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An Adaptive CFAR Processor based on Automatic Censoring Technique for Target Detection in Heterogeneous Environments

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Abstract

The performance of radar detection systems is affected by the presence of multiple interfering targets and/or clutter edges. In this paper, we propose an adaptive Constant False Alarm Rate (CFAR) detector for heterogeneous (non homogeneous) environments. The proposed Adaptive Cell Averaging Detector or ACAD-CFAR, uses an automatic cell by cell censoring technique to reject dynamically the unwanted echoes. In fact, the problem of target detection resides in the estimation of the transitions in the reference window. Also, the presence of unwanted irregularities in the considered reference canal increases the detection threshold. The suggested detector, which does not require any prior information about the observed background, provides a good detection of the unknown transitions and protects perfectly its adaptive threshold against the presence of undesired echoes. Depending on the obtained transitions, the proposed scheme follows a strategy to output its detection decision by using an IID (Independent and Identically Distributed) conversion. Monte-Carlo simulated results, under the assumption of Gaussian clutter and mono pulse treatment, show that the addressed CA- based processing performs like the conventional CA-CFAR (Cell Averaging-) detector in the homogeneous situation and exhibits good performance in non homogeneous environments caused by the presence of multiple secondary targets and/or clutter edges.

Keywords: Adaptive CFAR detection; automatic censoring; heterogeneous environments; probability of detection; probability of false alarm.

INTRODUCTION

In radar signal processing literature, many CFAR detectors have been designed in order to optimize the probability of detection (*Pd)* under the assumption of a constant probability of false alarm (*Pfa),* (Neyman- Pearson criterion). The first detector is the well known CA-CFAR (Cell Averaging-) [1]. Its estimator of the background is obtained by summing all the received data. This processor performs optimally in a homogeneous Gaussian environment where the samples are assumed IID. Conversely, if the IID hypothesis is not verified, it suffers from considerable loss in their performance [2]. To circumvent this difficulty, the GO-CFAR (Greatest Of-) [3] and then the SO-CFAR (Smallest Of-) [4] have been proposed. Their estimators are taken by the maximum and the minimum sums of the halves of the received data, respectively. Nevertheless, the *Pd* of GO- decreases intolerably when interfering targets appear in the reference canal and the SO- fails to maintain a constant *Pfa* at clutter edges [5].

To give other solutions, Order Statistics-based CFAR detectors using fixed censoring points have been proposed. In [6], the CMLD- (Censored Mean Level Detector-) was introduced in which the higher powered ordered samples are censored and then uses the remaining cells to estimate the noise level. Also, the OS- (Ordered Statistics-) [7] which selects one ranked sample to obtain its estimator. Whereas, the TM-CFAR(Trimmed Mean-) [2], is considered as a generalization of the CMLD- and OS-CFAR schemes. It eliminates the lower and the higher ordered cells and then estimates the background level by summing the rested cells. In fact, the cited detectors perform well in a specific conditions and need some a priori knowledge about the environment in order to discard the unwanted samples. However, if this information is not provided a considerable degradation in performance is remarked.

To enhance the performance in the above expected situation, a lot of automatic censoring techniques have been designed by dynamically determining their adaptive censoring points. In [8], the ACMLD- (Automatic CMLD-) and the GTL-CMLD- (Generalized Two Level- CMLD-) processors, which based on the same cell-by-cell procedure for discarding the unwanted samples, are introduced. In [9], the authors proposed the VI- (Variability Index-) which switches automatically to the CA-, GO-, or SO- CFAR's. Another switching of the VI- to the OS- is introduced in [10] to improve the performance when the outliers are located in both the halves of the reference window. The listed adaptive-thresholdings perform well in multiple targets or in clutter edges, whereas, the performance is degraded in the presence of both outliers simultaneously.

Recently, some adaptive CFAR detectors are designed to perform well in the case of heterogeneities caused by the multiple interfering targets and/or clutter boundaries. In [11], the ADCCA- (Automatic Dual Censoring Cell Averaging-) detector was proposed. It uses two adaptive thresholds and utilizes the fuzzy membership function to eliminate the undesired samples. In [12], the author proposed the GGDC- (Goodness-of-fit Generalized likelihood test with Dual Censoring-). This processor exploits a goodness-of-fit and a generalized likelihood ratio algorithms to test the homogeneous and the clutter edges situations, respectively, and then selects the ADCCA algorithm to perform goodly in multiple interferences. Another Automatic Censoring- CFAR (AC-) which switches dynamically to the CA-, CMLD- and TM- detectors is introduced in [13]. In addition, a new class of adaptive CFAR methods is presented in [14]. The authors analyzed also, in [14], the performance of one of the possible implementations of the considered class. It is the OFPI-CFAR (Outlier Free Positions Identification-). In the same subject, the researchers proposed other systems as in [15, 16, 17, 18]. In this work, we consider the problem of target detection with unknown transitions and unknown number-power of the unwanted echoes. We propose an Adaptive Cell Averaging Detector- (ACAD-CFAR) which assess its detection decision in heterogeneous Gaussian environment with mono pulse processing. Under the absence of any prior information about the background, the proposed detector uses an automatic censoring cell-by-cell procedure for detecting the transitions in the reference window and then discards dynamically the unwanted echoes. Depending on the estimated transitions, it follows a strategy to give its detection decision by using an IID conversion. The results show that the suggested CA-based processor performs like the CA- in a homogeneous background and exhibits good performance in the presence of multiple interfering targets and/or clutter boundaries.

The paper is organized as follows. **Section 2** is devoted to the discussion of the basic assumptions in a general CFAR detection and formulation of the problem. The description of the censoring procedure and the strategy of decision are illustrated in **section 3**. Results and discussions using Monte-Carlo simulations are considered in **section 4**. Finally, our conclusions with suggestions for future works are provided in **section 5**.

BASIC ASSUMPTIONS AND PROBLEM FORMULATION

In a general CFAR processor, the received data, outputs of the square-law *(SL)* device, are sent serially into a tapped delay line of length $N+1$, (Fig. 1). The $N+1$ rang bins correspond to the N reference cells, X_l , $l=1,...,N$, surrounding the cell under test (*CUT*) X_0. In this cell, the primary target under investigation, of power *SNR* (Signal to Noise Ratio), can be presented. The range cells are combined to yield an estimation of the background Z. The sample of X_0 is then compared to the threshold TZ according to the test of detection [1],

$$X_0 \underset{H_0}{\overset{H_1}{\gtrless}} TZ \tag{1}$$

the threshold multiplier T is fixed to maintain a constant *Pfa* at a desired value. Hypotheses H_1 and H_0 denote the presence and the absence of a target, respectively.

