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Research Article

Performance of Distributed CFAR Processors in Pearson Distributed Clutter

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This paper deals with the distributed constant false alarm rate (CFAR) radar detection of targets embedded in heavy-tailed Pearson distributed clutter. In particular, we extend the results obtained for the cell averaging (CA), order statistics (OS), and censored mean level CMLD CFAR processors operating in positive alpha-stable (P&S) random variables to more general situations, specifically to the presence of interfering targets and distributed CFAR detectors. The receiver operating characteristics of the greatest of (GO) and the smallest of (SO) CFAR processors are also determined. The performance characteristics of distributed systems are presented and compared in both homogeneous and in presence of interfering targets. We demonstrate, via simulation results, that the distributed systems when the clutter is modelled as positive alpha-stable distribution offer robustness properties against multiple target situations especially when using the "OR" fusion rule.

1. INTRODUCTION

In radar detection, the goal is to automatically detect a target in a nonstationary noise and clutter while maintaining a constant probability of false alarm. Classical detection using a matched filter receiver and a fixed threshold is no longer applicable due to the nonstationary nature of the background noise. Indeed, a small increase in the total noise power results in a corresponding increase of several orders of magnitude in the probability of false alarm. Therefore, adaptive threshold techniques are needed to maintain a constant false alarm rate. Hence, CFAR detectors have been designed to set the threshold adaptively according to local information on the background noise. More specifically, CFAR detectors estimate the characteristics of the noise by processing a window of reference cells surrounding the cell under test. The CA approach is such an adaptive procedure. However, the CA detector has a severely degraded performance in clutter edge and interfering targets echoes [1, 2]. Rohling modified the common CA-CFAR technique by replacing the arithmetic averaging estimator of the clutter power by a new module based on order statistics (OS) [3]. The OS-CFAR procedure protects against nonhomogeneous situations caused by clutter edges and interfering targets (which is of interest in this paper). Target detectability and robustness against interfering targets can also be enhanced using distributed detection [4, 5]. However, the design of a distributed detection is strongly affected by the clutter model assumed. Actual data, such as active sonar returns [6], sea clutter measurements [7], and monostatic clutter from the US Air Force Mountaintop Database [8], have been successfully modelled with heavy-tailed distributions; the tails of these distributions showed a power-law or algebraic asymptote, which is characteristic of the so-called alpha-stable family and was contrasted with the exponentially decaying tails of the K distribution [9] and Weibull families. Indeed, alpha-stable processes have to be effective in modelling many real-life engineering problems such as outliers and impulsive signals [10]. The probability density function (pdf) of alpha-stable processes does not have a closed form except for the cases $\alpha = 1$ (Cauchy distribution), $\alpha = 1/2$ (Levy or Pearson distribution) and $\alpha = 2$ (Gaussian distribution), where α is the characteristic exponent of the distribution. For this main reason, Pearson is the distribution of interest here. This is further justified by the fact that Pierce showed that the Pearson distribution closely models the modulation of certain sea clutter returns [7]. Tsakalides et al. [11] studied the design and performance of CFAR processors, notably OS, CA, and CMLD, for the case of positive alpha-stable (P&S) measurements. They showed that the processors studied give rise to a CFAR

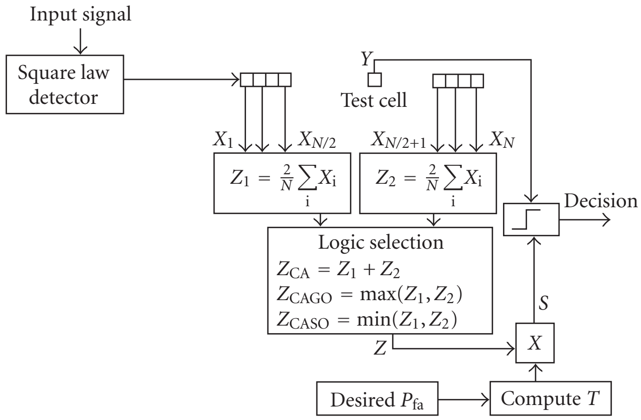

Figure 1: Block diagram of the CA, CAGO, and CASO-CFAR detector structure.

