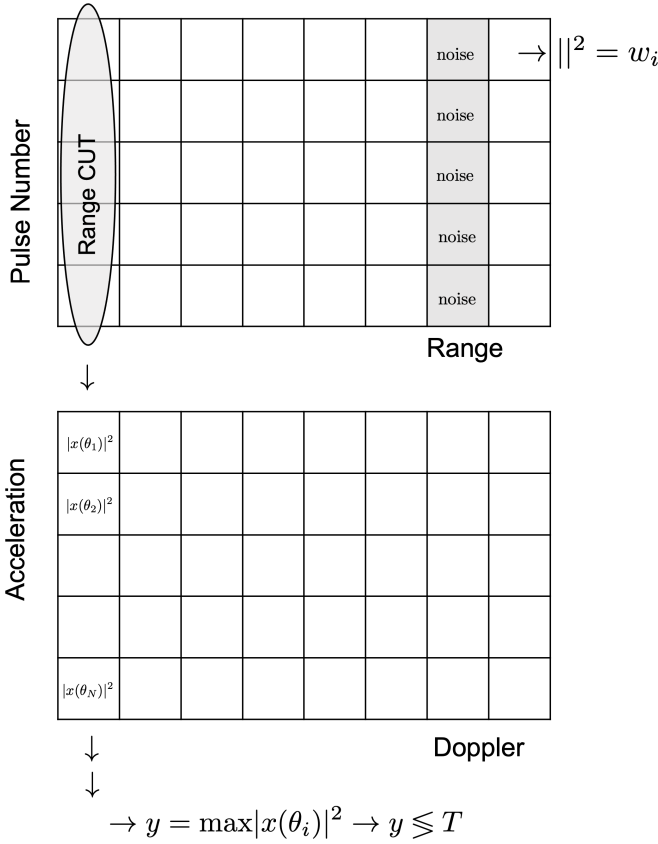


Fig. 10. Block diagram of the CFAR detector with Gaussian reference background (FTST-CFAR).

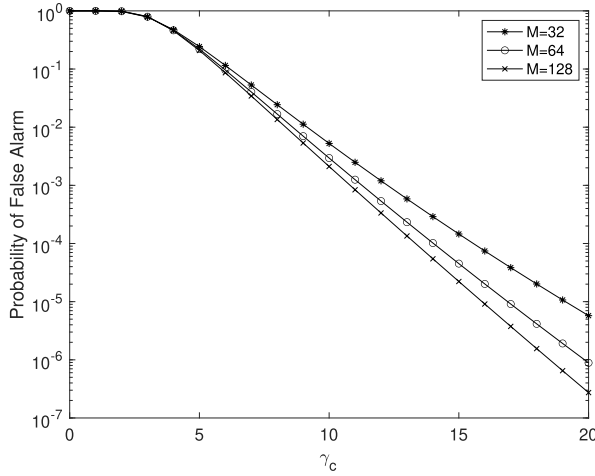


Fig. 11. FAR as a function of the CFA constant γ_c . Obtained by implementing (45) for $N = 512$ and $\alpha = 15.94$.

map and follows the scheme proposed in Fig. 10. The noise mean power is estimated from the slow-time versus fast-time diagram using M noise measurements w_i taken by a reference range cell that does not contain any targets. Because the noise mean power estimation occurs at the fast-time/slow-time stage, the noise reference samples w_i are independent and Gaussian distributed. As such, this algorithm requires the proposed statistical approximation only for the Cell Under Test (CUT).