Under the assumption of homogeneous Gaussian background and mono pulse processing, the samples in the reference window are IID processes and exponentially distributed [1]. That is, the probability density function (PDF) of the output of the l^{th} cell is given by [1]

$$f_{X_l}(X) = \frac{1}{\mu}.exp(-\frac{X}{\mu}) \tag{2}$$

where μ denotes the scale parameter of the total noise power. The value of μ depends on the content of the observed data. When the l^{th} reference cell contains an interfering target of *SWII (SWERLING II)* model [19], μ may be written as $\mu_t(1+INR)$, where *INR* is an Interference- to- Noise Ratio. Also, if some cells are embedded in clutter region, μ may be written as $\mu_t\,(1+CNR)$, where *CNR* is a Clutter- to- Noise Ratio. For the presence of both outliers, $\mu=\mu_t\,(1+INR+CNR)$. If $INR=0$ and $CNR=0$, this corresponds to the homogeneous situation with $\mu=\mu_t$, where μ_t is the thermal noise power (normalized to unity). The background estimator obtained by summing N reference cells IID and exponentially distributed follows Gamma law [20] with parameters (N, μ)

$$f_Z(Z) = \frac{Z^{(N-1)}}{\Gamma(N).\mu^N}.exp(-\frac{Z}{\mu}) \tag{3}$$

where Γ is the Gamma function. If the reference cells are ranked in ascending order according to their magnitudes, we obtain:

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

These ordered samples, $X(l)$ $l=1,...,N$, are not IID and their PDF is given by [21]

$$f_{X(l)}(X) = l.\binom{N}{l}.(1-exp(-X))^l \\ .exp(-(N-l+1)X) \tag{5}$$

To turn back to the IID characteristic, it is demonstrated in [21] that the random variables Y_l , $l=1,...,N$, defined by equation (6), are IID and also exponentially distributed.

$$Y_l = (N-l+1)(X(l)-X(l-1)), \quad X(0)=0. \tag{6}$$

The basic idea of the proposed detector is to find the adaptive homogeneous window (*AHW*) composed of ordered data and represents the uniform segment around the *CUT*. Based on the optimality of the CA-CFAR under the IID assumption, the proposed detector is switched to an CA$(N-\hat{\imath})$ by converting the ordered data of the *AHW* to IID samples, where $\hat{\imath}$ is the estimated number of censored cells. The automatic censoring algorithm is then selected. In order to estimate the unknown transitions (k_1 and k_2) edges of *AHW*, an iterative cell-by-cell tests are used, according to the algorithm, and consequently outputs the number $\hat{\imath}$. Note that, the proposed algorithm is associated to a look-up table of scaling factors, $T_{C,j}$, $j=1, ..., N-1$. These factors are used to achieve a design probability of false censoring *(Pfc)*, see Fig. 1.

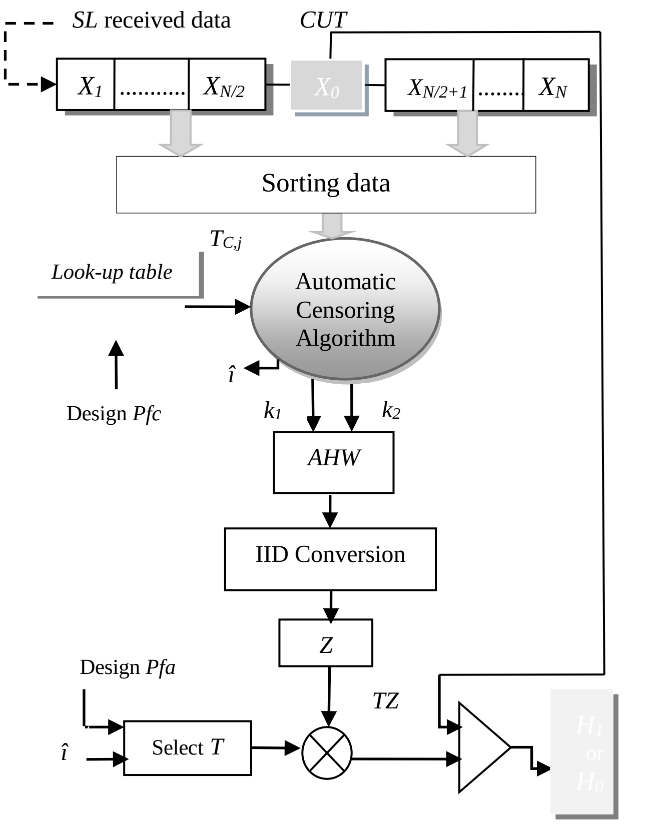

Figure 1. Architecture of the proposed ACAD-CFAR processor.

AUTOMATIC CENSORING ALGORITHM AND DECISION STRATEGY

Before describing the proposed censoring detector, the following conditions are assumed:

- Presence of heterogeneous environments defined by: homogeneous, multiple interfering targets, and clutter edges, situations.
- The power of noise region R_{ns} is assumed to be less than the power of clutter region R_{clt}. The latter is considered less than the power of interferences region R_{itf}.
- All interferences are immersed in clear.

At first, the reference cells, X_l , $l=1,\ldots,N$, are ranked in ascending order according to their magnitudes to yield the structure as illustrated in Fig. 2.

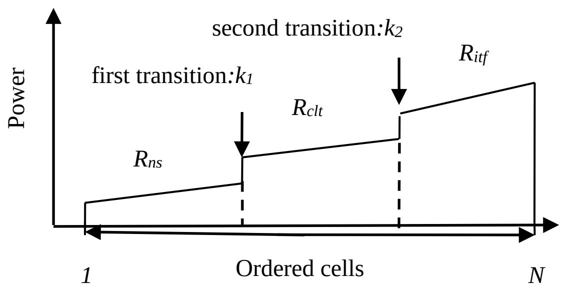

Figure 2. Power structure of the ranked cells.

The goal of the proposed censoring procedure is to estimate which one of R_{ns}, R_{clt}, and R_{itf} represents the uniform background around the *CUT* [14], and consequently, represents the *AHW*. Note that, the sample of X_0 is not concerned by the censoring algorithm which utilizes only the ordered data. The proposed algorithm is based on CA-principles [8] and composed of two passes for estimating the transitions. Such as, a transition is considered if and only if "$1\leq transition<N$".

