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A Backward Automatic Censored Cell Averaging Detector for Multiple Target Situations in Log-normal Clutter

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Abstract. A challenging problem in radar signal processing is to achieve reliable target detection in the presence of interferences. In this paper, we propose a novel algorithm for automatic censoring of radar interfering targets in log-normal clutter. The proposed algorithm, termed the backward automatic censored cell averaging detector (B-ACCAD), consists of two steps: removing the corrupted reference cells (censoring) and the actual detection. Both steps are performed dynamically by using a suitable set of ranked cells to estimate the unknown background level and set the adaptive thresholds accordingly. The B-ACCAD algorithm does not require any prior information about the clutter parameters nor does it require the number of interfering targets. The effectiveness of the B-ACCAD algorithm is assessed by computing, using Monte Carlo simulations, the probability of censoring and the probability of detection in different background environments.

1. Introduction

Log-normal clutter model has been, and still is, used to regulate false alarm rate in high resolution radars. Around 35 years ago, experimental sea clutter data presented in Cote (1973) has indicated that the clutter, taken with high resolution short-pulse (≤0.2μs) surface-search radars, can be closely modeled using log-normal statistics. Motivated by this fact and the results obtained in Schleher (1975), Billingsley (1999), and Shnidman (1999), research effort to develop adaptive threshold techniques to maintain constant false alarm rate (CFAR) in log-normal clutter with unknown distributional parameters has been conducted in the literature. In particular, the detection performance of harbor surveillance radars has been considered in Curtis (1977). In Goldstein (1973), an automatic detection procedure, termed "log-t" detector, is presented which maintains a CFAR in an extended-clutter environment wherein the clutter cross section is log-normally distributed. In Guida (1993), a biparametric CFAR procedure for log-normal clutter has been introduced and assessed. Its operation amounts to transforming the clutter probability density function (PDF) into a location-scale one through a logarithmic transformation, and to jointly estimating the location and scale parameters by the best unbiased estimators (BLUEs). In Weber (1985), a biparametric CFAR procedure has been proposed which produces an estimate of the detection threshold by processing two ordered statistics from the reference window. Analysis of this detector with numerical results showing its performance has been presented in Al-Hussaini (1988) under the assumption that the clutter echoes can be modeled as log-normal distribution. In Conte (1997), a hybrid technique has been proposed for false alarm regulation in the presence of a non-Gaussian clutter.

Note that the CFAR detectors aforementioned above perform well under the assumption of homogeneous environments. In practice, the environment is usually non-homogeneous due to the presence of multiple targets and/or clutter edges in the reference window. In such situations, order statistics (OS)-detectors (Guida, 1993; Weber, 1985; Al-Hussaini, 1988; Conte, 1997) have been known to yield good performance as long as the nonhomogeneous background and outlying returns are properly discarded. However, most of the work in the literature considers some type of censoring based on a priori knowledge or a judicial guess.

Some approaches (Himonas, 1992; Srinivasan, 2000; Smith, 2000; Farrouki, 2005) based on automatic censoring of unwanted cells have been proposed in the literature for Rayleigh clutter. In this work, we consider the problem of automatic censoring of unknown number of interfering targets in log-normal clutter. The main motivations behind the development of such an automatic censoring algorithm are due to the following: (i) the automatic censoring algorithms developed for Rayleigh clutter may not straightforwardly be extended to the case where clutter samples are drawn from log-normal distribution. For example, the ordered data variability index based on which the detector of Farrouki (2005) has been developed may be difficult to use for automatic censoring in log-normal clutter because this index is highly dependent on the shape parameter of clutter distribution; a parameter difficult to estimate reliably in practice; (ii) the adaptive threshold of OS-CFAR processors is formally defined in terms of ranked samples of reference cells. To reduce the CFAR loss and improve the detection probability of log-normal OS-CFAR processors, the largest sample of ranked cells, involved in the computation of detection threshold, can be properly selected when the exact number of interfering targets is accurately determined. Therefore, the results of this research work has an attractive feature in that it adds to the available log-normal CFAR detectors (Goldstein, 1973; Guida, 1993; Weber, 1985; Al-Hussaini, 1988) the potential to determine and censor (efficiently) the unwanted targets samples in the reference window, which may cause an excessive number of false alarm or a poor probability of detection.