detector for Pearson distributed heavy-tailed output signals. Our contribution extends the results found in [11] to more general situations. Namely, we consider two identical and different CFAR distributed detectors assuming positive alpha-stable distributed data in interfering targets environment and using the fusion rules "AND" and "OR." The organization of this paper is as follows: in Section 2, we briefly review the development and the computation structure of CFAR techniques. In Section 3, we derive the false alarm probabilities of the CAGO and CASO CFAR processors for Pearson distributed heavy-tailed output signals. The detection probabilities are computed by simulation method. In Section 4, we study the distributed CFAR system with different combinations in both absence and presence of three interfering targets. Finally, the results and conclusions are provided in Sections 5 and 6, respectively.

2. BASIC ASSUMPTION AND PROBLEM FORMULATION

CFAR technique is a signal processing technique used in automatic radar detection system to control the false alarm rate when the clutter parameters are unknown or slowly time varying. The CFAR algorithm adjusts the detection threshold on a cell by cell basis, so that, in clutter or noise interference environments, the false alarm probability is kept constant. In Figure 1, the local CA-CFAR detector block diagram is shown. For a system where square-law detects the output of a matched filter to obtain the test statistic, the problem can be modelled as the following hypothesis testing problem:

$$\begin{aligned} H_1 \text{ (target present)} &: \mathbf{Y} = s + c, \\ H_0 \text{ (target absent)} &: \mathbf{Y} = c, \end{aligned} \tag{1}$$

where s and c are the signal and clutter components, respectively.

Implementing a generalized likelihood ratio test, the decision for H_0 or H_1 is realized by the following thresholding operation:

$$e(\mathbf{Y}) = \begin{cases} \text{target present} & \text{if } \mathbf{Y} \geq S, \\ \text{target absent} & \text{if } \mathbf{Y} < S. \end{cases} \tag{2}$$

The threshold S is calculated as the product

$$S = T \cdot Z, \tag{3}$$

where Z is the estimate of the average clutter strength and T is a scaling factor used to achieve a derived P_{fa}. We briefly recall the single CA-CFAR results for the case of Pearson distributed data. Then, we extend the results to single greatest of CAGO and single smallest of CASO CFAR for the same case.

3. ANALYSIS OF SINGLE DETECTORS

The analytical results for the probability of false alarm of single CA, CAGO, and CASO-CFAR, when the cell samples follow the Pearson distribution, are derived as follows.

3.1. *Single CA-CFAR for Pearson distributed data*

The output measurements follow the Pearson distribution. It has been demonstrated that the CA-CFAR processor in Figure 1 is a CFAR processor for Pearson distribution data by showing that the false alarm probability P_{fa} is independent of the dispersion γ of the measurements [11].

3.1.1. *Probability of false alarm P_{fa}*

Assume that $X_1, \ldots, X_N$ follow the Pearson distribution with probability density function (pdf) given by [11]

$$p_{X_i}(x) = \begin{cases} \dfrac{\gamma}{\sqrt{2\pi}} \dfrac{1}{x^{3/2}} e^{-\gamma^2/2x}, & x \geq 0, \\ 0 & \text{otherwise}, \end{cases} \tag{4}$$

where γ is the scale parameter of the distribution. P_{fa} indicates the probability that a noise random variable Y_0 is interpreted as target echo during the thresholding decision (2). This probability is given by

$$P_{fa} = \Pr\{Y_0 \geq T \cdot Z\}. \tag{5}$$

The cell averaging (CA) CFAR method selects the average of the reference cell values as a measure of the clutter level Z, that is,

$$Z = Z_{CA} = \frac{1}{N}\sum_{i=1}^{N} X_i. \tag{6}$$

The P_{fa}^{CA} is expressed as

$$P_{fa}^{CA} = \sqrt{\frac{2N}{\pi}} \int_0^\infty \operatorname{erf}\left(\frac{y}{\sqrt{2T}}\right) e^{-Ny^2/2} dy, \tag{7}$$

where

$$\operatorname{erf}(y) = \frac{2}{\sqrt{\pi}} \int_0^y e^{-t^2} dt. \tag{8}$$

The important conclusion from (7) is that the false alarm probability is controlled by the scaling factor T and it does not depend on the dispersion parameter γ of the Pearson distributed parent population. As a consequence, the CA CFAR method may be considered as a CFAR method for Pearson background.