The first pass is programmed to test the transition k_1 between R_{ns} and R_{clt} regions. Firstly, we assume that $R_{ns}=[X(1)]$, $R_{clt}=\varnothing$, and $R_{itf}=\varnothing$. The sample $X(2)$ is then compared to the adaptive censoring threshold $T_{C,1}.S_1$, where $T_{C,1}$ is a scaling factor chosen to achieve a desired *Pfc* in this step and $S_1=X(1)$. If $X(2)$ is less than or equal $T_{C,1}.S_1$, $X(1)$ and $X(2)$ are both from the noise region R_{ns} and $k_1=2$. The algorithm then proceeds to the next step by comparing $X(3)$ to the new adaptive censoring threshold $T_{C,2}.S_2$, $T_{C,2}$ is the scaling factor of the second step and $S_2=X(1)+X(2)$.On the other hand, if $X(2)$ is greater than $T_{C,1}.S_1$, there is a transition from a low to high power. Thus, $X(1)$ and $X(2)$ have not the same nature and the sample $X(2)$ is declared from the clutter region R_{clt}, meaning that $k_1=1$ and the algorithm stops. At the j^{th} step, $X(j+1)$ is compared with the censoring threshold $T_{C,j}.S_j$ according to the following statistical test,

$$X(j+1)\underset{H_C}{\overset{H_{NC}}{\lessgtr}} T_{C,j}.S_j \qquad ,j=1,\ldots,N-1 \tag{7}$$

where $T_{C,j}$ is a scaling factor chosen to achieve a desired *Pfc* at the j^{th} step, and $S_j=X(1)+X(2)+\ldots+X(j)$. Through all this description, H_C and H_{NC} represent the censoring and the non-censoring hypotheses respectively. If $X(j+1)\leq T_{C,j}.S_j \rightarrow X(j+1)$ and $X(j)$ are echoes from the same region R_{ns}, that is, $k_1=j+1$. The algorithm continues in the same manner; under H_{NC} hypothesis; until $j=N-1$. If $X(j+1)>T_{C,j}.S_j$, hypothesis H_C is true. That is, $X(j+1)$ and $X(j)$ are samples from different regions, *i. e.* the population $\{X(1), X(2), \ldots, X(j)\}$ is from noise and the sample $X(j+1)\in R_{clt}$. Here, $k_1=j$ and the first pass stops.

Once k_1 is obtained, the following strategy of decision is considered:

If $k_1=N$, the *AHW* is logically represented by $R_{ns}=[X(1),$

$X(2), ..., X(N)]$. Now, the IID conversion is activated to output $R_{ns}^{IID}=[Y_1, Y_2, ..., Y_N]$. Then, the test (1) is selected by using the corresponding adaptive threshold $T_{\hat{\imath}}.Z$, $Z=\Sigma R_{ns}^{IID}$. Note that, $T_{\hat{\imath}}=[T_0, T_1, ..., T_{imax}]$ is the vector of the thresholds multipliers which is fixed to achieve a design *Pfa* , where i_{max} represents the maximum number of censored ordered data in a homogeneous environment. For the current case, $\hat{\imath}=0$.

If $k_1 \le N/2$, the first transition is confirmed. Then, the algorithm go to search the second transition k_2 between R_{clt} and R_{itf} in the rested vector $[X(k_1+1), ..., X(N)]$.

At first of the second pass, we assume that $R_{clt}=[X(k_1+1)]$ and $R_{itf}=\varnothing$. The sample $X(k_1+2)$ is then compared with the adaptive censoring threshold $T_{C,(k1+1)}.S_{(k1+1)}$,where $T_{C,(k1+1)}$ is a scaling factor chosen to achieve a desired *Pfc* in this step and $S_{(k1+1)}=X(k_1+1)$. If $X(k_1+2)$ is less than or equal $T_{C,(k1+1)}.S_{(k1+1)}$, $X(k_1+2)$ is generated from the same distribution as that of $X(k_1+1)$ and $k_2=k_1+2$. Then, the algorithm proceeds to the next step by comparing $X(k_1+3)$ with the adaptive censoring threshold $T_{C,(k1+2)}.S_{(k1+2)}$, where $T_{C,(k1+2)}$ is the scaling factor related to the new step and $S_{(k1+2)}=X(k_1+1)+X(k_1+2)$. In the inverse case, the two considered samples are decided from different regions. Thus, $X(k_1+2)$ is from R_{itf} , $k_2=k_1+1$, and the algorithm stops. At the k^{th} step, we consider the following statistical test,

$$X(k_1+k+1) \underset{H_C}{\overset{H_{NC}}{\lessgtr}} T_{C,(k_1+k)}.S_{(k_1+k)} \qquad k=1,\ldots,N-1-k_1 \tag{8}$$

The form of expression (8) can be transformed to the form of test (7) by substituting: $j=k_1+k$, where $j=k_1+1, ..., N-1$. That is, $T_{C,j}=T_{C,(k1+k)}$ represents the scaling constant related to the j^{th} or $(k_1+k)^{th}$ step and $S_j=S_{(k1+k)}$ where $S_{(k1+k)}=X(k_1+1)+X(k_1+2)+...+X(k_1+k)$. Thus, if $X(j+1) \le T_{C,j}.S_j \rightarrow X(j+1)$ and $X(j)$ have the same nature of R_{clt} and $k_2=j+1$. Under H_{NC} hypothesis, the algorithm continues as in the previous tests until $j=N-1$. If $X(j+1)>T_{C,j}.S_j$, H_C is true, the tested samples are from different regions, that is, $X(j+1) \in R_{itf}$. Here, $k_2=j$ and the second pass stops.

Under the consideration that $k_2>k_1$, the decision of detection is obtained as follows,

If $k_2=N$, only one transition is considered ($k_1 \le N/2$). In this case, $R_{ns}=[X(1), ..., X(k_1)]$, $R_{itf}=\varnothing$ and the *AHW* is addressed by $R_{clt}=[X(k_1+1), ..., X(N)]$.Then, the IID conversion is activated to output $R_{clt}^{IID}=[Y_{k1+1}, ..., Y_N]$. Thus, the test (1) is selected by using the corresponding adaptive threshold $T_{\hat{\imath}}.Z$, $\hat{\imath}=k_1$ and $Z=\Sigma R_{clt}^{IID}$.