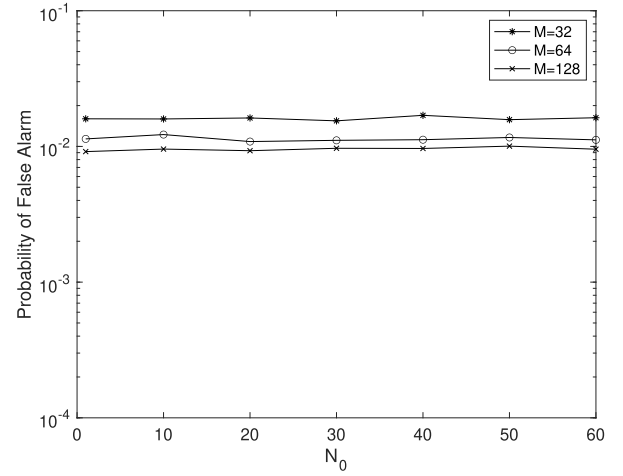


Fig. 12. Simulations of P_{fa} with varying N_0 for $\gamma_c = 8$. Obtained with 10^5 Monte Carlo simulations for each value of N_0 ($m = 5$ and $N = 512$).

The algorithm calculates the detection threshold from the data using the reference cells as follows:

$$T(\mathbf{w}) = \frac{\gamma_c N_p}{M} \sum_{i=1}^M w_i \quad (34)$$

where the vector $\mathbf{w} = [w_1, w_2, \dots, w_M]^T$ consists of the squared amplitude of the statistically independent complex Gaussian noise samples with mean power N_0/N_p taken from the slow-time fast-time diagram with joint p.d.f.

$$f_{\mathbf{w}}(\mathbf{w}) = \prod_{i=1}^M \frac{N_p}{N_0} e^{-\frac{N_p w_i}{N_0}} \quad (35)$$

and γ_c is a CFAR constant that is selected according to the desired probability of false alarm. Because the elements of $\mathbf{w}$ are zero-mean i.i.d. Gaussian distributed, their amplitude squared follows an exponential distribution. The probability that the CUT is greater than the threshold conditioned to the data is

$$P(y > T(\mathbf{w}) | \mathbf{w}) = 1 - \left(1 - e^{-T(\mathbf{w})/N_0}\right)^{\frac{N}{\alpha}} \quad (36)$$

and therefore the probability of false alarm can be expressed as

$$\overline{P_{fa}} = \int \int \left[1 - \left(1 - e^{-T(\mathbf{w})/N_0}\right)^{\frac{N}{\alpha}}\right] f_{\mathbf{w}}(\mathbf{w}) d\mathbf{w} \quad (37)$$

which is equal to

$$\overline{P_{fa}} = 1 - \int \int \left(1 - e^{-T(\mathbf{w})/N_0}\right)^{\frac{N}{\alpha}} f_{\mathbf{w}}(\mathbf{w}) d\mathbf{w}. \quad (38)$$

We can show that $\overline{P_{fa}}$ does not depend on N_0 mathematically by using a Taylor expansion of the LEV term in the integral, after observing that the function $(1-x)^\Psi$ of $x \in \mathbb{R}$ with $|x| < 1$ for a constant exponent $\Psi \in \mathbb{R}$ can be expressed as [15, pp. 14]

$$(1-x)^\Psi = \sum_{n=0}^{\infty} C_n(\Psi) (-1)^n \frac{x^n}{n!} \quad (39)$$

where

$$C_n(\Psi) = \prod_{i=1}^n (\Psi - (i-1)) \quad (40)$$

is the Pochhammer function with

$$C_0(\psi) = 1. \quad (41)$$

A simple algebraic manipulation of the integrals follows to rewrite the expressions as follows:

$$\overline{P_{fa}} = 1 - \int \int \sum_{n=0}^{\infty} C_n \left(\frac{N}{\alpha} \right) (-1)^n \frac{e^{-\frac{nT(w)}{N_0}}}{n!} f_w(w) dw \quad (42)$$

$$= 1 - \sum_{n=0}^{\infty} C_n \left(\frac{N}{\alpha} \right) \frac{(-1)^n}{n!} \prod_{i=1}^M \frac{N_p}{N_0} \int e^{-\frac{nN_p\gamma_c w_i}{MN_0}} e^{-\frac{N_p w_i}{N_0}} dw_i \quad (43)$$

$$= 1 - \sum_{n=0}^{\infty} C_n \left(\frac{N}{\alpha} \right) \frac{(-1)^n}{n!} \prod_{i=1}^M \frac{N_p}{N_0} \frac{MN_0}{n\gamma_c N_p + MN_p} \quad (44)$$

