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Performance comparison of some censoring CA-based CFAR processors in heterogeneous environments

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Abstract: Performance comparison of automatic censoring CA-based CFAR processors contribute to the development of more efficient censoring detectors. In this paper, the authors analyze the performance of the detection schemes which named: ACCA-odv- (Automatic Censored Cell Averaging -ordered data variability-), ADCCA- (Automatic Dual Censoring Cell Averaging-), ACGCA- (Automatic Censoring Greatest Cell Averaging-), and GGDC- (Goodness-of-fit Generalized likelihood test with Dual Censoring-)-CFAR's in heterogeneous environments. The assumed environments are represented by three situations: first, the homogeneous situation, second, the presence of interfering targets, and the third case is allowed to the presence of clutter edges. The obtained results, under the assumption of a Gaussian clutter and a mono pulse processing, show that most of the studied detectors perform well in a specific conditions and there is a need to further developments to ensure the required performances for recent target detection application.

Keywords: Adaptive CFAR detection, Automatic censoring, heterogeneous environments, Probability of detection, Probability of false alarm.

1. INTRODUCTION

The first Constant- False- Alarm- Rate detector proposed in radar detection is the CA-CFAR (Cell Averaging-) [1]. This processor performs optimally in a Gaussian clutter when the returns are assumed independent and identically distributed (*IID*). Otherwise, it suffers from poor detection in the presence of interferers and /or clutter edges [2]. To circumvent the problem of clutter regions, the GO-CFAR (Greatest Of-) has been proposed [3]. Also, in order to prevent the suppression of closely spaced targets, the SO-CFAR (Smallest Of-) has been introduced [4]. The study of [5] has shown that the detection probability of the GO- decreases intolerably when interfering targets appear in the reference window and the SO- processor fails to maintain a constant false alarm rate at clutter edges. The CA-, GO-, and SO-CFAR's are called the conventional mean level detectors.
After that, a family of Order Statistics-based CFAR using fixed censoring points have been proposed [6]-[7]. However, these censoring schemes need some a priori knowledge about the environment in order to reject the unwanted samples. To give more efficient solutions, many automatic censoring techniques have been designed by dynamically determining the optimal adaptive censoring points [8]-[9]-[10]-[11]-[12]. These procedures do not require any prior information about the environment. For more details, the processors as in [8] and [10] provide a modified versions of the GO- and the CA-CFAR schemes respectively. Also, the approach proposed in [9] presents an automatic scenario to switch to the CA-, SO-, or the GO- CFAR's. Similarly, the detector proposed in [11] is programmed to switch to the CA-, CMLD- (Censored Mean Level Detector-) [6], and TM- (Trimmed Mean-) [2] CFAR's. In order to maintain more robust performance, the authors in [12] exploit the information of the original positions "outlier -free cells" before sorting data. All these detectors have a different comportments in heterogeneous environments and they designed to optimize the probability of detection *Pd* under the assumption of a constant probability of false alarm *Pfa* (Neyman- Pearson criterion).
In this work, we analyze the performance of some censoring CA-based CFAR detectors in heterogeneous Gaussian environments. The considered detectors are named: ACCA-odv- [13], ADCCA- [14], ACGCA- [15], and GGDC- CFAR's [16]. The performance, to be analyzed, is represented by the variation of the probability of detection *Pd* and the false alarm control *Pfa*. We evaluate and compare their characteristics in a homogeneous clutter, in closely spaced targets of *SWI* (*SWERLING I*) model, and then in edge clutter regions. Furthermore, the obtained results are

compared also with those of the classical CA-CFAR.
The paper is organized as follows. **Section 2** is devoted to the discussion of the basic assumptions and problem formulation in a general CFAR detection. The algorithms corresponding to the above processors are illustrated in **section 3**, whereas results and discussions using Monte-Carlo simulations are considered in **section 4**. Finally, our conclusions with a suggestions for future works are provided in **section 5**.