If $K_2 \le N/2$, the two transitions are confirmed where $R_{ns}=[X(1), ..., X(k_1)]$, $R_{clt}=[X(k_1+1), ..., X(k_2)]$, and $R_{itf}=[X(k_2+1), ..., X(N)]$. This last segment represents the *AHW*. For this situation, the sample of X_0 is a sum of the two mixed echoes of primary and secondary targets which are merged into a single peak [14]. The IID conversion is selected to output $R_{itf}^{IID}=[Y_{k2+1}, ..., Y_N]$. Again, the test (1) is selected by using the corresponding adaptive threshold $T_{\hat{\imath}}.Z$, $\hat{\imath}=k_2$ and $Z=\Sigma R_{itf}^{IID}$.

If $N/2<k_2<N$, also two transitions are confirmed and the *AHW* is addressed by $R_{clt}=[X(k_1+1), ..., X(k_2)]$. As in the previous cases, $R_{clt}^{IID}=[Y_{k1+1}, ...,Y_{k2}]$ is obtained. The processor selects the test (1) with the corresponding adaptive threshold $T_{\hat{\imath}}.Z$, $\hat{\imath}=k_1+(N-k_2)$ and $Z=\Sigma R_{clt}^{IID}$.

Finally, if $N/2<k_1<N$, one transition is detected (k_1) and it is not necessary to test the second. Consequently, the *AHW* is addressed by $R_{ns}=[X(1), ..., X(k_1)]$ and the algorithm censors all the remaining ordered samples, $\{X(k_1+1), X(k_1+2), ..., X(N)\}$, and generates the vector $R_{ns}^{IID}=[Y_1, ..., Y_{k1}]$. The test (1) is selected by using the corresponding adaptive threshold $T_{\hat{\imath}}.Z$, $\hat{\imath}=N-k_1$ and $Z=\Sigma R_{ns}^{IID}$.

As all CFAR censoring detectors, the proposed processor suffers from the critical cases, *i. e.* if $k_1=N/2$ or if $k_2=N/2$. As pre-mentioned in **section 2**, the *CUT* is located between the cells indexed by $N/2$ and $N/2+1$. Thus, in the event $k_1=N/2$ or $k_2=N/2$, the transition may occur in either the $N/2^{th}$ ordered cell or the *CUT*. For $k_1=N/2$, the *AHW* is chosen by the corresponding R_{clt} for which we avoid un excessive number of false alarms. For the second case $k_2=N/2$, the *AHW* can be represented by R_{itf}, $(\hat{\imath}=k_2)$, or by R_{clt}, $(\hat{\imath}=k_1+(N-k_2))$. In either event, the loss in detection will be increased considerably.

To summarize, we can give the main steps of the proposed ACAD-CFAR as follows,

$X(1) \le X(2) \le \ldots \le X(N)$

***Begin**: estimation of* k_1 : $R_{ns}=[X(1)]$, $R_{clt}=\varnothing$, $R_{itf}=\varnothing$.

For $j=1$ *to* $(N-1)$

$S_j=\sum_{l=1}^{j} X(l)$, *select the corresponding* $T_{C,j}$.

If $X(j+1) \le T_{C,j}.S_j$, $k_1=j+1$, *repeat until* $j=N-1$.

Else , $k_1=j$, *Stop first pass.*

a- If $k_1=N$, *AHW*$\leftarrow R_{ns}=[X(1), X(2), ... , X(N)]$.

- *Generate* R_{ns}^{IID}.
- *Select test (1) with the corresponding Z and* $\hat{\imath}$.

b- If $k_1 \le N/2$, *go to estimate* k_2 *by using the data:*

$X(k_1+1) \le X(k_1+2) \le \ldots \le X(N)$

$R_{ns}=[X(1), ..., X(k_1)]$, $R_{clt}=[X(k_1+1)]$, $R_{itf}=\varnothing$.

For $j=(k_1+1)$ *to* $(N-1)$

$S_j=\sum_{l=k_1+1}^{j} X(l)$, *select the corresponding* $T_{C,j}$.

If $X(j+1) \le T_{C,j}.S_j$, $k_2=j+1$, *repeat until* $j=N-1$.

Else , $k_2=j$, *Stop second pass.*

with: $k_2>k_1$

b-1- If $k_2=N$, *AHW*$\leftarrow R_{clt}=[X(k_1+1), ..., X(N)]$.

- *Generate* R_{clt}^{IID} .
- *Select test (1) with the corresponding Z and* $\hat{\imath}$.

b-2- If $k_2 \le N/2$, *AHW*$\leftarrow R_{itf}=[X(k_2+1), ..., X(N)]$.

- *Generate* R_{itf}^{IID}.
- *Select test (1) with the corresponding Z and* $\hat{\imath}$.

b-3- If $N/2<k_2<N$, *AHW*$\leftarrow R_{clt}=[X(k_1+1), ..., X(k_2)]$.

- *Generate* R_{clt}^{IID}.
- *Select test (1) with the corresponding Z and* $\hat{\imath}$.

c- If $N/2<k_1<N$, *AHW*$\leftarrow R_{ns}=[X(1), ..., X(k_1)]$.

- *Generate* R_{ns}^{IID}.
- *Select test (1) with the corresponding Z and* $\hat{\imath}$.

End.

H_1 *or* H_0 **.**

The *Pfc* of the proposed censoring procedure can be given as in [8],

$$Pfc = \frac{N!}{k_1!(N-j)!(j-k_1-1)!} \cdot \frac{1}{[1+(N-j).T_{C,j}]^{(j-k_1-1)}} \cdot \sum_{v=0}^{k_1} \binom{k_1}{v} .(-1)^v . \frac{1}{v+(j-k_1).[1+(N-j).T_{C,j}]} \quad , \quad j=1,...,N-1 \qquad (9)$$

The scaling factors, $T_{C,j}$, $j=1, ..., N-1$, are pre-computed iteratively from equation (9), see **Appendix A**.

Due to the fact that the samples Y_l*'s*, corresponding to the resulting *AHW's*, are IID and when exactly *i* among *N* cells have been censored, expression of *Pfa* can be shown to be [20],

$$Pfa(i)=(1+T_i)^{(i-N)} \qquad (10)$$

For a given *N* and a design *Pfa(i)*, The threshold multiplier T_i is simply computed from equation (10).