$$= 1 - \sum_{n=0}^{\infty} C_n \left(\frac{N}{\alpha} \right) \frac{(-1)^n}{n!} \left(\frac{M}{n\gamma_c + M} \right)^M \quad (45)$$

and show the CFAR properties with respect to the noise mean power N_0 (i.e., 45 does not depend on N_0).² By recalling that the standard series expansion of the Beta function is

$$B(z_1, z_2) = \sum_{n=0}^{\infty} C_n (z_2 - 1) \frac{(-1)^n}{n! (z_1 + n)} \quad (46)$$

and that

$$\begin{aligned} \frac{\partial^{M-1}}{\partial z_1^{M-1}} B(z_1, z_2) &= (-1)^{M-1} (M-1)! \\ &\times \sum_{n=0}^{\infty} C_n (z_2 - 1) \frac{(-1)^n}{n! (z_1 + n)^M} \end{aligned} \quad (47)$$

the probability of false alarm in 45 can also be expressed as follows:

$$\overline{P_{fa}} = 1 - \frac{(-1)^{M-1}}{(M-1)!} \left(\frac{M}{\gamma_c} \right)^M \frac{\partial^{M-1}}{\partial z_1^{M-1}} B \left(z_1, \frac{N}{\alpha} + 1 \right) \Big|_{z_1 = \frac{M}{\gamma_c}}. \quad (48)$$

Fig. 11 plots the value of the probability of false alarm as a function of the CFAR constant γ_c for $M = 32$, $M = 64$, and $M = 128$. The curves were obtained by a direct implementation of 45 for $N = 512$ and $\alpha = 15.94$. Fig. 12 shows that the FAR obtained on simulated data for $\gamma_c = 8$ (that is for a P_{fa} around 10^{-2}) does not depend on the value of noise power as expected.

B. Range Doppler Map CFAR

An alternative CFAR detection strategy evaluates the threshold on the range-Doppler map and follows the scheme in Fig. 13. This CFAR algorithm is applied directly in the range-Doppler map after the acceleration has been compensated. The noise parameters are estimated across the statistically independent range bins using the LEV distribution approximation and the threshold

$$T(y) = \frac{\gamma_c}{M} \sum_{i=1}^M y_i \quad (49)$$

²Noting that $T(w)/N_0 > 0$ (i.e., $e^{-T(w)/N_0} < 1$) with unit probability, the proposed Taylor expansion has been chosen as it leads to a convenient mathematical expression of $\overline{P_{fa}}$. With this expansion, (45) can be approximated using just a few tens summation terms.