2. PROBLEM FORMULATION

In a CFAR processor, the square- low detected received signal is sampled in range by the range resolution cells. The resulting samples are stored in a taped delay line, as shown in Fig.1. The output of the test cell *(CUT)* which is the one in the middle of the taped delay line is denoted by X_0 . The outputs of the cells surrounding the test cell, X_i , (i=1,…,N), are combined to yield an estimate Z of the noise level in the test cell, that is,

$$Z = f(X_1 ,..., X_N) \tag{1}$$

Where the operator f denotes the processing of the received observations. The output of X_0 is then compared with the adaptive threshold TZ according to the test of detection [1]

$$X_0 \underset{H_0}{\overset{H_1}{\gtrless}} TZ \tag{2}$$

Where the scaling constant factor T is selected so that the design probability of false alarm Pfa is achieved. Hypothesis H_1 denotes the presence of a target in the test cell, while hypothesis H_0 is the null hypothesis. H_1 and H_0 form the so called "Detection Decision". The probabilities of detection Pd and of false alarm Pfa, in general, are defined by [1]

$$Pfa = Probability[X_0 > TZ \mid H_0] \tag{3}$$

$$Pd = Probability[X_0 > TZ \mid H_1] \tag{4}$$

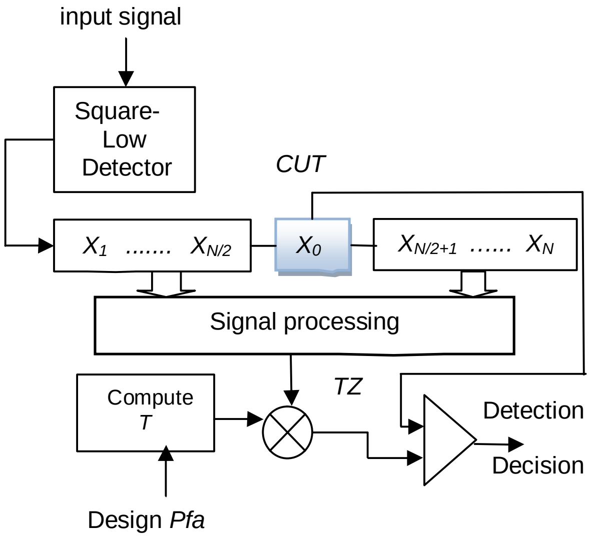

Fig. 1 CFAR detector

We assume that the cell outputs are observations from statistically independent and identically distributed (*IID*) random variables. That is, the Probability Density Function (*PDF)* of the output of the i^{th} cell is given by [1]

$$f_{X_i}(x) = \frac{1}{\mu}.exp\left(-\frac{x}{\mu}\right) \qquad x \geq 0 \tag{5}$$

μ denotes the scale parameter of the exponential distribution corresponding to the total noise power. The value of μ depends on the content of the observed data. When the i^{th} reference cell is immersed in a Gaussian clutter and contains an interfering target, μ may be written as $\mu_t(1+INR)$ where *INR* denotes Interference- to- Noise Ratio*.* On the other hand, if some cells are embedded in clutter region*,* μ may be written as $\mu_t(1+CNR)$, where *CNR* denotes Clutter- to- Noise Ratio. If *INR* = 0 and *CNR*=0*,* this corresponds to the homogenous situation with $\mu = \mu_t$, where μ_t denotes the thermal noise power (normalized to unity).
According to the classical CA-CFAR detection, the sum of N reference cells *IID* and exponentially distributed follows Gamma distribution [17] with parameters *(μ, N)*

$$f_Z(z) = \frac{z^{N-1}}{\Gamma(N).\mu^N}.exp\left(-\frac{z}{\mu}\right) \qquad z \geq 0 \tag{6}$$

Where, Γ denotes the Gamma function. In adaptive CA-based censoring detection, and after rejecting the unwanted samples located in the reference canal, the size N is changed to $(N-\hat{\imath})$. Where $\hat{\imath}$ is the estimated number of the censored cells from the reference window. Consequently, the mean level background estimator □ , which is given by the sum of the rested samples, is also Gamma distributed [17] but with parameters *(μ, (N- î))*

$$f_{\hat{Z}}(\hat{z}) = \frac{\hat{z}^{(N-\hat{\imath})-1}}{\Gamma(N-\hat{\imath}).\mu^{(N-\hat{\imath})}}.exp\left(-\frac{\hat{z}}{\mu}\right) \qquad \hat{z} \geq 0 \tag{7}$$

3. ALGORITHMS

In this section, we present the algorithms of the processors at hand, with brief explications therein, as follows.