3.1.2. Probability of detection

We consider the case of a Rayleigh fluctuating target with parameter $\sigma_s{}^2$ in a heavy-tailed background noise scenario when the CFAR processor is presented by a square-law detector. The probability of detection is given by

$$P_d^{\mathrm{CA}} = \Pr\{Y_1 \geq TZ\} = \int_0^\infty \Pr\{Y_1 \geq Tz\} p_{Z_{\mathrm{CA}}}(z)dz. \quad (9)$$

Exact analytical evaluation of this expression is not easy. In fact, to specify Y_1 under H_1 would require specifying the inphase and quadrature components of both the clutter and the useful signal, whereas only their amplitudes pdfs are given. Therefore, we have to resort to computer simulation. Hence, the test-cell measurement is considered as a scalar product of the two vectors: the clutter and the useful signal, respectively. So that

$$Y_1 = s + c + \sqrt{s \cdot c} \cdot \cos(\varphi), \quad (10)$$

where φ is the angle between the vectors s and c and is uniformly distributed in $[0,2\pi]$, and s and c are the signal and clutter components, respectively.

Notice that, the detection probability is a function of the clutter dispersion γ and the power parameter of the Rayleigh fluctuation target σ_s.

3.2. Greatest-of (CAGO) CFAR

In this section, the clutter level is estimated by selecting the greatest of the leading and lagging sets of the reference cells. Therefore the statistic Z_{CAGO} is given by

$$Z_{\mathrm{CAGO}} = \max(Z_1, Z_2), \quad (11)$$

where Z_1 is the average of the leading reference window, that is,

$$Z_1 = \left(\frac{2}{N}\right) \sum_{i=1}^{N/2} X_i, \quad (12)$$

and Z_2 is the average of the lagging reference window, that is,

$$Z_2 = \left(\frac{2}{N}\right) \sum_{i=N/2}^{N} X_i. \quad (13)$$

Likewise, Z_1 and Z_2 are Pearson distributed random variables since these are the average of the sum of $N/2$ Pearson distributed random variables, respectively. The dispersion of Z_1, Z_2 is equal to $\gamma_{Z1} = \sqrt{N/2}\gamma_{Xi}$. Hence, the pdf of $Z_1(Z_2)$ is given by

$$p_{Z1}(z) = \begin{cases} \dfrac{\sqrt{N/2}\gamma}{\sqrt{2\pi}} \dfrac{1}{z^{3/2}} e^{-N\gamma^2/4z}, & z \geq 0, \\ 0 & \text{otherwise}, \end{cases} \quad (14)$$

and the corresponding pdf of $Z_1(Z_2)$ is

$$P_{Z_1}(z) = \begin{cases} 2\left(1 - \phi\left(\dfrac{\sqrt{N}\gamma}{\sqrt{2z}}\right)\right), & z \geq 0, \\ 0 & \text{otherwise}. \end{cases} \quad (15)$$

In this case, the pdf of Z_{CAGO} has the following formula [12]:

$$p_{Z_{\mathrm{CAGO}}}(z) = 2p_{Z_1}(z)P_{Z1}(z). \quad (16)$$

The evaluation of the probability of false alarm P_{fa} for this scheme gives

$$\begin{aligned} P_{\mathrm{fa}}^{\mathrm{CAGO}} &= \Pr\{Y_0 \geq TZ\} \\ &= \int_0^\infty \Pr\{Y_0 \geq Tz\} p_{Z_{\mathrm{CAGO}}}(z)dz, \end{aligned} \quad (17)$$

$$\begin{aligned} P_{\mathrm{fa}}^{\mathrm{CAGO}} &= 2\sqrt{\frac{N}{\pi}} \int_0^\infty \operatorname{erf}\left(\frac{y}{\sqrt{2T}}\right) \\ &\quad \times \left(1 - \operatorname{erf}\left(\frac{\sqrt{N}}{2}y\right)\right) e^{-N(y^2/4)}dy. \end{aligned} \quad (18)$$

As we can see from (18), the false alarm probability is controlled by the scaling factor T and it does not depend on the dispersion parameter γ of the Pearson distributed parent population. As a consequence, the CAGO-CFAR method may be considered as a CFAR method for Pearson background.