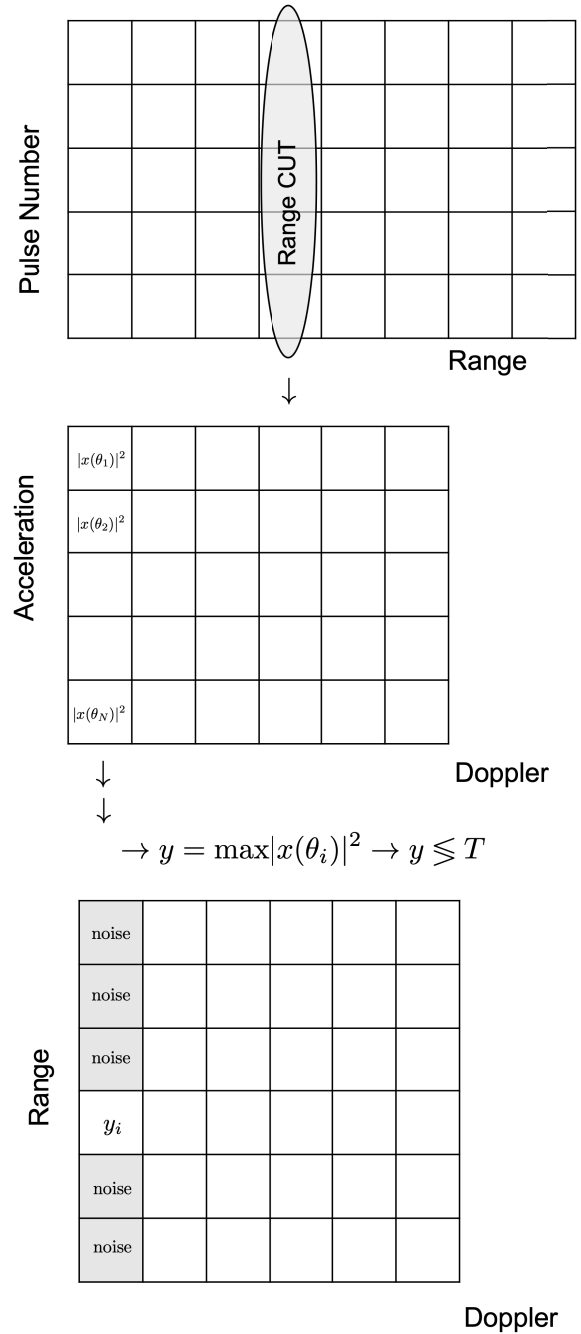


Fig. 13. Block diagram of the CFAR detector with LEV reference background (RD-CFAR).

is found by using M reference cells y_i . In this case, the probability of false alarm can be expressed as follows:

$$\overline{P_{fa}} = \int \int \left[1 - \left(1 - e^{-T(y)/N_0} \right)^{\frac{N}{\alpha}} \right] f_y(y) dy \quad (50)$$

where y consists of independent LEV distributed random variables with the same distribution as the CUT. The integral can therefore be expanded as follows:

$$\begin{aligned} \overline{P_{fa}} &= 1 - \int \int (1 - e^{-T(y)/N_0})^{\frac{N}{\alpha}} \\ &\times \prod_{i=1}^M \frac{N}{N_0 \alpha} (1 - e^{-y_i/N_0})^{N/\alpha-1} e^{-y_i/N_0} dy_i \end{aligned} \quad (51)$$

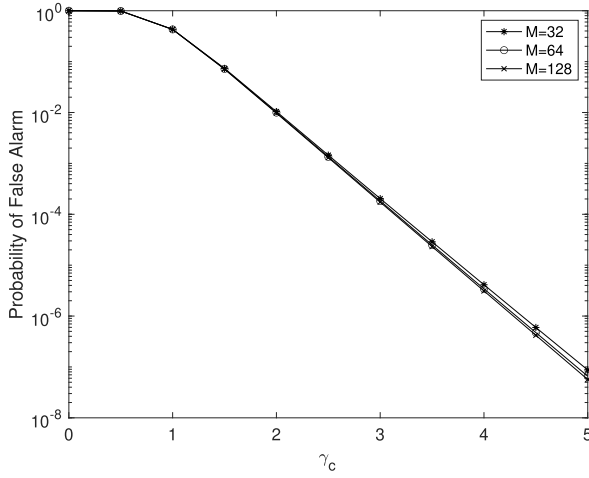


Fig. 14. FAR as a function of the CFA constant γ_c . Obtained for $N = 512$ and $\alpha = 15.94$. Results have been obtained by direct implementation of (56).

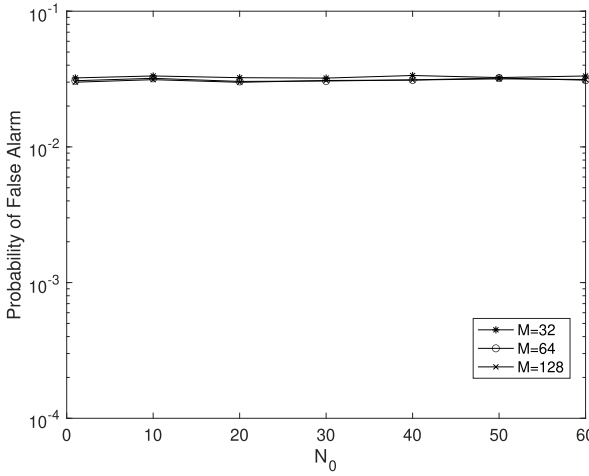


Fig. 15. Simulations of P_{fa} with varying N_0 for $\gamma_c = 2$. Obtained with 10^5 Monte Carlo simulations for each value of N_0 ($m = 5$ and $N = 512$).

