Non-Coherent CFAR Detector Using Compound Gaussian Clutter

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***Abstract*—In practical, the problem of radar signal detection is to automatically detect a target embedded in clutter. For high resolution radars, the modeling of sea clutter showed that compound Gaussian distributions are appropriate to describe the clutter returns. In this paper, we introduced a novel Constant False Alarm Rate (CFAR) detector in a non-coherent context, where the clutter follows a non-Gaussian distribution. The simulations via Monte Carlo showed that this new detector is robust for three Compound Gaussian (CG) clutter models; namely the K distribution, Compound Gaussian with inverse gamma texture (Generalized Pareto model, GP) and Compound Inverse Gaussian (CIG) distribution. The false alarm regulation was then examined within the presence of interfering targets. Finally, the performance of the proposed algorithm was validated using real data sea clutter.**

***Index Terms*—CFAR; Compound Gaussian; Non Coherent Process; Robust Detector.**

I. Introduction

Constant False Alarm Rate (CFAR) detection schemes with adaptive thresholding play an important role for radar target detection against clutter [1, 2]. For these schemes, the design algorithm of an adaptive threshold is the key to adapt and maintain the probability of false alarm (PFA) at a constant rate and to enhance the detection performance. Therefore, the CFAR schemes have an important role in radar target detection for coherent and non-coherent strategies. The main concept of CFAR process is that the PFA is maintained approximately constant by an optimal threshold, which is calculated using clutter data statistics. In some applications of CFAR detection, the hypothesis of a Gaussian clutter is no longer valid [3, 4], especially for high resolution receivers operating at low grazing angles. Lately, CFAR detection process in Compound Gaussian environments received a lot of attention [6], and it is still an open research orientation because the Compound Gaussian model fits well the data from X-band high resolution radars, operating at low grazing angles. In the past decades, the K-distribution has been the most suitable model in Compound Gaussian process for the amplitude statistic of radar target detection as it describes the characteristics of sea clutter very well [5, 6], and the amplitude scintillations caused by atmosphere on starlight [7]. Recently, the GP model has been confirmed as the adopted model after the K-distribution in radar application for X-band high resolution sea clutter [8, 9] due to the simplicity of estimating its parameters and Probability Density Function (PDF). This model also proved to be the best choice to distinguish the spikier sea clutter compared with the K and CIG distributions [10]. In recent years, the CIG distribution has been validated for the measured radar lake clutter [4], which shows better fits than its competitors [11]. The CIG model is obtained when the clutter power follows the Inverse Gaussian law [12]. In [13], Finn and Johnson proposed the use of reference channel, from which an estimate of the noise environment and upon which the decision threshold is adapted. In [14], Goldstein presented his optimal receiver called Log-t detector. This detector confirms the CFAR-ness process under the operation of Log-normal and Weibull environments. Himonas and Barkat [15] proposed the generalized two-level censored mean level detector, which uses an automatic censoring algorithm of the unwanted samples. Then in [16], Conte et al. proposed a canonical detector whose structure is independent of the clutter distribution. In [17], an intelligent CFAR processor based on data variability was proposed. In [18], Jakubiak introduced the Log-t detector for the K-distributed clutter, which possesses the CFAR property for a shape parameter higher than one. Recently, Weinberg and Glenny in [19] demonstrated the robustness of the Log-t detector against Pareto background and they modified and enhanced the performance of this detector in terms of managing the interferences.

This paper deals with the proposition of a novel non-parametric radar receiver capable of attaining the CFAR process when operating against the CG clutter, such as the K, GP and CIG distributions. We also analyzed the performance of the proposed detector in terms of false alarm regulation, in the case of the presence of interfering targets. Finally, we validated the performance of this detector on experimental data of IPIX radar. The rest of the letter is structured in the following way. In Section II, we provide a brief description of the Compound Gaussian model with the PDF of the three clutter models under consideration. In Section III, the proposed non-coherent CFAR algorithm against CG background is then studied. We proved that the proposed detector attains the CFAR property independently of the clutter parameters. In Section IV, we present some simulation results with discussions concerning the CFAR property of the proposed optimal detector in homogeneous and non-homogeneous (interfering targets) backgrounds. In Section V, the proposed detector is evaluated against the empirical IPIX data**.** Finally, conclusions are drawn in Section VI.