2. Preliminaries

The general structure of the proposed CFAR processor is depicted in Fig. 1. The envelope-detected matched filer outputs Y_i are passed through a logarithmic processor and then sent serially into a tapped delay line of length N+1. The N+1 samples correspond to the even number N of reference cells $\{ X_i : i = 1, 2, \ldots, N \}$ surrounding the test cell X_0.

We assume that, if clutter alone is present (H_0 hypothesis), then Y_i are IID random variables drawn from log-normal probability density function (PDF) with scale parameter μ and shape parameter σ. Hence, the transformed variats X_i are of location-scale type, and precisely have the Gaussian distribution PDF; that is:

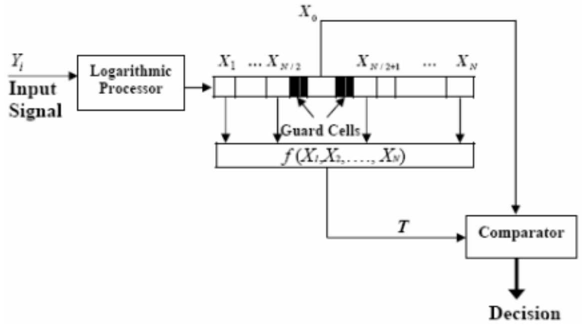

Fig. 1. Blockdiagram of the proposed CFAR processor.

$$f(x, \mu, \sigma) = \frac{1}{\sqrt{2\pi}\,\sigma} \exp\left[-\left(\frac{x-\mu}{\sigma} \right)^2 \right], \; -\infty < x < \infty \quad (1)$$

With exact knowledge of clutter parameters, the threshold ensuring a given probability of false alarm (P_{fa}) is given by:

$$T = \mu + \gamma\,\sigma \quad (2)$$

where γ is the (1- P_{fa})-quantile of the standard clutter distribution. However, lacking prior knowledge of the distributional clutter parameters, the adaptive threshold can be adjusted to take the form:

$$\hat{T} = \hat{\mu} + \hat{\gamma}\,\hat{\sigma} \quad (3)$$

where $\hat{\mu}$ and $\hat{\sigma}$ represent equivalent estimators of location and scale parameters, and $\hat{\gamma}$ is a suitable coefficient to be set according to the designed P_{fa}.

3. Estimation of Location and Scale Parameters

There are several ways (David, 2003) to obtain equivalent estimators of μ and σ, including maximum likelihood estimators (MLEs) and linear estimators such as best linear unbiased (BLU) and best linear invariant (BLI) estimators. Here, we focus on a simple linear approach which avoids solving nonlinear equations as in MLEs or the need for covariance matrix computations as in BLU and BLI estimators. Let,

$$X(1) \le X(2) \le \ldots \le X(\mathrm{N}) \quad (4)$$

be ordered samples of all reference window range cells. Linear estimators of μ and σ based on (possibly) N-*j* censored samples from the upper end are defined as:

$$\hat{\mu}_j = \sum_{i=1}^{j} a_i X(i) \quad (5)$$

$$\hat{\sigma}_j = \sum_{i=1}^{j} b_i X(i) \quad (6)$$

where a_i and b_i are suitable coefficients chosen to satisfy:

$$\sum_{i=1}^{j} a_i = 1 \quad (7)$$

$$\sum_{i=1}^{j} b_i = 0 \quad (8)$$

which are necessary constraints for $\hat{\mu}_j$ and $\hat{\sigma}_j$ to be equivalent estimators. Define:

$$S(1) \leq S(2) \leq \ldots \leq S(j) \quad (9)$$

to be ordered variates from a Gaussian PDF which has zero mean and unit variance. Following the approach of Gupta (1952), the coefficients a_i and b_i are determined as follows:

$$a_i = \frac{1}{j} - \frac{\bar{\alpha}(\alpha_i - \bar{\alpha})}{\sum_m (\alpha_m - \bar{\alpha})^2} \quad (10)$$