3.3. Smallest-of (CASO) CFAR

In the CASO-CFAR scheme, the clutter level estimate is the smallest of the sums of the leading and lagging sets of the reference cells. That is,

$$Z_{\mathrm{CASO}} = \min(Z_1, Z_2). \quad (19)$$

In this case, the pdf of Z_{CASO} is given by [12]

$$p_{Z_{\mathrm{CASO}}}(z) = 2p_{Z_1}(1 - P_{Z_1}(z)). \quad (20)$$

The corresponding probability of false alarm is

$$\begin{aligned} P_{\mathrm{fa}}^{\mathrm{CASO}} &= \Pr\{Y_0 \geq TZ\} \\ &= \int_0^\infty \Pr\{Y_0 \geq Tz\} p_{Z_{\mathrm{CASO}}}(z)dz, \end{aligned} \quad (21)$$

$$P_{\mathrm{fa}}^{\mathrm{CASO}} = 2\sqrt{\frac{N}{\pi}} \int_0^\infty \operatorname{erf}\left(\frac{y}{\sqrt{2T}}\right) \operatorname{erf}\left(\frac{\sqrt{N}}{2}y\right) e^{-N(y^2/4)}dy. \quad (22)$$

From (22), we see that CASO is also a CFAR method for Pearson background.

If some interfering targets appear in both the leading and lagging sets of the reference cells, the three detectors (CA, CAGO and CASO-CFAR) are not optimal. They show a severe degradation in detection performance. This remains a major problem in detection. Target detectability can be enhanced using distributed detection. In the following, we will

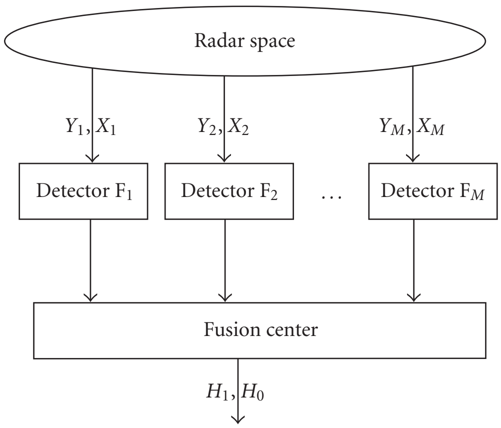

Figure 2: Decentralized detection scheme.

study the distributed CFAR systems and analyze their performance. Namely, we consider two identical or different constant false alarm rate (CFAR) distributed detectors assuming positive alpha-stable distributed data in both the absence and presence of interfering targets and using the fusion rules "AND" and "OR." The rational is to study the resistance of the "OR" and "AND" fusion rules to undesired effects. It is worth observing, via simulation results, that the combination of two different CFAR processors, such as CA-CAGO gives larger gain and robustness against multiple targets.

4. DECENTRALIZED CFAR DETECTORS FOR PEARSON DISTRIBUTED DATA

The scheme under consideration is depicted in Figure 2, where the relevant symbols are also introduced. Specifically, for $i = 1, \ldots, M$, with M the number of local detectors employed, F_i is the ith local detector, Y_i is the square envelope of the return from the test cell to the ith detector. It is assumed to follow a positive alpha-stable distribution under Hypothesis H_0, and Rayleigh fluctuating target plus a positive alpha-stable noise under Hypothesis H_1 (presence of a target). $\mathbf{X}_i$ is the vector whose components are the N_i square envelopes of the returns from the cells in the reference window to the ith detector; the "AND" decision rule consists of declaring the presence of a target when all the remote sensors decide in favor of target presence while in the "OR" logic the overall decision is H_1 if any of the M detectors decides for the presence of a target.

If the fusion centre makes a decision according to the "AND" logic, the overall system performance is

$$P_{\text{fa}} = \prod_{i=1}^{M} P_{\text{fai}}, \qquad P_d = \prod_{i=1}^{M} P_{\text{di}}. \tag{23}$$

When adopting the "OR" logic, it is

$$P_{\text{fa}} = 1 - \prod_{i=1}^{M} (1 - P_{\text{fai}}), \qquad P_d = 1 - \prod_{i=1}^{M} (1 - P_{\text{di}}). \tag{24}$$

We assume that the generalized signal-to-noise ratio (GSNR) is the same at each sensor. The GSNR is defined in [11] as

$$\text{GSNR} = 20 \log \frac{\sigma_s}{\gamma}, \tag{25}$$

where σ_s is the parameter of the Rayleigh fluctuating target.