II. Review Of Compound Gaussian Clutter Models

In the previous years, the CG models have received a lot of attention with their types of texture in CFAR radar detection process. These models have been adopted successfully to describe the modulation for sea clutter in high resolution radar. Compared with the Gaussian model, they are characterized by a heavy tail. The complex domain random variable X can be represented as follows [10, 20]:

$$x = \sqrt{r}u \quad (1)$$

where: x = Complex Gaussian clutter vector
r = Texture component
u = Speckle component

The PDF of x is as follows:

$$P_X(x) = \frac{1}{\pi^S|V|}\int_0^\infty \frac{1}{r^S}\exp\left(-\frac{X^H V^{-1} X}{r}\right)P_R(r)dr \quad (2)$$

where: u = S-dimensional complex-Gaussian vector with zero-mean, a unit power
V = Finite positive definite covariance matrix, in short notation $u \sim CN(0,V)$ in which *CN* means Complex Normal
$P_R(r)$ = PDF of r

It is apparent that the PDF of the variable r directly characterizes the particular case of the compound-Gaussian family.

A. GP Distribution

The Generalized Pareto is obtained when the texture component conforms to the inverse gamma distribution [10]. It is given by:

$$P_X(x) = \frac{\alpha\beta^\alpha}{(x+\beta)^{\alpha+1}} \quad (3)$$

where: α = Shape parameter
β = Scale parameter

The values of α close to 1 correspond to a spiky clutter.

B. K Distribution

The K distribution is obtained when the texture is modeled as a Gamma distributed random variable with the mean β and order parameter ν:

$$P_X(x) = \frac{2}{\beta\Gamma(\nu+1)}\left(\frac{x}{2\beta}\right)^{\nu+1} K_\nu\left(\frac{x}{\beta}\right) \quad (4)$$
$$x > 0 \quad \nu > 0 \quad \beta > 0$$

where: x = Amplitude of the envelope
$\Gamma(.)$ = Gamma function
$K_\nu(.)$ = Modified Bessel function

C. CIG Distribution

The CIG model is obtained when the random variable R fluctuates, according to the inverse Gaussian law [20]:

$$P_X(x) = \frac{\lambda^{\frac{1}{2}}}{\sqrt{2\pi}X^{\frac{3}{2}}} exp\left(-\lambda\frac{(x-\mu)^2}{2\mu^2 x}\right) \quad 0 \le x \le \infty \quad (5)$$
$$\lambda > 0, \mu > 0$$

where: λ = Shape parameter
μ = Mean

Note that λ relies upon the sea conditions and the radar parameters. In general, the concept of CFAR processing consists of the passing of the received data through an envelope/square law detector and the comparison of each resolution cell to an adaptive threshold, multiplied by a scaling factor. The adaptive threshold is calculated using reference cells outputs, which are assumed to be independent and identically distributed to maintain the (PFA) at a desired value. We assume that the cell under test is the one in the middle. The presence of the target or the lack thereof is obtained by comparing the cell under testing with adaptive threshold $T.X_0$, as shown in Figure 1.

Goldstein proposed the Log-t detector [14], which attains the CFAR property for a class of clutter models, including the Log Normal and Weibull distributions. Then, Weinberg demonstrated that this detector attains the CFAR property when operating in Pareto Type 1 distributed clutter. The following proposed algorithm is an extension of the Log-t detector and it is designed to be CFAR for two parameters distributions. As such, it will be shown that the proposed algorithm is CFAR for the K, GP and CIG distributions.

As shown in Figure 1, the content of the cell under test X_0 is compared to the adaptive threshold T to decide the presence (Hypothesis H_1) or the absence (Hypothesis H_0) of a target, according to the test:

$$X_0 \underset{H_0}{\overset{H_1}{\gtrless}} T = \frac{Var(X)\tau + Mean(X)}{N} \quad (6)$$