$$b_i = \frac{(\alpha_i - \bar{\alpha})}{\sum_m (\alpha_m - \bar{\alpha})^2} \quad (11)$$

where $\bar{\alpha}$ is the average value of $\{\alpha_i : i = 1, 2, \ldots, j\}$ and

$$\alpha_i = E\{S(i)\} = \int_{-\infty}^{\infty} x\, f_i(x)\, dx \quad (12)$$

where E{·} is the expectation operation and $f_i(x)$ is the PDF of the variates $S(i)$. Denoting by F(x) the cumulative distribution function (CDF) of the standard Gaussian PDF f(x,0,1) of (1), the values of α_i can be computed as follows (Barkat, 2005):

$$\alpha_i = i \binom{N}{i} \int_{-\infty}^{\infty} x \left[1 - F(x)\right]^{N-i} \left[F(x)\right]^{i-1} f(x,0,1)\, dx \quad (13)$$

The expectations α_i are the only estimates needed in the linear estimation method outlined above, and must be computed once and for all according to (13).

Also, the resulting coefficients a_i and b_i given by (10) and (11) satisfy the conditions imposed by (7) and (8), respectively. Hence, $\hat{\mu}_j$ and $\hat{\sigma}_j$ are equivalent estimators.

For detection in homogeneous environments, it is appropriate to set j=N. However, when there are k interfering targets in the reference window, the value of j is best selected such that j=N-k. Therefore, our objective in this work is to develop a new censoring algorithm that has the task of determining the best value of k. Once the number of interfering targets is determined automatically, the output of the cell under test X_0 is then compared with the adaptive threshold $\hat{T}$ according to:

$$X_0 \underset{H_0}{\overset{H_1}{\gtrless}} \hat{T} \quad (14)$$

where the adaptive threshold $\hat{T}$ (or equivalently the parameter $\hat{\gamma}$) is selected so that the design P_{fa} is achieved. H_1 denotes the presence of a target in the test cell, while hypothesis H_0 is the null hypothesis, i.e., no target is present.

4. The Proposed Censoring Algorithm

In this section, we propose a novel detector for automatic censoring of possible interfering targets that may lie in the reference window of the cell under test. The censoring procedure first ranks the outputs of all reference range cells in ascending order according to their magnitudes to yield:

$$X(1) \leq X(2) \leq \ldots \leq X(p) \leq \ldots \leq X(N) \quad (15)$$

The proposed algorithm is termed, according to the sequence through which the censoring is performed, the backward automatic censored cell averaging detector (B-ACCAD). The basic idea of the B-ACCAD algorithm is to consider that the p lowest cells represent the initial estimation of the background level. The parameter p has to be carefully selected to yield a robust performance in both homogeneous background and non-ideal environment. Values of p>N/2, as in Farrouki (2005), have been found to yield a reasonable performance.

4.1. The B-ACCAD algorithm

This algorithm proceeds as follows. Sample X(N) is compared with the adaptive threshold $\hat{T}_0$ defined as:

$$\hat{T}_0 = \hat{\mu}_p + z_0\hat{\sigma}_p \quad (16)$$

where z_0 is a threshold coefficient chosen to achieve the desired probability of false censoring, P_{fc}. If X(N)< $\hat{T}_0$, the algorithm decides that X(N) corresponds to a clutter sample without interference and it terminates. If, on the other hand, X(N)> $\hat{T}_0$, the algorithm decides that the sample X(N) is a return echo from an interfering target. In this case, X(N) is censored and the algorithm proceeds to compare the sample X(N-1) with the threshold:

$$\hat{T}_1 = \hat{\mu}_p + z_1\hat{\sigma}_p \quad (17)$$

to determine whether it corresponds to an interfering target or a clutter sample without interference. At the $(k+1)^{th}$ step, the sample X(N-k) is compared with threshold $\hat{T}_k$ and a decision is made according to the test:

$$X(N-k) \underset{H_0}{\overset{H_1}{\gtrless}} \hat{T}_k \quad (18)$$

where $\hat{T}_k = \hat{\mu}_p + z_k\hat{\sigma}_p$. Hypothesis H_1 represents the case where X(N-k) and consequently X(N-k+1), X(N-k+2), …, X(N) correspond to clutter samples with interference, while H_0 denotes the case where X(N-k) is a clutter sample without interference. The successive tests are repeated while the hypothesis H_1 is true. The algorithm stops when the cell under investigation is declared homogeneous (i.e. clutter sample) or, in the extreme case, when all the N-p highest cells are tested; that is, k=N-p. Figure 2 shows the block diagram of the B-ACCAD algorithm.