Let us consider the case of two distributed CA-CFAR system operating in homogeneous Pearson distributed data, with the same characteristics, that is, $p_{\text{fa}\,1}^{\text{CA}} = p_{\text{fa}\,2}^{\text{CA}} = 10^{-4}$. So that $T_1 = T_2 = T$. The probability of false alarm of each sensor is

$$P_{\text{fa}\,1}^{\text{CA}} = \sqrt{\frac{2N_1}{\pi}} \int_0^\infty \text{erf}\left(\frac{y_1}{\sqrt{2T_1}}\right) e^{-N_1 {y_1}^2/2} dy_1, \qquad P_{\text{fa}\,2}^{\text{CA}} = \sqrt{\frac{2N_2}{\pi}} \int_0^\infty \text{erf}\left(\frac{y_2}{\sqrt{2T_2}}\right) e^{-N_2 {y_2}^2/2} dy_2, \tag{26}$$

where N_1, N_2 are the number of reference cells in the two CA CFAR detectors, respectively. By substituting (26) into (23) we get the overall probability of false alarm for the "AND" fusion rule; that is,

$$\begin{aligned} P_{\text{fa}} &= \sqrt{\frac{2N_1}{\pi}} \int_0^\infty \text{erf}\left(\frac{y_1}{\sqrt{2T}}\right) e^{-N_1 {y_1}^2/2} dy_1 \\ &\quad \times \sqrt{\frac{2N_2}{\pi}} \int_0^\infty \text{erf}\left(\frac{y_2}{\sqrt{2T}}\right) e^{-N_2 {y_2}^2/2} dy_2 \\ &= \frac{2}{\pi}\sqrt{N_1 N_2} \int_0^\infty \text{erf}\left(\frac{y_1}{\sqrt{2T}}\right) e^{-N_1 {y_1}^2/2} dy_1 \\ &\quad \times \int_0^\infty \text{erf}\left(\frac{y_2}{\sqrt{2T}}\right) e^{-N_2 {y_2}^2/2} dy_2. \end{aligned} \tag{27}$$

The overall probability of detection is the product of the two partially detection probabilities P_{d1}^{CA} and P_{d2}^{CA} as shown in (23):

$$P_d = P_{d1}^{\text{CA}} P_{d2}^{\text{CA}}, \tag{28}$$

where P_{d1}^{CA} and P_{d2}^{CA} are calculated by the simulation method discussed above.

Likewise, when employing the "OR" fusion rule for the same case and by applying (24), we find the overall probability of false alarm and the overall probability of detection.

Similarly, we examine the performance of other combinations, namely we consider two distributed CFAR systems such that the detectors are different; notably the CA-CAGO CFAR system and CA-CASO CFAR system. The overall probability of false alarm and the overall probability of detection for the "AND" and "OR" fusion rules are found by using (23) and (24), respectively.

We note here that there does not seem to be a clear advantage in designing a distributed CFAR system using different sample sizes. However, the combination of different sensors offers performance improvements and better robustness against interfering targets. It is worth noting that almost no gain is achieved when the "AND" fusion rule is used even if we adopt a larger reference windows. Conversely, with the "OR" logic a consistent gain can be attained. Also, we notice that the combination and the increase in the number of sensors are more effective than enlarging the reference windows, as far as the detection probability is concerned. Hence, a large number of detectors operating in homogeneous or nonhomogeneous positive alpha-stable background behave considerably better than a single sensor when the "OR" fusion rule is adopted.