RESULTS AND DISCUSSIONS

The performance of the proposed system is evaluated and tested on simulated data using Monte-Carlo simulations under various clutter scenarios [22]. The detection probability and the false alarm control are studied in Gaussian background with a mono-pulse processing. The design *Pfa* is fixed at 10^{-4} for both $N=16$ and $N=24$, preferred sizes of the reference window, with $Pfc=10^{-4}$ and $Pfc=10^{-2}$, respectively. In addition, only one type of clutter is considered for all clutter edges and each target is fluctuated according to the *SWII* model with the consideration of identical radar cross-section; *i.e. SNR=INR*.

The presentation of the obtained results is firstly shown by the thresholds of the proposed CA-based CFAR and the conventional CA- for $N=16$ and $N=24$, see Figs. 3 and 4, respectively. For this realization, some profiles are created as in [23, 24]. Also, the probability of detecting the transitions (P_{tr}) in the reference window is illustrated for the presence of the following echoes:

- *4* interferers and then *7* clutter samples plus *4* interferers for $N=16$, see Figs. 5 and 6, respectively.
- *8* interferers for $N=24$, see Fig. 7.

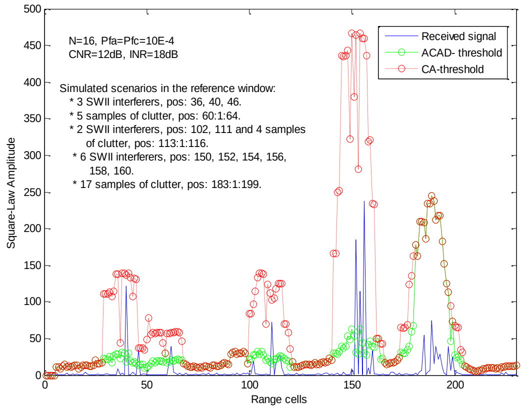

Figure 3. ACAD- and CA- thresholds for *N=16*.

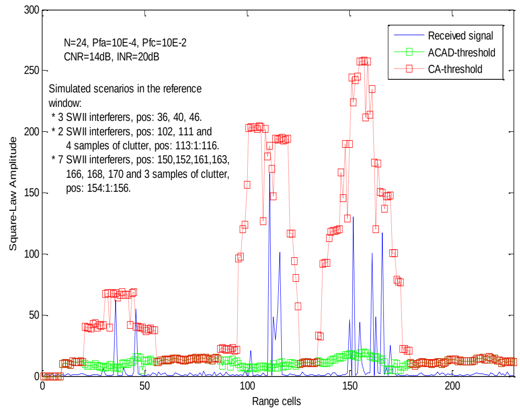

Figure 4. ACAD- and CA- thresholds for *N=24*.

From Figs. 3 and 4, we observe that the ACAD- and the CA-detectors provide the same adaptive threshold in homogeneous regions. This confirms a high probability (*0.9997*) of non-detecting a transitions, and consequently, the proposed detector censors "zero ordered cells, $\hat{\imath}=0$" in such an environment. Concerning the last scenario of Fig. 3, the region composed of *17* clutter samples located in the positions *183* to *199* with power *12dB*, is uniform. Conversely, when the reference window sweeps over the multiple targets or clutter edges regions, the CA-based scheme threshold is much smaller than that of the CA-CFAR and so, good detection performances of the proposed censoring processor are expected.

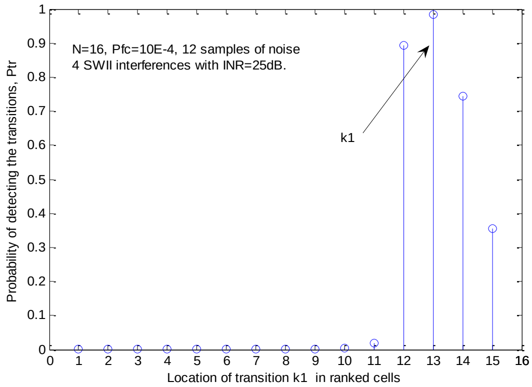

Figure 5. Probability of detecting the first transition (k_1), presence of *4 SWII* interferences, *N=16*.

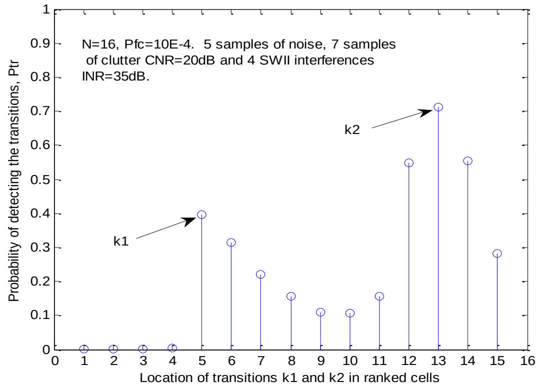

Figure 6. Probability of detecting the transitions k_1 and k_2, presence of 7 samples of clutter and *4 SWII* interferences, *N=16*.

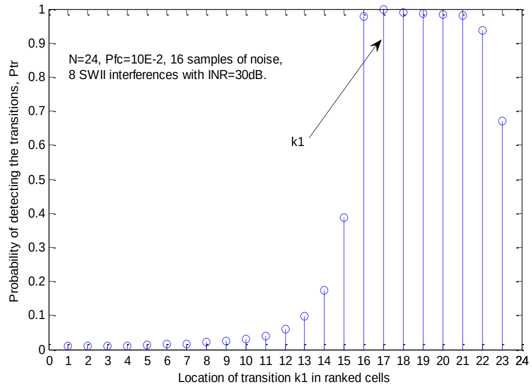

Figure 7. Probability of detecting the first transition (k_1), presence of *8 SWII* interferences, *N=24*.

In Fig. 5, the transition k_1 is localized in the ranked cell of position *13* with a higher probability $P_{tr}=0.9826$. This means that *4* samples of interferences *(INR=25dB)*, *i. e . X(13)*, *X(14)*, *X(15)*, and *X(16)* will be censored. In Fig. 6, k_1 and k_2 are centered in the locations *5* and *13*, respectively. As pre-mentioned for this event ($k_1<N/2$ and $k_2>N/2$), the *AHW* is addressed by the region R_{clt} and the remaining cells will be rejected. From Fig. 7, it is seen that k_1 is centered in the location *17* with $P_{tr}=0.9992$. That is, *8* samples of interferences *(INR=30dB)* will be discarded, *i.e. X(17)* to *X(24)*. We remark also that the estimation of the transitions is more exact at strong peaks, *i.e. power>20dB.* For the uniform regions, P_{tr} is about *0.0003* which confirms the high probability (*0.9997*) of non-detecting the transitions in these regions, as shown in Figs. 3 and 4.