4.2. Selection of detection thresholds

The B-ACCAD algorithm requires knowledge of the threshold coefficients $\hat{\gamma}_k$ (or equivalently $\hat{\gamma}_{N-j}$, where j=N, N-1, …, p). Table 1 gives the values of $\hat{\gamma}_{N-j}$ for different values of N and p. These coefficients are selected such that P_{fa} is maintained constant in a homogeneous environments. That is,

$$\text{design } P_{fa} = \text{Prob}\{X_0 > \hat{T}/H_0\} \quad (19)$$

Because an analytical expression for the PDF of $\hat{T}$ is

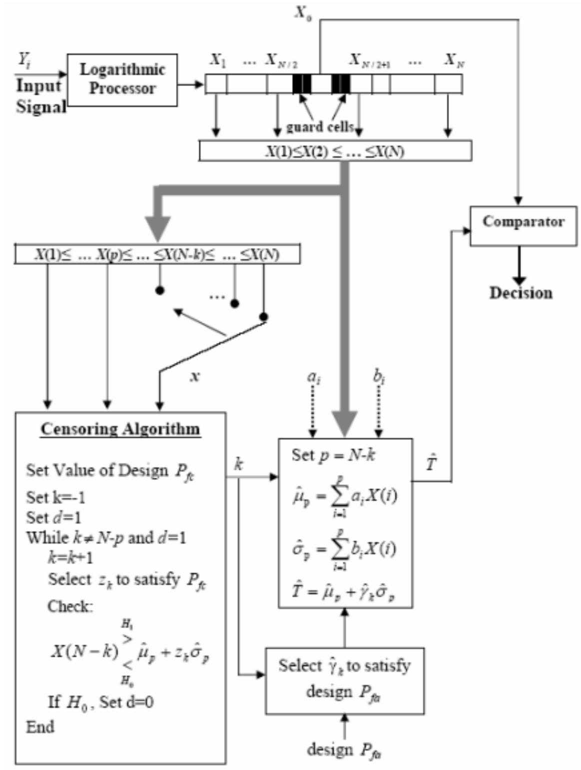

Fig. 2. Blockdiagram of the B-ACCAD algorithm.

not available, the results of Table 1 have been obtained using Monte Carlo simulations with 500,000 independent runs. Note that as the value of p increases, the threshold coefficients $\hat{\gamma}_{N-j}$ decreases. This is intuitively not surprising because increasing the value of p increases the accuracy of estimating the clutter parameters μ and σ.

Table 1. Threshold coefficients $\hat{\gamma}_{N-j}$ for different values of N

(N,p)	$\hat{\gamma}_{N-j}$							
	$\hat{\gamma}_0$	$\hat{\gamma}_1$	$\hat{\gamma}_2$	$\hat{\gamma}_3$	$\hat{\gamma}_4$	$\hat{\gamma}_5$	$\hat{\gamma}_6$	$\hat{\gamma}_7$
(16,12)	4.5	4.25	4.1	3.9	3.8	--	--	--
(32,24)	3.7	3.66	3.56	3.55	3.46	3.45	3.43	3.4

The B-ACCAD algorithm requires the values of the thresholds z_k. These thresholds are determined such that a low probability of hypothesis test error e_k is achieved. For the B-ACCAD algorithm, e_k is defined, at each value of k, as follows:

$$e_k = \text{Prob}\left\{X(N-k) > \hat{T}_k/H_0\right\} \quad (20)$$

Monte Carlo simulations have been used to determine the values of threshold coefficient z_k by setting:

$$e_0 = e_1 = \ldots = e_k = \text{design } P_{fc} \quad (21)$$

and the result are displayed in Table 2. It is of interest to note that the thresholds z_k form an ordered sequence with respect to *k*.