CA-CFAR

Input: N, T_{CA} (scaling constant factor) ,
- Start: $X = [X_1, \ldots, X_{N/2}, X_{N/2+1}, \ldots, X_N]$, $X_0 = CUT$,
***** Compute, $Z = \sum_{i=1}^{N} X_i$
***** Apply the test , $X_0 \underset{H_0}{\overset{H_1}{\gtrless}} T_{CA} Z$
- End
Decision: H_1 or H_0

ACCA-odv-CFAR

Input: N, $T_{\hat{\imath},odv}$ (scaling factors) , p_1 (chosen parameter) , $S_{k,odv}$ (censoring thresholds),
- Start: $X = [X_1, \ldots, X_{N/2}, X_{N/2+1}, \ldots, X_N]$, $X_0 = CUT$,
***** Form the ordered powered samples, $X_{(1)} \leq .. \leq X_{(p_1)} \leq .. \leq X_{(N)}$
***** Assuming the homogeneity of the initial population $[X_{(1)}, .., X_{(p_1)}]$ of length p_1.
***** To find the non homogeneity point in the rested interval $[X_{(p_1+1)}, .., X_{(N)}]$ form

the subset $[X_{(1)},..,X_{(p_1)},q]$ of length p_1+1. With $q=X_{(N-k)}$, k=0,1,.., N-p_1-1.

***** Apply the censoring test , $ODV(q) \underset{H_h}{\overset{H_{nh}}{\gtrless}} S_{k,odv}$ to obtain $\hat{\imath}_{odv}=k$ .Note that,

$$ODV(q)=\frac{\mu_{p_1}+q^2}{(\sigma_{p_1}+q)^2} \quad \text{with} \quad \mu_{p_1}=\sum_{i=1}^{p_1} X_{(i)}^2 \quad \text{and} \quad \sigma_{p_1}=\sum_{i=1}^{p_1} X_{(i)}$$

***** Select the corresponding $T_{\hat{\imath},odv}$

***** Compute, $\hat{Z}=\sum_{i=1}^{N-\hat{\imath}} X_{(i)}$

***** Apply the test, $X_0 \underset{H_0}{\overset{H_1}{\gtrless}} T_{\hat{\imath},odv}\hat{Z}$

- End

Decision: H_1 or H_0

ADCCA-CFAR

Input: N, $T_{\hat{\imath},DC}$ (scaling factors) , k (the k^{th} ordered sample of OS- CFAR), t^l_{ce} and t^s_{ce} (censoring thresholds of large and small samples respectively),

- Start: $X=[X_1,...,X_{N/2}, X_{N/2+1},..., X_N]$, $X_0=CUT$,

***** Compute the observation, $u_i=\frac{X_i}{X_k}$, $\quad i=1,2,...,N$

***** Compute the membership function,

$$V(u_i)=\frac{N!}{(N-k)!}.\left(\prod_{s=0}^{k-1}(N-s+u_i)\right)^{-1}$$

*****Apply the test of censoring large samples (of high power), $V(u_i) \underset{H_h}{\overset{H_{nh}}{\lessgtr}} t^l_{ce}$

***** Apply the test of censoring small samples (of low power),

$$V(u_i) \underset{H_h}{\overset{H_{nh}}{\gtrless}} (1-t^s_{ce})$$

*****Obtain the estimated number of censoring large and small samples, $\hat{\imath}_{DC}=\sum_{i=1}^{N} w_i$

where the weights, $w_i=\begin{cases} 1 & t^l_{ce}\le V(u_i) \le (1-t^s_{ce}) \\ 0 & otherwise \end{cases}$

***** Select the corresponding $T_{\hat{\imath},DC}$.

***** Compute, $\hat{Z}=\sum_{i=1}^{N} w_i.X_i$

***** Apply the test, $X_0 \underset{H_0}{\overset{H_1}{\gtrless}} T_{\hat{\imath},DC}\hat{Z}$

- End

Decision: H_1 or H_0

ACGCA-CFAR

Input: N, $T_{\hat{\imath},G}$ (scaling factors), p_2 (chosen parameter), $S_{k,odv}$ (censoring thresholds) of the ACCA-odv *(N/2)*

- Start: $X = [X_1, \ldots, X_{N/2}, X_{N/2+1}, \ldots, X_N]$, $X_0 = CUT$,

***** Leading window $([X_1, \ldots, X_{N/2}])$: apply the ACCA-odv *(N/2, p_2)* algorithm to obtain $\square_1$ and $\hat{\imath}_G$.