which after a Taylor expansion becomes

$$\begin{aligned} \overline{P_{fa}} &= 1 - \int_0^\infty \sum_{n=0}^\infty C_n \left(\frac{N}{\alpha} \right) \frac{(-1)^n}{n!} \frac{e^{-\frac{n\gamma_c \sum y_k}{MN_0}}}{n!} \\ &\quad \times \prod_{i=1}^M \frac{N}{N_0 \alpha} (1 - e^{-y_i/N_0})^{N/\alpha-1} e^{-y_i/N_0} dy_i \end{aligned} \quad (52)$$

$$\begin{aligned} \overline{P_{fa}} &= 1 - \int_0^\infty \sum_{n=0}^\infty C_n \left(\frac{N}{\alpha} \right) \frac{(-1)^n}{n!} \prod_{k=1}^M e^{-\frac{n\gamma_c y_k}{MN_0}} \\ &\quad \times \left(\frac{N}{N_0 \alpha} \right)^M \prod_{i=1}^M (1 - e^{-y_i/N_0})^{N/\alpha-1} e^{-y_i/N_0} dy_i \end{aligned} \quad (53)$$

$$\begin{aligned} \overline{P_{fa}} &= 1 - \sum_{n=0}^\infty C_n \left(\frac{N}{\alpha} \right) \frac{(-1)^n}{n!} \left(\frac{N}{N_0 \alpha} \right)^M \\ &\quad \times \prod_{i=1}^M \int_0^\infty (1 - e^{-y_i/N_0})^{N/\alpha-1} e^{-y_i/N_0} e^{-\frac{n\gamma_c y_i}{MN_0}} dy_i. \end{aligned} \quad (54)$$

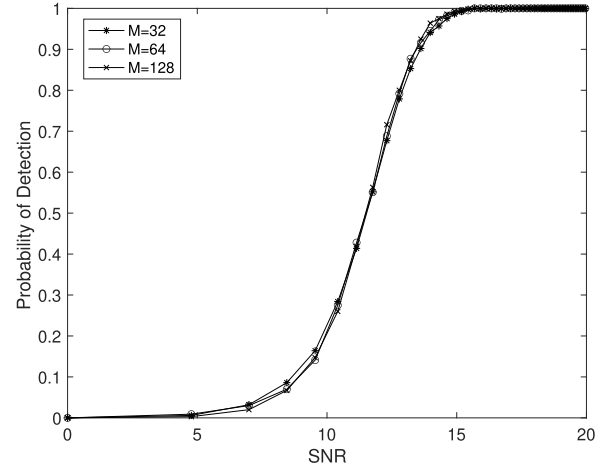


Fig. 16. Probability of detection as a function of SNR for the FTST-CFAR for $N = 512$, $m = 5$ and $\gamma_c = 15$.

A simple change of variable $z_i = e^{-y_i/N_0}$ leads to

$$\begin{aligned} \overline{P_{fa}} &= 1 - \sum_{n=0}^\infty C_n \left(\frac{N}{\alpha} \right) \frac{(-1)^n}{n!} \left(\frac{N}{\alpha} \right)^M \\ &\quad \times \prod_{i=1}^M \int_0^1 (1 - z_i)^{N/\alpha-1} z_i^{\frac{n\gamma_c}{M}} dz_i \end{aligned} \quad (55)$$

which is clearly CFAR with respect to N_0 and that can be expressed as a function of the Beta function as follows:

$$\overline{P_{fa}} = 1 - \sum_{n=0}^\infty C_n \left(\frac{N}{\alpha} \right) \frac{(-1)^n}{n!} \left[\frac{N}{\alpha} B \left(\frac{n\gamma_c}{M} + 1, \frac{N}{\alpha} \right) \right]^M. \quad (56)$$