Homogeneous Environment

In the homogeneous situation, only the noise region is considered, *i.e. INR=0* and *CNR=0*. The performance *Pd* against *SNR*, shown in Fig. 8, is compared to the following detectors:

- CA-, ACMLD-, OS-, and the optimal detector (Opt) for *N=16*.
- CA-, AC-, ADCCA- , and Opt for *N=24*.

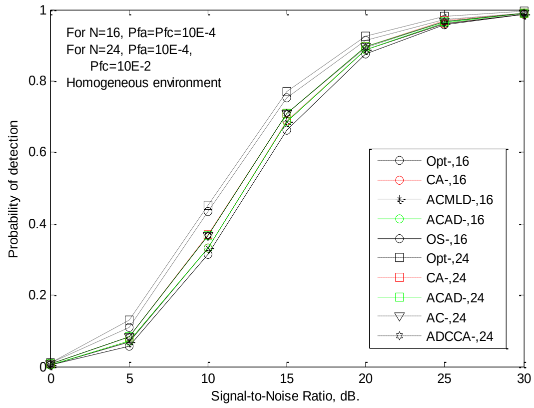

Figure 8. Pd of ACAD-, CA-, ACMLD-, OS-, AC-, and ADCCA- and Opt detectors in homogeneous environment.

As shown in Fig. 8, the proposed detector and the other processors, apart the OS- , perform like the CA-CFAR in homogeneous environment and exhibit some CFAR loss in comparison to the Opt detector for both *N=16* and *N=24*.

Multiple Interfering Targets

To evaluate the robustness of the proposed detector versus multiple interfering targets of power *INR*, the performance *Pd* is shown in the presence of the following situations:

- *2, 4, 6* and *2, 4, 6, 8* interferers for *N=16* and *N=24*, respectively. The *Pd* of ACAD-CFAR is illustrated in Fig. 9.
- *2* and *4* interferers, *N=16*. The results are compared with those of the CA-, OS- and ACMLD-, see Fig. 10.
- *4* interferers, *N=24*. The results are compared with

those of the CA-, AC-, and ADCCA-, see Fig. 11.

- *8* interferers, *N=24*. The comparison is between the ACAD-, CA-, and ADCCA-, see Fig. 12.

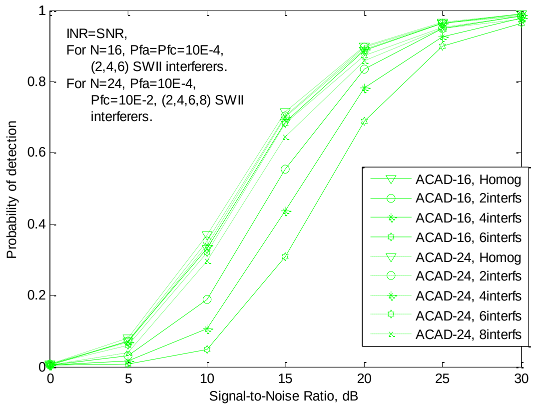

Figure 9. *Pd* of ACAD-CFAR in multiple *SWII* interferers, for *N=16* and *N=24.*

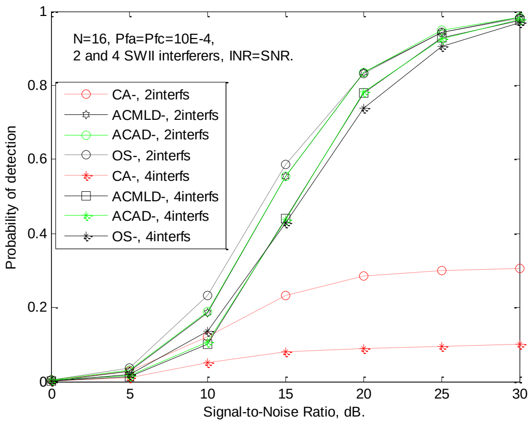

Figure 10. *Pd* of ACAD-, CA-, OS-, and ACMLD- detectors, presence of *2* and *4 SWII* interferers, *N=16.*

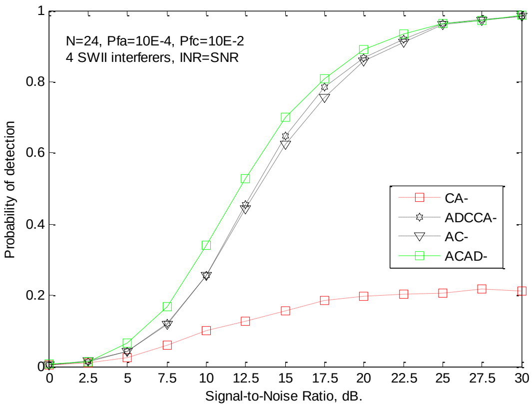

Figure 11. *Pd* of ACAD-, CA-, AC-, and ADCCA- detectors, presence of *4 SWII* interferers, *N=24*.

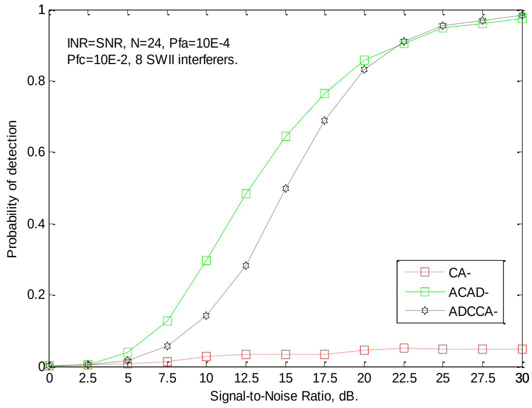

Figure 12. *Pd* of ACAD-, CA-, and ADCCA- detectors, presence of *8 SWII* interferers, *N=24*.