***** Lagging window $([X_{N/2+1}, \ldots, X_N])$: apply the CA(*N/2*) algorithm to obtain Z_2.

***** Compute, $\square = max(\square_1, Z_2)$.

***** Select the corresponding $T_{\hat{\imath},G}$.

***** Apply the test, $X_0 \underset{H_0}{\overset{H_1}{\gtrless}} T_{\hat{\imath},G}\, \hat{Z}$

- End

Decision: H_1 or H_0 , then shift clock the controller. This makes the powered samples cannot pass to the lagging window [18] .

GGDC-CFAR

Input: N, T_{GG} (scaling factors) , and the inputs of algorithms applied in tasks **1**, **2**, and **3**.

- To search the homogeneous vector data, $\Omega \subset X$

- Start: $X = [X_1, \ldots, X_{N/2}, X_{N/2+1}, \ldots, X_N]$, $X_0 = CUT$,

1- Test of homogeneity: apply the HG-OF [16] algorithm

$$\text{if} \begin{cases} X \text{, homogeneous} & \text{go to } \mathbf{4} \text{ with } \Omega = X \\ \text{otherwise} & \text{go to } \mathbf{2} \end{cases}$$

2- Test of clutter edge: apply the GLR-based [16] algorithm

$$\text{if} \begin{cases} \text{- clutter edge is confirmed in } X \text{, select the corresponding new adaptive vector } d \subset X \\ \quad \text{where, } \Omega \subset d \text{, and then go to } \mathbf{3} \\ \text{- clutter edge is not confirmed, then go to } \mathbf{3} \text{ with } d = X \end{cases}$$

3- Test of interferers: apply the ADCCA algorithm

$$\text{if} \begin{cases} \text{- interferers are confirmed in } X \text{, select the corresponding vector data } \Omega \subset d \\ \quad \text{then go to } \mathbf{4} \\ \text{- interferers are not confirmed, select } d \text{ and go to } \mathbf{4} \end{cases}$$

***** Compute, $\hat{Z} = \sum_{i=1}^{\hat{n}} \frac{\Omega_i}{\hat{n}}$ where $\hat{n}$ is the size of Ω .

***** Select the corresponding detection threshold T_{GG} .

4-Apply the test, $X_0 \underset{H_0}{\overset{H_1}{\gtrless}} T_{GG}\, \hat{Z}$

- End

Decision: H_1 or H_0

Among all the above algorithms, H_{nh} and H_h correspond to the censoring and the non-censoring hypotheses tests respectively.

4. RESULTS AND DISCUSSIONS

In this section, we realize different scenarios using Monte-Carlo simulations in order to present the detection performance of the mentioned processors in heterogeneous environments . The performance is showed by the probability of detection *Pd* and the false alarm rate control *Pfa*. We take *N*=32 as a preferred size of the reference window. According to [13]-[14]-[15]-[16], the parameters values, of the detectors at hand, are fixed as follows: for ACCA-odv- and ACGCA-, p_1=28 and p_2 =12 , for both ADCCA- and GGDC- , t^I_{ce}=0.001, t^S_{ce}=0.01, *k=N/*2 . Also, the thresholds of HG-OF and GLR- based algorithms associated to the GGDC- detector are set greater than 1.75 and equal to 6 values [16] respectively. Through all tests, a Gaussian clutter distribution and a single pulse processing are considered with taking *Pfa* = 10^{-3} , 10^{-4}, 10^{-5}, and *Pfc* =10^{-2} (Probability of false censoring). In addition, the Swerling I *(SWI)* target model is used for the primary target in the *CUT* and also for the interferers assuming the same radar section across *SNR=INR.*

4. 1. Performance analysis in homogeneous background

In the homogeneous background, the results of the probability of detection *Pd* as a function of *SNR* for the mentioned CFAR detectors are plotted in Fig. 2 with *Pfa* =10^{-5} . Whereas, the regulation of the false alarm as a function of the noise power is provided in Fig. 3 with *Pfa* =10^{-4} . From Fig. 2, the ACCA-odv-, ADCCA-, and GGDC- CFAR's perform the same as that of the CA*(N)* and exhibit some CFAR loss relative to the ideal detector of Neyman-Pearson *(NP).* On the other hand, the ACGCA- performs likely the GO- and exhibits a loss in detection greater than that presented by the other processors. This comportment is simply because it exploits only one half of the dada in the reference canal □ *=max(*□ $_1$, Z_2*).* The regulation of the false alarm versus the noise power level is similar for all detectors and appears clearly in Fig. 3. This confirms the fact that the probability of false alarm is independent of the noise power under the *IID* assumption which is equivalent to the homogeneous situation.