Fig. 14 plots the value of the probability of false alarm as a function of the CFAR constant γ_c for $M = 32$, $M = 64$, and $M = 128$. Fig. 15 shows that the FAR obtained on simulated data does not depend on the value of noise power as expected. They also show that because the results are obtained for $\gamma_c = 2$ (that is for a P_{fa} around 10^{-2}), the FAR loss resulting from this CFAR strategy is more evident than that observed for the fast-time/slow-time map CFAR (FTST-CFAR), where the statistical approximation is used only for the CUT. Therefore, while the Range Doppler Map CFAR (RD-CFAR) is more efficient, not requiring to evaluate the adaptive threshold by averaging directly the background echoes in the fast-time/slow time-plane, it is not characterized by the same accuracy in predicting analytically the resulting value of the CFAR.

C. Probability of Detection Performance

Figs. 16 and 17 show the probability of detection as a function of the SNR for the two CFAR algorithms, obtained with 1000 Monte Carlo simulations. The results are relative to a steady stationary target and have been obtained with $\gamma_c = 15$ for the CFAR algorithm with Gaussian reference background and with $\gamma_c = 3.5$ for the CFAR algorithm with LEV reference background, corresponding to a probability of false alarm $P_{fa} = 10^{-5}$ for both algorithm. Results do not show any significant deviations in the detection performance between the two algorithms.

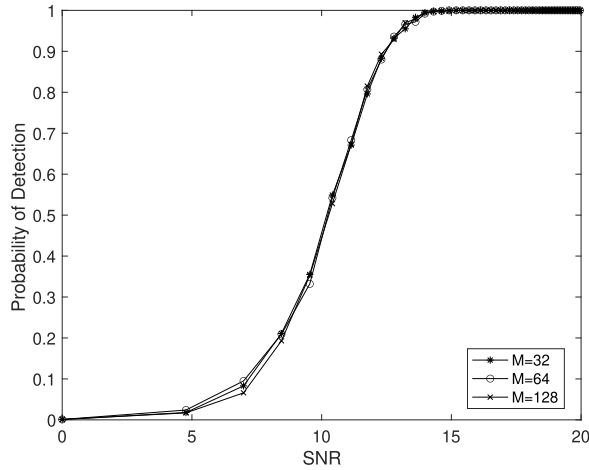


Fig. 17. Probability of detection as a function of SNR for the RD-CFAR for $N = 512$, $m = 5$, and $\gamma_c = 3.5$.

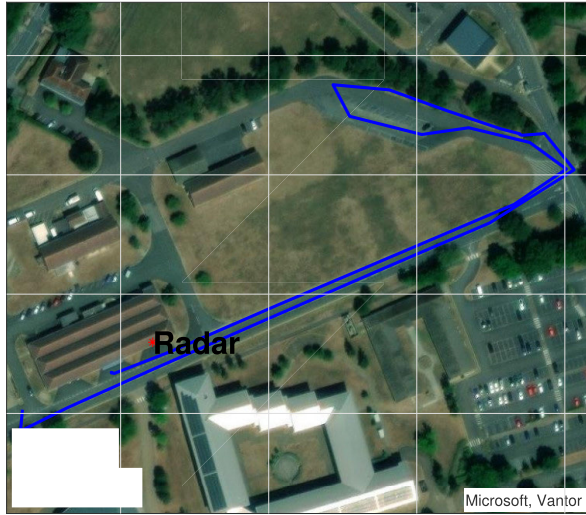


Fig. 18. Satellite view of the experimental setup. The blue curve indicates the target trajectory and the red star indicates the position of the radar. The radar antenna was pointing toward the right side of the image.