5. RESULTS AND DISCUSSIONS

To investigate the effectiveness of the analytical results, a simulation study based on Monte-Carlo counting procedure is conducted. In Figure 3 the probabilities of detection P_d^{CA}, P_d^{CAGO}, and P_d^{CASO} are plotted versus the generalized signal-to-noise ratio (GSNR) for the probabilities of false alarm $P_{\mathrm{fa}}^{\mathrm{CA}} = P_{\mathrm{fa}}^{\mathrm{CAGO}} = P_{\mathrm{fa}}^{\mathrm{CASO}} = 10^{-4}$, operating in homogeneous Pearson distributed clutter. For the sake of comparison between the single CA, CAGO, and CASO-CFAR detectors, we assume that these detectors have identical characteristics, that is, equal N_i.

As expected, the CASO CFAR detector achieves better detection probability than both the CA and CAGO CFAR detectors, the performance of the CA is better than the CAGO CFAR. At a GSNR > 90 dB, CA and CAGO-CFAR give the same results. In the presence of three interfering targets with equal generalized interference signal-to-noise ratio (GINR), $\mathrm{GINR}_1 = \mathrm{GINR}_2 = \mathrm{GINR}_3 = 50$ dB, the performances of the above detectors are evaluated when the probabilities of false alarm equal $P_{\mathrm{fa}}^{\mathrm{CA}} = P_{\mathrm{fa}}^{\mathrm{CAGO}} = P_{\mathrm{fa}}^{\mathrm{CASO}} = 10^{-4}$. The detection probabilities as a function of the primary GSNR are shown in Figure 4. From this figure, we notice that an intolerable performance degradation occurs in the CAGO and CA schemes. This is due to an over estimation of the mean power of the background, the CASO scheme has the best performance in a multiple target situation. Therefore, the CASO processor is capable of resolving multiple targets in the reference window when all the interfering targets appear in either side of the cell under test. We notice here that the threshold multipliers T_i are determined on the assumption that no interfering targets are present in the cells of reference window. The threshold multipliers used to achieve a desired P_{fa} ($P_{\mathrm{fa}}^{\mathrm{CA}} = P_{\mathrm{fa}}^{\mathrm{CAGO}} = P_{\mathrm{fa}}^{\mathrm{CASO}} = 10^{-4}$) for the three detectors are computed by solving numerically (7), (18), and (22), respectively. The results are summarised in Table 1. Table 1 demonstrates that the CAGO exhibits the lowest threshold.

The performances under homogeneous Pearson environments, for two distributed CA CACFAR and the combination CA CAGOCFAR systems, are shown in Figures 5 and

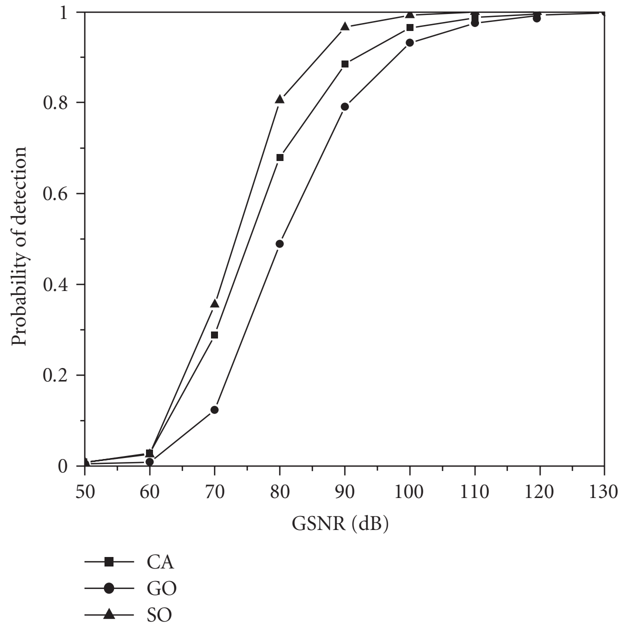

FIGURE 3: Probability of detection of CA, CAGO, and CASO CFAR processors in homogeneous Pearson background as a function of GSNR $= 20\log(\sigma_s/\gamma)$. Reference window size is $N = 32$, $P_{\mathrm{fa}}^{\mathrm{CA}} = P_{\mathrm{fa}}^{\mathrm{CAGO}} = P_{\mathrm{fa}}^{\mathrm{CASO}} = 10^{-4}$.