From Fig. 9, it is seen that the *Pd* of the proposed detector increases by increasing *SNR* and also the size *N* of the reference window. For a fixed value of *SNR*, corresponding to either *N=16* or *N=24*, the performance decreases as the number of interfering targets increases. From Fig. 10, we remark that the adaptive processors, ACAD- and ACMLD-, give the same performance which exceeds that of the OS-, specially, for the case of *4 SWII* interferences when *SNR>15dB*. From Fig. 11, we observe clearly that the proposed scheme performs better than the censoring ADCCA-, and AC- detectors, precisely, for moderate *SNR*, *i.e.* between *5dB* and *20dB*. In Fig. 12, we remark that the ACAD- detector can perfectly protect its robustness against the presence of *8 SWII* interferences in the reference canal apart when *SNR>20dB* where a similar comportment with that of the ADCCA- is appeared. In the illustrated curves, substantial and successive degradation in performance of the CA-CFAR is observed.

Clutter Edges

For the false alarm control *Pfa*, we assume a scenario in which a clutter edge enters the reference window with different powers of *CNR* as follows:

- *CNR=5, 10,* and *30dB:* control the *Pfa* of ACAD- detector for *N=16*, see Fig. 13.
- *CNR=10dB:* comparison of the *Pfa* of ACAD- with that of the AC- and ADCCA- detectors for *N=24*, see Fig. 14.

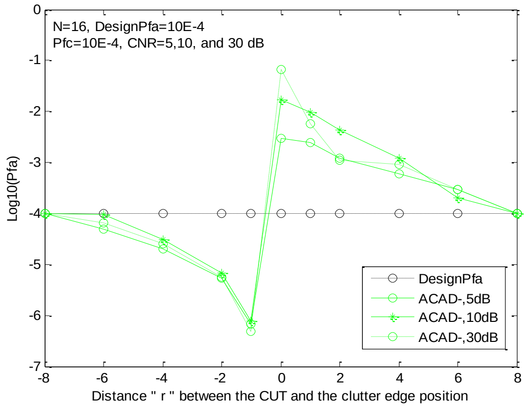

Figure 13. *Pfa* of ACAD-CFAR for *CNR=5, 10,* and *30dB, N=16*.

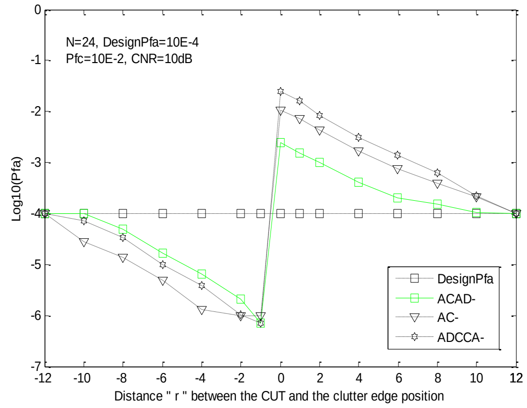

Figure 14. *Pfa* of ACAD-, AC-, and ADCCA- detectors for *CNR=10dB, N=24*.

As shown in Figs. 13 and 14, the loss in regulation between the *Pfa* design and the *Pfa* of the processors at hand increases as the distance *r* between the clutter edge position and the *CUT* decreases. A sharp spiky in false alarm probability is observed at *r=0*. This results when the clutter edge enters the *CUT*. From Fig. 13, we observe an overlap of the curves when *r = -8 to -1*. For the other side, a convergence between the curves of *5dB* and *30dB* is seen. In Fig. 14, we remark that the loss in performance of the proposed CFAR is smaller than that of the AC- and ADCCA- detectors when the clutter edge is located in either the leading or the lagging windows, and consequently, a regulation of the false alarm is verified.

Multiple Interfering Targets and Clutter Edges

For the presence of both undesired outliers in the reference window, the *Pd* is shown by assuming the presence of the following scenarios:

- *4* interferers and *2* clutter samples with *CUT* in clear for *N=16*. The results are compared with those of the OS-, see Fig. 15.
- *2* interferers and *14* clutter samples with *CUT* in clutter for *N=24*. The results are compared with those of the AC-, see Fig. 16.

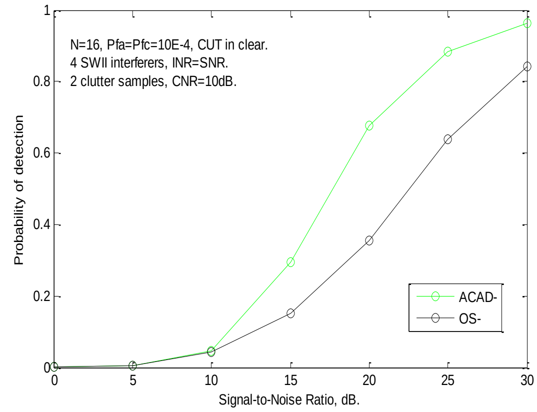

Figure 15. *Pd* of ACAD- and OS- detectors, presence of *4 SWII* interferers and *2* clutter samples (*CNR=10dB*), with X_0 in clear, *N=16*.

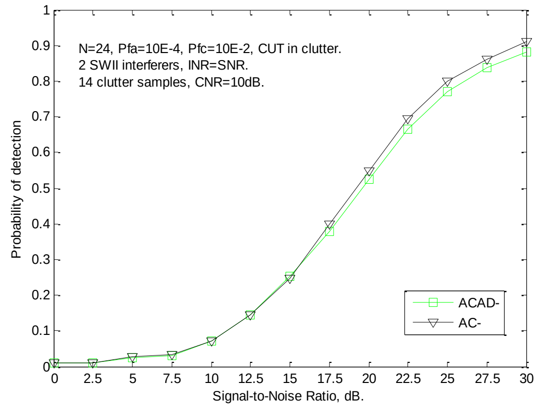

Figure 16. *Pd* of ACAD- and AC- detectors. Presence of *2 SWII* interferers and *14* clutter samples (*CNR=10dB*), X_0 in clutter, *N=24*.

From Fig. 15, we remark that the proposed detector protects its robustness against the presence of both outliers in comparison to the OS- detector, precisely, when *SNR>10dB*. Concerning Fig. 16, the obtained results show a similar comportment of the ACAD- and AC- detectors for *SNR<17.5dB* and some loss in performance presented by the ACAD- at high *SNR*'s.