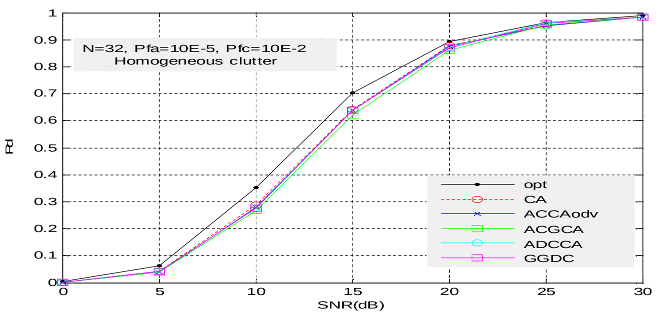

Fig. 2 *Pd* in homogeneous clutter

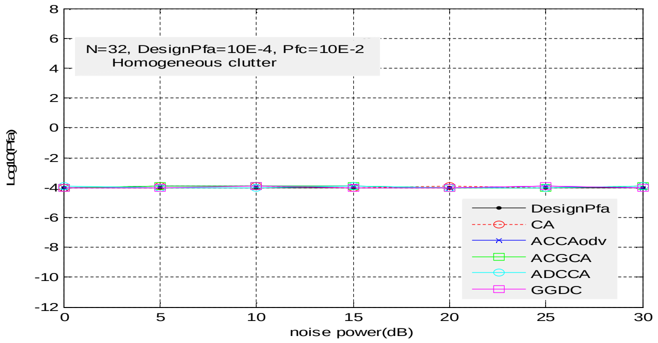

Fig. 3 *Pfa* in homogeneous clutter

4. 2. Performance analysis in multiple target situations

To evaluate and compare the comportments of the studied detectors in multiple target situations, we consider three scenarios as follows. First, the number of interferers < $(N- p_1)$, second, the number of interferers $=(N- p_1)$, third, the number of interferers $>(N- p_1)$. Note that $(N- p_1)$ is equivalent to $(N/2- p_2)$. Thus, we choose one interference in the range cell 5 for the first case, four interferers in the range cells 1, 4, 7, 10, for the second case and five interferers in the range cells 1, 4, 7, 10, 13 for the third scenario [16]. Notice that, all the chosen positions of the secondary targets are located in the leading window. This is because the ACGCA- detector is not applicable, according to their shift register, when the strong interferers are presented in the lagging window [15]. The corresponding results are illustrated in Figs. 4. 5 and 6 respectively, with *Pfa*= 10^{-5}. From Fig. 4 and Fig. 5, we remark that all the censoring detectors present a good performance and protect their robust comportments against interferers. The curves of Fig. 6 show the capability of the ADCCA- and GGDC- [16] to be robust versus *INR* echoes while the ACGCA- and the ACCA-odv- present a considerable degradation. Also, the results of Fig. 6, mean that the performance of the ACGCA- and ACCA-odv- is degraded in the case of the third scenario in which the number of outliers is greater than four. Through these figures, substantial and successive performance degradation of the conventional mean level detector CA- is observed [1].