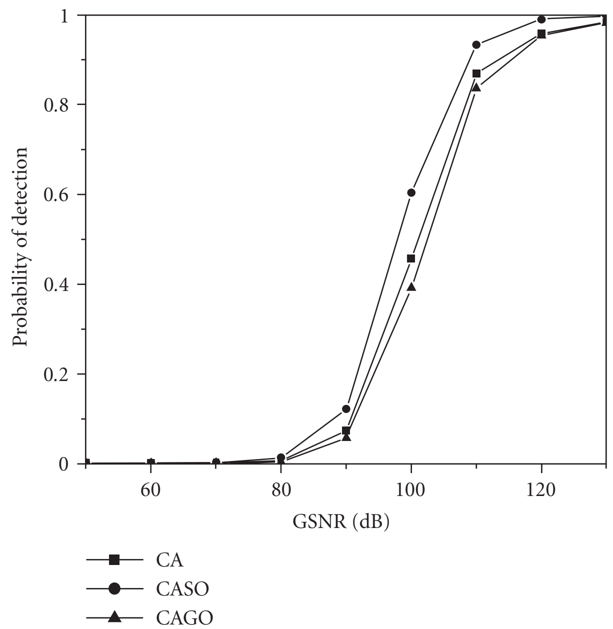

FIGURE 4: Probability of detection of CA, CAGO, and CASO CFAR processors in homogeneous Pearson background and in presence of three interfering targets ($\mathrm{GINR}_1 = \mathrm{GINR}_2 = \mathrm{GINR}_3 = 50$ dB) as a function of GSNR. Reference window size is $N = 32$. $P_{\mathrm{fa}}^{\mathrm{CA}} = P_{\mathrm{fa}}^{\mathrm{CAGO}} = P_{\mathrm{fa}}^{\mathrm{CASO}} = 10^{-4}$.

Table 1: The threshold multipliers T_i of the detectors CA, CAGO, and CASO.

Detectors	CA	CAGO	CASO
Thresholds T_i	1.560×10^6	7.250×10^5	9.885×10^5

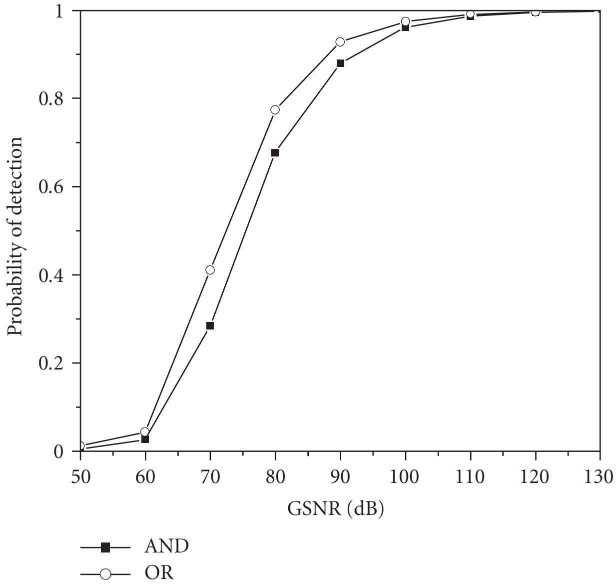

Figure 5: Probability of detection of two distributed CA-CACFAR system in homogeneous Pearson background, adopting the "AND" and "OR" fusion rules. $N_1 = 32$, $N_2 = 32$. $P_{fa} = 10^{-4}$.

6, respectively, in terms of the detection probability versus the generalized signal-to-noise ratio (GSNR). The latter is assumed to be equal at each sensor. A comparison between the two classical fusion rules, "AND" and "OR," reveals that the "OR" logic is superior to the "AND" logic for all proposed distributed system.

We can easily see, from Figure 7, that the robustness of distributed CA CACFAR system against interfering targets is better than the single CACFAR. These figures highlight that it does not seem to be a clear advantage in designing a distributed CFAR system using different samples sizes. However, the combination of different sensors produces a better performance than identical detectors and better robustness against interfering targets. It is worth noting that almost no gain is achieved with the "AND" fusion rule, neither by adopting larger reference windows, nor by increasing M (number of sensors). Conversely, with the "OR" logic a consistent gain can be attained. We see also that the combination of different sensors is more effective than enlarging the reference windows, as far as the detection probability is concerned. Hence a large number of detectors, operating in homogeneous Pearson background and in the presence of interfering targets, behave considerably better than a single sensor when the "OR" fusion rule is adopted.