V. EXPERIMENTAL RESULTS

The results of the simulations are corroborated with experimental data obtained in a monostatic radar configuration at a carrier frequency of 4.255 GHz. The receiver used in the experiments is a NI-2943 USRP receiving on two channels simultaneously; a reference channel connected directly to an Anritsu signal generator to obtain a copy of the transmitted signal and a receiving channel connected to a receiving antenna to collect target echoes. The transmitted signal consisted of a train of 20 μ s long chirp pulses with a bandwidth of 10 MHz and a PRF of 2 kHz, providing a range resolution of 15 m. These were collected with a sample rate $F_s = 10$ MHz and organized in data frames of 0.25 s. The antenna used on transmit was a Narda standard horn antenna whilst the antenna used at the receiver was an A-Info wideband antenna. Experiments were carried out at the Defense Academy of the U.K. using a car as the target. The data analyzed are obtained after matched-filtering the copy of the transmitted signal to the signal received at the surveillance channel on a pulse to pulse



Fig. 19. Photo of the radar used to collect data with the antennas used to transmit and receive.

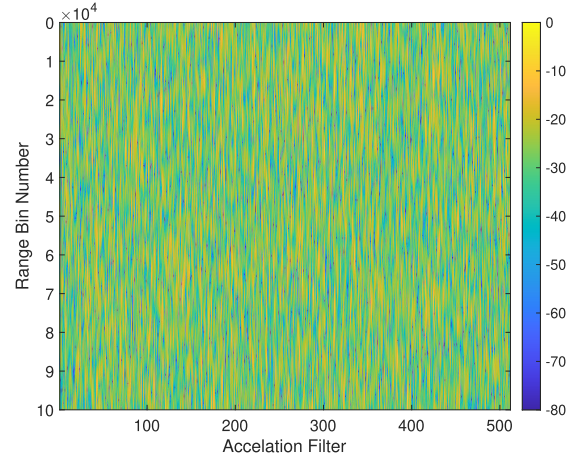


Fig. 20. Example of noise output from the acceleration filters for $N = 512$ filter. The maximum on each row is used to determine the probability of false alarm.

basis. Fig. 18 shows a satellite view of the experimental setup with the position of the radar and the target trajectory. Fig. 19 shows a photo of the radar node together with the A-Info and Narda antennas.

An example of the experimental output of the acceleration filters is shown in Fig. 20. For each row, the maximum value is selected for comparison with the threshold obtained by inverting (33) using the $\hat{a}$ obtained from the simulations to reach the required probability of false alarm. The results of the algorithm presented in Section III applied to the experimental data are shown in Fig. 21 for $m = 4$ and $N = 512$, 1024, and 2048. The noise mean power is estimated from the entire dataset and results are obtained by averaging across the number of available range bins which were sampled at exactly the bandwidth of the transmitted chirp (that is to ensure the noise samples in range were uncorrelated). They clearly show

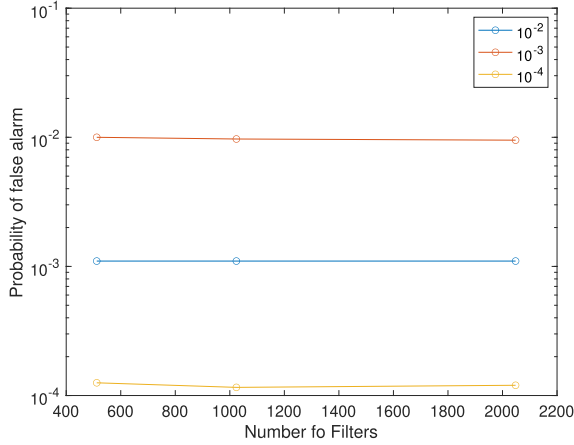


Fig. 21. Experimental results of the probability of false alarm evaluated for $m = 4$.

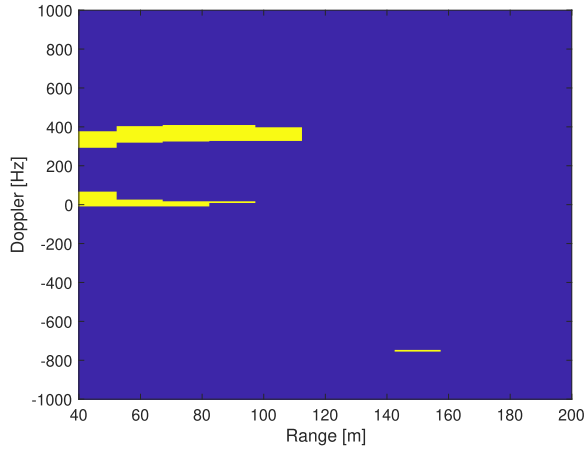


Fig. 22. CFAR detector output relative to the FTST-CFAR ($\gamma_c = 15$, $N = 512$, $m = 5$, and $M = 64$).