where: τ = Constant chosen to achieve a desired PFA

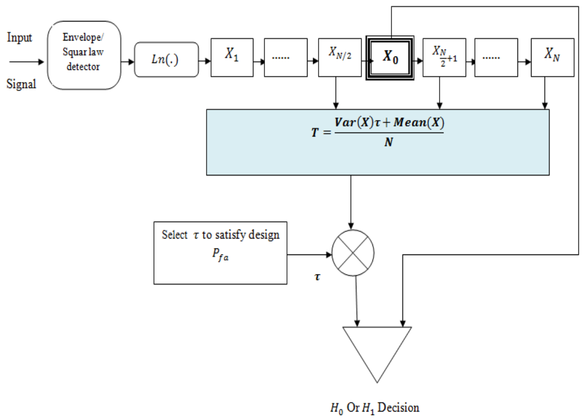


Figure 1: Architecture of the proposed CFAR algorithms

The expression of T was found intuitively using a trial and error method. It is clear that it is difficult to obtain an analytical expression of the PDF of the adaptive detection threshold in (6). For this, the CFAR property will be proved using the Monte-Carlo simulations.

III. Results And Discussions

A. Performance Analysis of the Proposed Detector in Homogeneous Case

1) GP Distribution Case

The curves of Figure 2 and 3 show the variation of PFA as a function of τ for β=1, and β=3, which are the different values of the shape parameter, a number of runs $n = 10^7$ and a number of reference cells N=8 and N=4 respectively. We observed that the curves almost overlap regardless the value of β and α. After several other tests, the value N=4 provided the best performance for false alarm regulation. The same tests were also conducted for the K and CIG distributions and the best results were also obtained for N=4. This is due to the fact that the proposed threshold in (6) is almost independent of the clutter parameters.

2) K Distribution Case

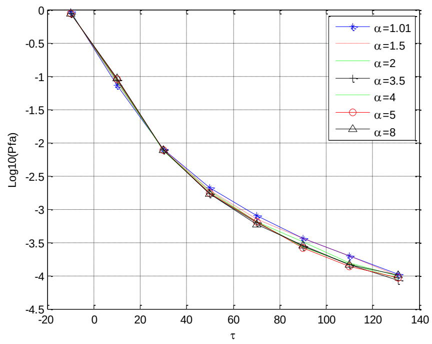
Figure 4(a) plots P_{FA} versus τ with varying ν for a K distributed clutter (β=1), and it was compared with that of the Log-t detector (Figure 4(b)). We noted that the proposed processor is almost CFAR, especially for a shape parameter which is higher than 1 contrarily to the Log-t detector in [18].

3) CIG Distribution Case

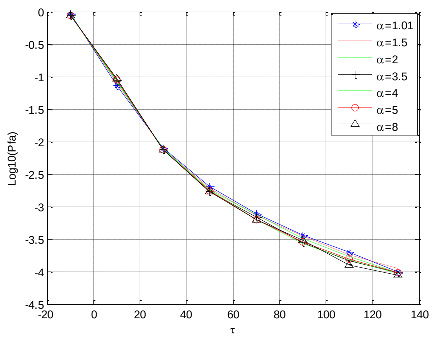
Figure 5(a) and 5(b) repeated the plots of Figure 3 with different values of the shape parameter and two different values of the mean (μ=1 and μ=3). Here again, the same scenario was observed; that is the curves almost overlap, which proves that the proposed detector is CFAR to an acceptable extend for this type of clutter.