Table 2. Threshold parameters z_k in a homogeneous background with log-normal PDF

(N,p)	P_{fc}	z_0	z_1	z_2	z_3	z_4	z_5	z_6	z_7
(16,12)	10^{-2}	4.35	3.09	2.34	1.75	---	---	---	---
	5×10^{-3}	4.85	3.41	2.60	1.94	---	---	---	---
	10^{-3}	5.95	4.23	3.20	2.40	---	---	---	---
(32,24)	10^{-2}	4.07	3.09	2.60	2.24	1.96	1.70	1.485	1.28
	5×10^{-3}	4.35	3.33	2.75	2.40	2.09	1.82	1.59	1.37
	10^{-3}	5.06	3.83	3.20	2.76	2.41	2.10	1.82	1.57

5. Performance Evaluation

In this section, we evaluate the performance of the proposed B-ACCAD algorithm using different values of N and p and at different interference-to-clutter ratios (ICR). The complex envelop of the received signal has been considered to have Rayleigh distributed amplitude and uniform phase. As far as one is concerned with single-hit detection, this corresponds to both Swerling I and Swerling II fluctuating models. We assume in our evaluation that the reference window contains m unknown targets, where 0 ≤ m ≤ N–p and m=0 corresponds to the homogeneous case.

5.1. Effect of initial population

The B-ACCAD algorithm has been developed under the assumption that the cell averaging samples, which define the thresholds $\hat{T}_k$, are clutter samples without interference. Note that the behavior of the algorithm may change according to whether the initial population is homogeneous or non-homogeneous.

Let β be the probability that the initial population, defined by if, at least, the smallest cell containing an interference plus clutter is less than or equal to the p^{th} sample containing clutter only. When there is no interfering targets, β=1. In the presence of *m* interfering targets, the initial population cells *X*(1), *X*(2), …, *X*(*p*) may contain interference plus clutter samples. Therefore, β can be defined as follows:

$$\beta = 1 - \text{Prob}(X_{i1} \leq X_{cp}) \quad (22)$$

where X_{i1} represents the smallest interfering target sample after the samples ranked in order, i.e., $X_{i1} \leq X_{i2} \leq \ldots \leq X_{im}$ and X_{cp} denotes the p^{th} sample of the order statistics $X_{c1} \leq X_{c2} \leq \ldots \leq X_{cp} \leq \ldots \leq X_{c(N-m)}$ where X_{cj}, (*j*=1, 2, …, N-m), contains the clutter samples only.

The probabilities β obtained for different values of ICR and m are presented in Table 3. We observe that, when ICR increases, β remains close to 1 even when several interferences are present.

Table 3. Probabilities β that initial population is homogeneous in multiple target situations

(N,p)	m	ICR 10dB	20dB	30dB	40dB
(16,12)	1	0.9494	0.9948	0.9995	0.9999
	2	0.8743	0.9862	0.9986	0.9998
	4	0.5431	0.9335	0.9929	0.9993
(36,24)	4	0.8420	0.9829	0.9982	0.9998
	8	0.5736	0.9432	0.9941	0.9994
	12	0.1197	0.7619	0.9721	0.9970

5.2. Probability of censoring

Figure 3 shows the probability of censoring for N=36, *p*=24, σ=0.355, and m=8 interferences with different ICR. P_{fc} has been fixed at 10^{-2}. Note that the B-ACCAD algorithm has the capability to determine the exact number of interferences with probability of 52.2% at ICR=25dB, 54.4% at ICR=30dB, and 55.5% at ICR=35dB. The algorithm is also characterized by a lower probability of under-censoring (P_u) compared to that of over-censoring (P_o) at higher values of ICR. In practice, under-censoring may degrade the performance of the censoring algorithm, whereas over-censoring is a desirable property when the number of interferences is unknown (Farrouki, 2005).

Figure 4 shows the effect of the shape parameter σ on the performance of the B-ACCAD algorithm in the presence of *m*=6 interfering targets. Note that, as σ increases, probability of under-censoring (P_u) also increases.