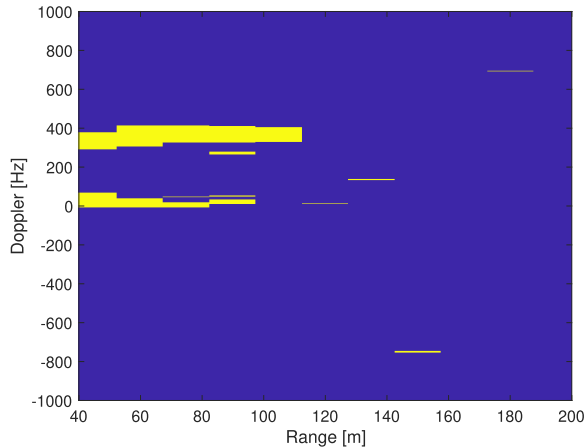


Fig. 23. CFAR detector output relative to the RD-CFAR ($\gamma_c = 3.5$, $N = 512$, $m = 5$, and $M = 64$).

that by using $\hat{\alpha}$ the probability of false alarm can be controlled well.

Figs. 22 and 23 show the application of the two CFAR algorithms to the real data. Results are relative to the car moving toward the radar and are the output of super-imposing five frames to show the target track over 5 s. For each frame,

detections are obtained with a dwell time of 200 ms. Due to the short dwell time and the target speed being within 10–15 m/s, range migration compensations were not required. Results show the approaching car can be detected across frames at approximately 400 Hz in Doppler, using both algorithms whilst controlling the probability of false alarm. They also show that the RD-CFAR image presents more false alarms than the FTST-CFAR, a result consistent with the CFAR loss behavior observed in the simulation results. The detections about zero-Doppler are due to clutter.

VI. CONCLUSION

We have studied the problem of controlling the probability of false alarm of the optimal detector for accelerating targets. The statistical properties of the background noise at the output of the detector have been derived and a modified parametric LEV distribution has been proposed to model the probability of false alarm. This distribution depends on a varying single parameter which, however, we have shown to converge to a fixed value when the number of acceleration filters increases. This fixed value can therefore be used to control the probability of false alarm. This was exploited in the article by proposing two alternative CFAR schemes, whose detection performance have also been fully characterized to allow their practical application both by analytical approximation and by simulation. Results are corroborated via experimental trials at C-band with a software defined radio, which confirms the validity of the analysis and the effectiveness of the proposed CFAR detection schemes.

The realistic application of this technique inside a specific detection scheme has a computational load that can be quite high, depending on the range of Doppler and accelerations parameters to be possibly included in the search. Moreover, it is subject to the exploitation of appropriate signal processing solutions to handle possible target range migration (especially in high-resolution systems). However, the proposed solutions can be considered as a basic building block for the practical implementations.

An interesting avenue for future research could be the extension of the results presented in this article to different types of background clutter other than Gaussian noise.

DATA AVAILABILITY STATEMENT

Data supporting this study cannot be made available due to commercial restrictions.

ACKNOWLEDGMENT

This work was initiated during a 1-month visit of Prof. Alessio Balleri at the Department of Information Engineering, Electronics and Telecommunications at Sapienza University of Rome, Italy. Alessio Balleri thanks Sapienza University of Rome for providing the financial support required to allow the visit.

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CFAR detection of high-accelerating targets: a study of the probability of false alarm

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2026

Institute of Electrical and Electronics Engineers (IEEE)

<https://doi.org/10.1109/trs.2026.3679015>

Balleri A, Colone F, Lombardo P. (2026) CFAR detection of high-accelerating targets: a study of the probability of false alarm. IEEE Transactions on Radar Systems, Volume 4, 2026, pp. 697-708