B. Non Homogeneous Environment Case

1) GP Distribution Case

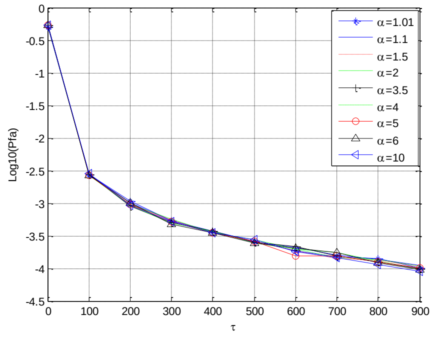


(a) PFA against the scale factor τ with β=1, N=8 and n=10^7

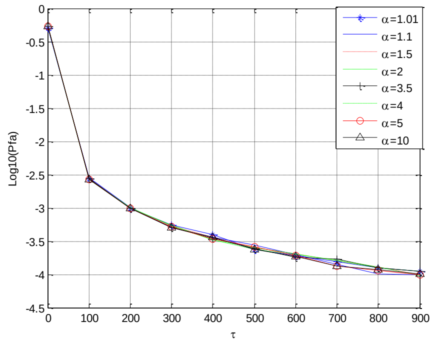


(b) PFA against the scale factor τ with β=3, N=8 and n=10^7

Figure 2: Performance of the proposed detector in Generalized Pareto Clutter



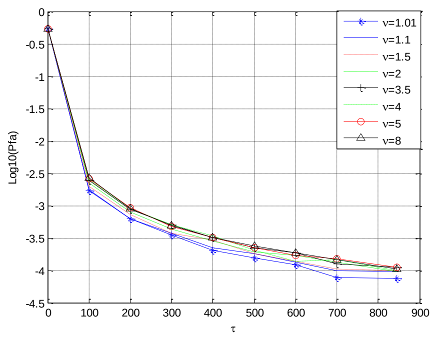
(a) PFA against the scale factor τ with β=1, N=4 and n=10^7



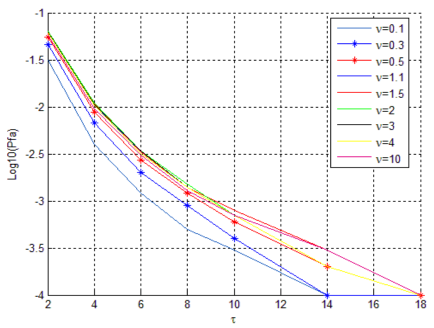
(b) PFA against the scale factor τ with β=3, N=4 and n=10^7

Figure 3: Performance of the proposed detector in Generalized Pareto Clutter

2) K Distribution Case



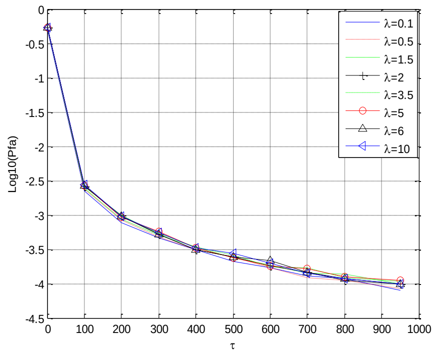
(a) PFA against the scale factor τ with β=1, N=4 and n=10^7



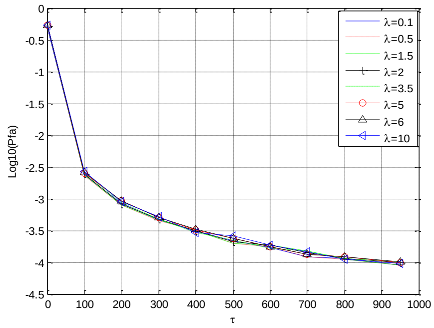
(b) PFA against the factor τ of the log-t detector in K clutter with β=1, N=16 and n=10^7

Figure 4: Performance of the proposed detector in K Clutter

3) CIG Distribution Case



(a) PFA against the scale factor τ with $\mu = 1$, N=4 and n=10^7

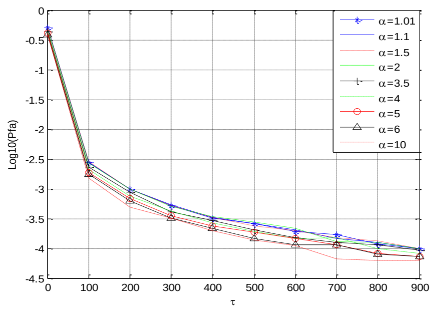


(b) PFA against the scale factor τ with $\mu = 3$, N=4 and n=10^7

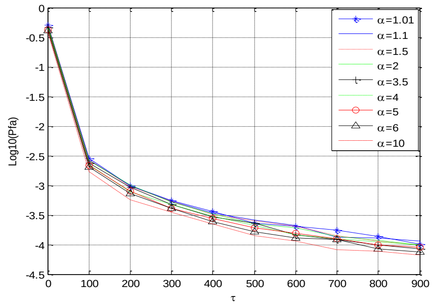
Figure 5: Performance of the proposed detector in CIG Clutter

C. Performance Analysis of the Proposed Detector in Presence of Interfering Targets Case

The case of the presence of interfering targets was investigated by injecting one target in the reference cells with Interference to Clutter Ratio (ICR) equals to 10 dB for a GP K and CIG clutters. For this, the proposed detector was modified by taking N=5, and then censoring the largest sample. To test the robustness of the proposed detector, we plotted in Figure 6, 7 and 8 the PFA for different values of the parameters and compared them to the case of the absence of interfering targets. We noticed that the same pattern was observed which proves that the proposed detector conserves its performance.