The effect of P_{fc} on the performance of the proposed B-ACCAD algorithm has been also examined. Figure 5 shows the probability of censoring of B-ACCAD algorithm computed in the

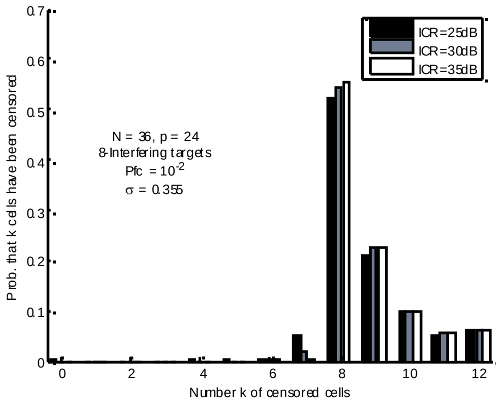

Fig. 3. Probability of censoring in multiple target situations.

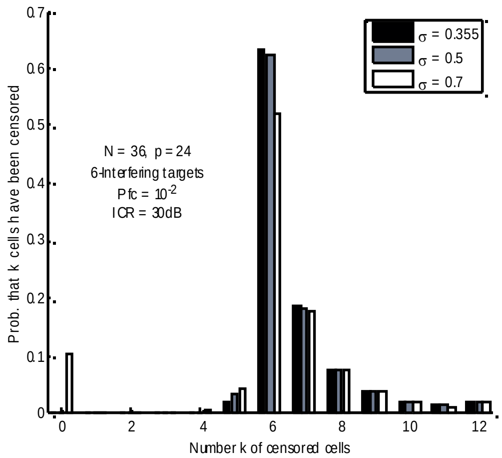

Fig. 4. Probability of censoring in multiple targets situations.

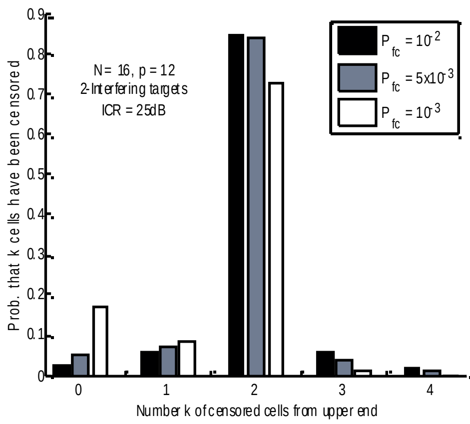

Fig. 5. Probability of censoring in two interfering targets environment with P_{fc} as a parameter.

presence of two interferences. We have set N=16, p=12, σ=0.355, and ICR=25dB. The P_{fc} has been given the values $10^{-2}, 5\times10^{-3}$ and 10^{-3}. As the figure shows, increasing P_{fc} results in higher probability of determining the exact number of interferences.

5.3. Probability of detection

In this section, the detection performance of the B-ACCAD algorithm in log-normal clutter is evaluated. Single pulse detection is considered and a Rayleigh fading model is assumed for the fluctuating targets. Unless otherwise stated, the ICR has been set equal to signal-to-clutter ratio (SCR). That is, the outlying targets are assumed to have the same radar cross-section as the primary target. In Fig. 6, the detection performance of the B-ACCAD algorithm for (N,p)=(36,24) and (N,p)=(16,12) configurations in a homogeneous background is presented. The results are compared with that of the ideal processor whose detection threshold is adjusted according to (2). As the figure shows, the curve of the B-ACCAD algorithm closely matches that of the ideal detector when (N,p)=(36,24). However, there is a slight degradation in algorithm's performance when (N,p)=(16,12), which is expected and may be attributed to the small number of reference window samples exploited in estimating the unknown clutter distributional parameters.

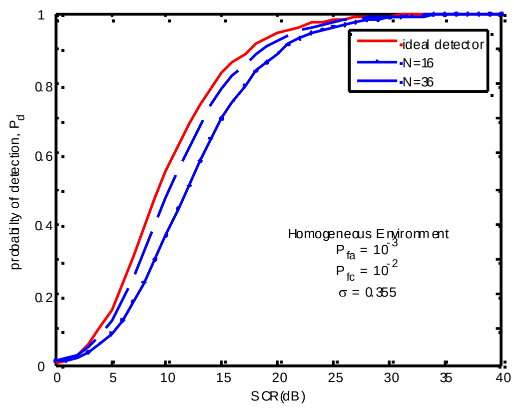

Fig. 6. P_d against SCR of B-ACCAD detector in homogeneous environments.