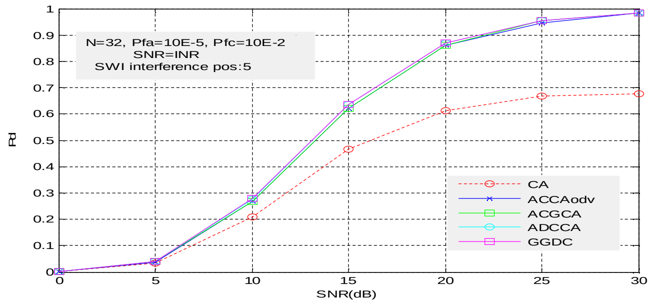

Fig. 4 *Pd* in multiple target situations, one interferer

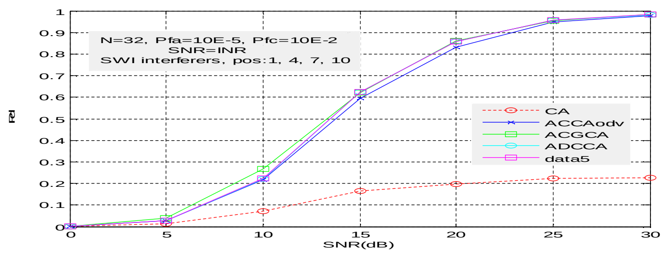

Fig. 5 *Pd* in multiple target situations, four interferers

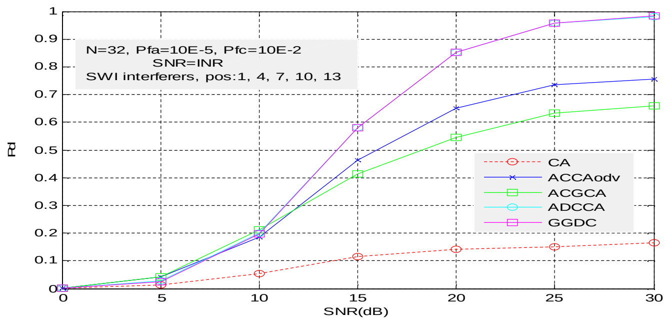

Fig. 6 *Pd* in multiple target situations, five interferers

4. 3. Performance analysis at clutter edges

To control the false alarm rate of the studied processors in the presence of clutter edges, we consider a dynamic clutter transitions of *CNR*=10*dB* in the reference window for *Pfa*=10^{-3}. We assume that there is only one type of clutter in the canal. The performance is plotted versus the distance *r* between clutter edge position and the *CUT* and it is provided in Fig. 7. The results show that, for the important case when *-16*< *r* <0, the GGDC- is the better regulator [16] of the false alarm. Also, in this situation, the ADCCA- performs better than the ACGCA- and the ACCA-odv- which presents for their part a significant loss in *Pfa*. On the contrast, when 0< *r* <16, the ACGCA- provides a good regulation than the other detectors. The difference between the performance at *-16*< *r* <0 and 0< *r* <16 regions is resulted when the clutter transitions are passed from the leading to the lagging window. At this last, the cell under test X_0 and the clutter echoes are with the same nature. Moreover, at the critical case when *r = -1,* all the leadings are in the clutter and on the other hand all the laggings are in the clear with X_0. In addition, the sharp spiky in the false alarm probability at *r*=0 is caused when the *CUT* is in the clutter with power $\mu=\mu_t\,(1+CNR)$. Finally, the conventional CA-CFAR scheme suffers from poor performance detection and presents the worst controller.

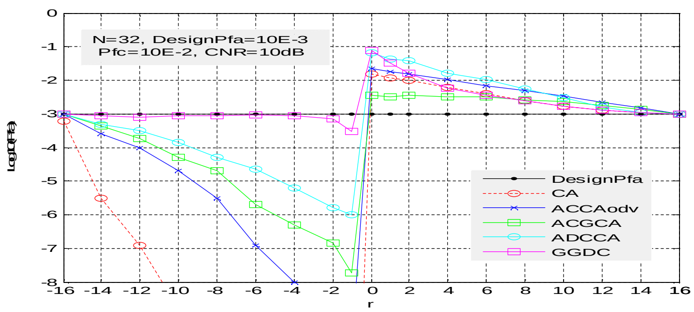

Fig. 7 Pfa in clutter edges, 10*dB*

5. CONCLUSION

In this paper, we have analyzed four censoring CA-based CFAR processors and compared their performance in heterogeneous environments. The considered detectors are named: ACCA-odv-, ADCCA-, ACGCA-, and GGDC- CFAR's. The studied performance, under the assumption of a mono pulse processing and a Gaussian clutter distribution, has been represented by the detection probability *Pd* and the false alarm regulation *Pfa*. The obtained results have shown that the above detectors perform like the CA*(N)* in a homogeneous clutter apart the ACGCA- detector which switches to an GO-CFAR. In various situations of closely spaced targets of *SWI* model embedded in clear background, the CA*(N-î)* censoring schemes perform perfectly. However, the performance of the ACGCA- and the ACCA-odv- has been degraded when the number of outliers exceeds their

corresponding parameters *(N/2-p_2)* and *(N-p_1)* respectively. About the case of the presence of clutter edges in the reference window, the GGDC- is the better regulator of the false alarm, but in general, a simplification of their complex algorithm is required. The ADCCA- and the ACGCA-detectors are relatively good controllers in their corresponding specific conditions. On the other hand, the ACCA-odv- exhibits an excessive number of false alarms in the assumed clutter boundaries.
As a suggestion to a perspective work, we propose the extension of this study to non-Gaussian environments for the case of non homogeneity caused by the presence of both multiple outliers and clutter transitions.

Acknowledgments

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