(a) PFA versus the scale factor τ with β=1, N=5 and n=10^7



(b) PFA versus the scale factor τ with β=3, N=5 and n=10^7

Figure 6: Performance of the proposed detector in GP clutter with one interfering target

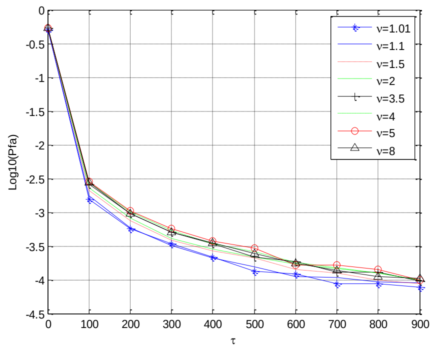


Figure 7: Performance of the proposed detector in K clutter with one interfering target. β=1, N=5 *and* n=10^7

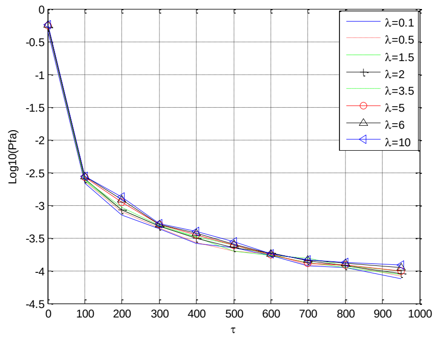


Figure 8: Performance of the proposed detector for the CIG distribution with one interfering targets. μ=3, N=5 *and* n=10^7

IV. IPIX DATA

In this section, we evaluated the false alarm regulation performance when applying the experimental data recorded by IPIX radar. The data were collected at Dartmouth and it is coherent and polarimetric with a range resolution of 3, 15 and 30 m and azimuth beamwidth of 0.9° [20, 21]. Figure 9 shows that the CFAR property is maintained for relatively high values of PFA regardless the cell resolution. For low values of PFA the gap between the curves increases, but remains acceptable. This could be explained by the fact that low values of PFA require more samples and since this number is limited, the obtained results are less accurate.

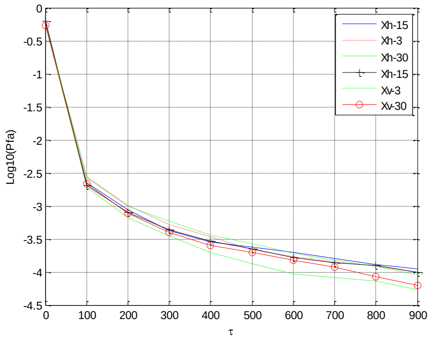


Figure 9: PFA versus the scale factor τ with , N=4 and n=10^7

V. CONCLUSION

A non-parametric CFAR detector in the context of non-coherent detection has been proposed for a class of CG clutters. The results obtained confirmed that the CFAR rule is almost conserved when the clutter conforms to the K, GP and CIG distributions. It was also shown that in the presence of one interfering target, the modified version of the proposed detector conserves the CFAR rule. Finally, our results were validated by using real data from the IPIX database for different range resolutions. In addition, the proposed detector used a reduced number of reference samples to compute the threshold, which is advantageous in real time applications.

REFERENCES

[1] M.A. Weiner, “Binary integration of fluctuating targets,” *IEEE Transactions on Aerospace and Electronic Systems*. Vol. 27, N° 1, pp. 11-17, 1991.

[2] M. Schwartz, “A coincidence procedure for signal detection,” *IRE Trans. Inf.* Vol. 2, N° 4, pp. 135-139, 1956.

[3]] M. Barkat. 'Signal Detection and Estimation' 2nd ed., Norwood, MA: Artech House, 2005.

[4] E. Ollila, David E. Tyler, V. Koivunen, and H. Vincent Poor, “Compound-Gaussian clutter modeling with an inverse Gaussian texture distribution,”, *IEEE Signal Processing Letters.* Vol. 19, N° 12, pp. 876-879, 2012.