In Fig. 7, the detection performance of the B-ACCAD algorithm in the presence of m interfering targets is presented. We note that as the number of interfering targets present in the reference window increases, the detection probability decreases. However, this degradation in probability of detection is more pronounced at higher values of σ.

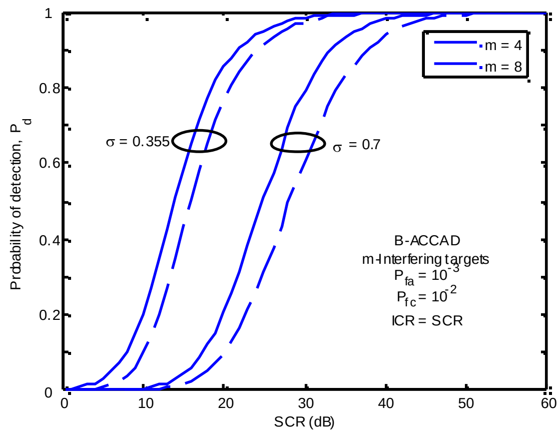

Fig. 7. P_d of B-ACCAD detector in multiple target situations for two values of σ.

6. Summary and Conclusion

In this paper, we have considered the problem of automatic censoring of unknown number of interfering targets in log-normal clutter. A novel technique has been proposed; namely, the B-ACCAD algorithm. This algorithm uses pre-computed thresholds to discriminate between homogeneous and non-homogeneous populations in log-normal clutter. The effectiveness of the proposed B-ACCAD algorithm has been assessed by computing the probability of censoring and probability of detection for different numbers of interfering targets and at different values of ICR. Simulation results show that the proposed B-ACCAD algorithm performs robustly in the presence of high and moderate levels of interferences. The B-ACCAD algorithm is also characterized at moderate and high levels of ICR by having small probability of under-censoring and is capable to maintain good performance even at relatively high values of shape parameter σ.

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معا ات ا راقبة الآلية بوجود أهداف متداخلة بيئة الضجيج الطبيعي اللوغاريتمي

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(قدم للنشر في٠٧/٠٤/٢٠٠٧م؛ وقبل للنشر في ٢٢/٠١/٢٠٠٨م)

الكلمات ا فتاحية: معدل الإنذار الكاذب، بيئة الضجيج الطبيعي اللوغاريتمي ، معالجات المراقبة الآلية ، احتمال الإنذار الكاذب، احتمال مراقبة خاطئة.

ملخص البحث. من المشاكل الصعبة في معالجة إشارة الرادار هو تحقيق اكتشاف فاعل مع وجود تداخل. سننظر في هذه الورقة لهذه المشكلة مع نمذجة الضجيج بالتوزيع اللوغارتمي الطبيعي. يتميز هذا التوزيع بذيل طويل جدًّا وبالتالي يمثل بيئة ضجيج قوي أكثر ملائمة من نموذج رالي لتمثيل سلوك النتئات الحادة في الرادارات عالية الوضوح.

تم اقتراح خوارزميات مبتكرة للمُرَاقَبَة الآلية لتداخل أهدافِ الرادارِ في الضجيج اللوغاريتمي الطبيعي. تشمل الخوارزميات المُقتَرَحة خطوتين رئيسيتين: إزالة الخلايا المرجعية المعطوبة، والكشف الفعلي. تتم الخطوتان بفاعلية من خلال استخدام المجموعة المناسبة من الخلايا المُصنَّفةِ لتَخمين مستوى الخلفية المجهول وتحديد العتبات التكيفية وفقًا لذلك. لا تتطلب الكاشفات المُقتَرَحة أيّ معلومات مسبقة عن قيم الضجيج أو عن عدد الأهداف المتداخلة. إن فعالية الخوارزميات المُقتَرَحة مُقَدرة بطريقة تشبيه مونتي كارلو لحساب احتمال المُرَاقَبَة واحتمال الكشف في بيئاتِ خلفية مختلفة.