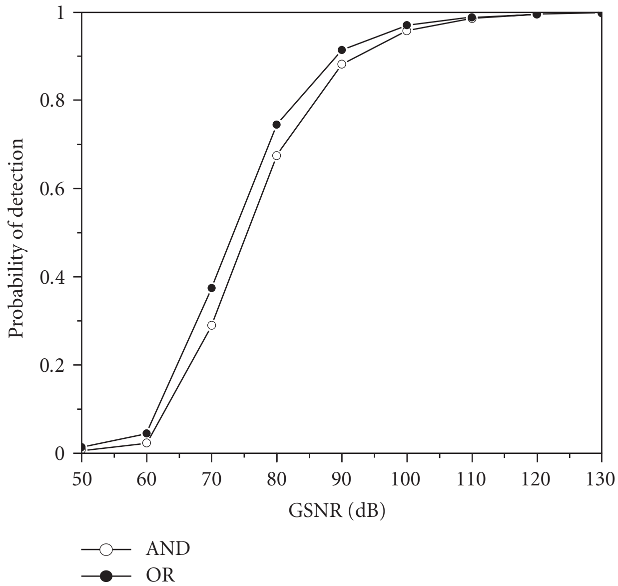

Figure 6: Probability of detection of two distributed CA CAGOCFAR system in homogeneous Pearson background adopting the "AND" and "OR" fusion rules. $N_1 = N_2 = 32$. $P_{fa} = 10^{-4}$.

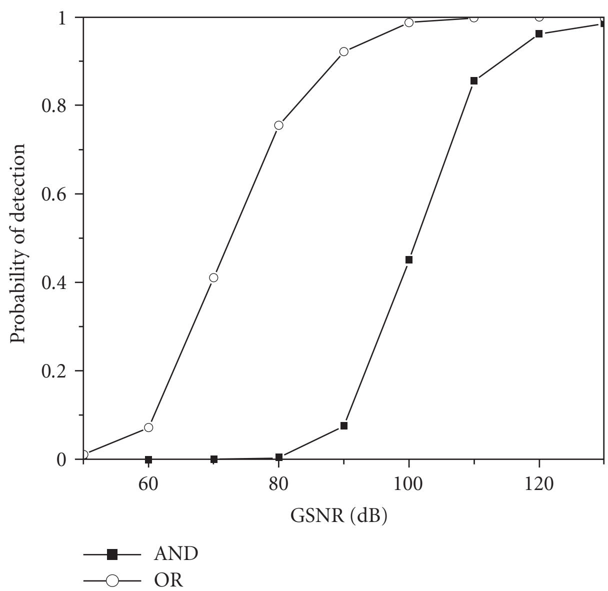

Figure 7: Probability of detection of two distributed CA CACFAR system in homogeneous Pearson background and in presence of three interfering targets in one detector ($GINR_1 = GINR_2 = GINR_3 = 50$ dB) adopting the "AND" and "OR" fusion rules. $N_1 = 32$, $N_2 = 16$. $P_{fa} = 10^{-4}$.

6. CONCLUSIONS

In this work, we have assessed the performance of decentralized CFAR detectors in homogeneous positive alpha-stable operating environment and in the presence of interfering targets. The local sensors are assumed to be identical or different CFAR processors taking their own decisions about the presence of a target. Such binary information is subsequently sent to a fusion centre for the final decision which is taken according to "AND" or "OR" fusion logic. In [11], the performance of single CFAR detectors is addressed for the case of homogeneous Pearson background. However, as in many practical situations, the radar system is expected to work in nonnominal disturbance situations. This has motivated us to investigate the performances in more general scenarios and extend their results to distributed CFAR systems. Thus, we have considered the presence in the local sensor reference windows of spurious targets. The performances assessment, conducted via Monte Carlo simulations have shown that the distributed systems, especially the combination of different CFAR processors when the clutter is modelled as positive alpha-stable measurements and using OR fusion rule, offer robustness proprieties against multiple targets.

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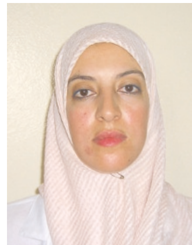

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