[5] Y. Dong, “Distribution of X-Band high resolution and high grazing angle sea clutter,” *Electronic Warfare and Radar Division Defence Science and Technology Organization*, 2006.

[6] E. Conte, A. De Maio, and C. Galdi, “Statistical analysis of real clutter at different range resolutions, “ IEEE Trans. Aerosp. Electron. Syst., Vol. 40, No. 3, pp. 903-918, july. 2004.

[7] K. D. Ward, C. J. Baker, and S. Watts, “Maritime surveillance radar. Part 1: Radar scattering from the ocean surface,” Inst. Elect. Eng. Proc. F, Vol. 137, No. 2,pp. 51-62, Apr. 1990.

[8] G.V. Weinberg, “Assessing Pareto fit ti high resolution high grazing angle sea clutter,” *Electronics Letters,* Vol. 47, N°. 8, pp. 516-517, 2011.

[9] L. Rosenberg and S. Bocquet, “Application of the Pareto plus noise distribution to medium grazing angle sea clutter,” *IEEE journal of selected topics in applied earth observations and remote sensing*, Vol. 8, N° 1, pp. 255-261, 2015.

[10] A. Balleri, A. Nehorai, J. Wang, “Maximum Likelihood Estimation for Compound-Gaussian Clutter with Inverse-Gamma Texture,” *IEEE Transactions on Aerospace and Electronic Systems,* Vol. 43, N° 2, pp. 775-779, 2007.

[11] J. L. Folks and R.S. Chikara, “Inverse Gaussian distribution and its application,” *Electronics and communications in Japan (Part 3: Fundamental Electronic science* , Vol. 77, N°. 1, pp. 32-42, 1994.

[12] A. Mezache, M.Sahed , F. Soltani and I. Chalabi, “A model for non Rayleigh Clutter Amplitudes using Compound Inverse Gaussian Distribution : an experimentale analysis,” *IEEE Transactions on Aerospace and Electronic Systems,* Vol. 51, N° 1, pp. 142-153, 2015.

[13] M. M. Finn, R. S. Johnson, “Adaptive detection mode with threshold control as a function of spatially sampled clutter level estimates,” *RCA Rev*., 30, pp. 414-465, 1968.

[14] G. B. Goldstein, “False-Alarm Regulation in Log-Normal and Weibull Clutter,” *IEEE Transactions on Aerospace and Electronic Systems,* Vol. 9, N°. 1, pp. 84-92, 1973.

[15] S.D. Himonas, and M. Barkat, “Automatic Censored CFAR Detection for non homogeneous Environments,” *IEEE Transactions on Aerospace and Electronic Systems,* Vol. 28, N° 1, pp. 286-304, 1992.

[16] E. Conte, M. Lops, G. Ricci, ‘Incoherent Radar Detection in Compound-Gaussian Clutter, » IEEE Trans. Aerosp. Electron. Syst., Vol. 35, No. 3, pp. 790-800, july. 1999.

[17] M.E. Smith, and P.K. Varshney, “Intelligent CFAR Processor Based on Data Variability,” *IEEE Transactions on Aerospace and Electronic Systems,* Vol. 36, N° 3, pp. 837-847, 2000.

[18] A. Jakubiak, “False Alarm Probabilities for a Log-t Detector in K distributed Clutter”, *Electronic Letters*, Vol. 19, N°18, September 2003.

[19] G. V. Weinberg and V. G. Glenny, “Enhancing Goldstein’s Log-t Detector in Pareto Distributed Clutter,” *IEEE Transactions on Aerospace and Electronic Systems,* Vol. 53, N° 2, pp. 1035-1044, 2017.

[20] A. Mezache., A. Bentoumi., M., Sahed., “Parameter estimation for compound-Gaussian clutter with inverse-Gaussian texture,” *IET Radar Sonar and Navigation*, vol. 11, no. 4, pp. 586-596, 2017.

[21] P. Chung, W. Roberts, and J. Bohme, “Recursive K-distribution parameters estimation,” *IEEE Transactions on Signal Processing,* Vol. 53, N°2, pp. 397-402 ,2005.