CONCLUSION

In this work, we have proposed an adaptive CFAR detector, named ACAD-, to perform suitably in heterogeneous environments. The proposed detector, which does not require any prior knowledge about the background, uses an automatic censoring technique to estimate the unknown transitions in the reference window and then discards, dynamically, the undesired echoes. Depending on the detected transitions, the addressed detector follows a strategy to give its decision of detection by using an IID conversion. For evaluation, the performance of detection is compared with that of the other competitive CFAR's such as the CA-, ACMLD-, OS-, AC-, and ADCCA-. It is seen that the ACAD-CFAR performs like the conventional CA- in the homogeneous environment. For non-homogeneous situations, the results show that the proposed CA*(N-î)* system performs perfectly in multiple *SWII* interferences in comparison to the processors at hand, and their performances in clutter edges and also in the presence of both unwanted outliers are acceptable.

For future works, we suggest as an extension of this study to consider the case of interfering targets immersed in clutter for Gaussian and Compound-Gaussian environments.

Appendix. A

The *Pfc* of the proposed censoring procedure is equivalent to that obtained in [8] for the GTL-CMLD- detector. The values of the factors $T_{C,j}$, $j=1, ..., N-1$, are provided in the following matrices M_C^t (the transpose of the matrices M_C of size $(N/2+1)\times(N-1)$). Note that, any factor can be selected from the matrices M_C as follows:

- $M_C(1, j)$ for the first pass.
- $M_C(k_1+1, j-k_1)$ for the second pass.

The scaling factors $T_{C,j}$, $j=1, ..., N-1$, of ACAD-CFAR for $N=16$ and a design $Pfc=10^{-4}$,

$$M_C^t=\begin{pmatrix}
10666.6 & 110.550 & 24.668 & 11.840 & 07.717 & 05.868 & 04.880 & 04.302 & 03.957\\
78.173 & 15.547 & 07.049 & 04.443 & 03.306 & 02.708 & 02.362 & 02.155 & 02.040\\
13.583 & 05.759 & 03.489 & 02.529 & 02.035 & 01.752 & 01.583 & 01.487 & 01.448\\
05.360 & 03.111 & 02.193 & 01.730 & 01.469 & 01.313 & 01.224 & 01.184 & 01.193\\
02.976 & 02.037 & 01.574 & 01.316 & 01.164 & 01.075 & 01.034 & 01.036 & 01.097\\
01.976 & 01.495 & 01.231 & 01.075 & 00.984 & 00.939 & 00.936 & 00.987 & 01.144\\
01.463 & 01.185 & 01.022 & 00.927 & 00.878 & 00.870 & 00.913 & 01.054 & 01.549\\
01.165 & 00.993 & 00.891 & 00.838 & 00.824 & 00.861 & 00.991 & 01.451 & 0\\
00.980 & 00.871 & 00.812 & 00.794 & 00.825 & 00.945 & 01.379 & 0 & 0\\
00.862 & 00.797 & 00.774 & 00.800 & 00.912 & 01.326 & 0 & 0 & 0\\
00.790 & 00.762 & 00.783 & 00.889 & 01.288 & 0 & 0 & 0 & 0\\
00.757 & 00.773 & 00.873 & 01.260 & 0 & 0 & 0 & 0 & 0\\
00.768 & 00.863 & 01.240 & 0 & 0 & 0 & 0 & 0 & 0\\
00.859 & 01.229 & 0 & 0 & 0 & 0 & 0 & 0 & 0\\
01.223 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0
\end{pmatrix}$$

The scaling factors $T_{C,j}$, $j=1, ..., N-1$, of ACAD-CFAR for $N=24$ and a design $Pfc=10^{-2}$,

$$M_C^t=\begin{pmatrix}
104.000 & 10.600 & 04.990 & 03.430 & 02.744 & 02.370 & 02.140 & 01.986 & 01.880 & 01.800 & 01.742 & 01.699 & 01.669\\
07.500 & 03.150 & 02.042 & 01.580 & 01.339 & 01.190 & 01.091 & 01.023 & 00.974 & 00.938 & 00.911 & 00.892 & 00.879\\
02.750 & 01.670 & 01.244 & 01.024 & 00.894 & 00.810 & 00.752 & 00.710 & 00.680 & 00.657 & 00.640 & 00.629 & 00.622\\
01.554 & 01.110 & 00.889 & 00.761 & 00.679 & 00.623 & 00.584 & 00.555 & 00.533 & 00.518 & 00.507 & 00.500 & 00.497\\
01.062 & 00.826 & 00.693 & 00.609 & 00.552 & 00.512 & 00.483 & 00.462 & 00.447 & 00.436 & 00.429 & 00.425 & 00.425\\
00.801 & 00.658 & 00.569 & 00.557 & 00.469 & 00.439 & 00.417 & 00.401 & 00.390 & 00.382 & 00.378 & 00.378 & 00.381\\
00.644 & 00.548 & 00.485 & 00.442 & 00.410 & 00.388 & 00.371 & 00.359 & 00.351 & 00.346 & 00.344 & 00.347 & 00.354\\
00.539 & 00.471 & 00.424 & 00.391 & 00.367 & 00.350 & 00.337 & 00.328 & 00.322 & 00.320 & 00.322 & 00.328 & 00.341\\
00.465 & 00.415 & 00.379 & 00.354 & 00.335 & 00.321 & 00.311 & 00.305 & 00.302 & 00.303 & 00.308 & 00.320 & 00.344\\
00.410 & 00.372 & 00.345 & 00.324 & 00.309 & 00.299 & 00.292 & 00.288 & 00.288 & 00.293 & 00.304 & 00.326 & 00.374\\
00.369 & 00.339 & 00.317 & 00.301 & 00.290 & 00.282 & 00.278 & 00.277 & 00.281 & 00.291 & 00.312 & 00.357 & 00.495\\
00.337 & 00.313 & 00.296 & 00.284 & 00.275 & 00.270 & 00.269 & 00.272 & 00.281 & 00.301 & 00.344 & 00.476 & 0\\
00.311 & 00.292 & 00.279 & 00.270 & 00.264 & 00.262 & 00.264 & 00.273 & 00.292 & 00.333 & 00.460 & 0 & 0\\
00.291 & 00.276 & 00.266 & 00.260 & 00.257 & 00.259 & 00.267 & 00.284 & 00.324 & 00.448 & 0 & 0 & 0\\
00.275 & 00.264 & 00.256 & 00.253 & 00.254 & 00.261 & 00.278 & 00.317 & 00.437 & 0 & 0 & 0 & 0\\
00.262 & 00.255 & 00.251 & 00.268 & 00.257 & 00.273 & 00.311 & 00.428 & 0 & 0 & 0 & 0 & 0\\
00.253 & 00.249 & 00.249 & 00.254 & 00.270 & 00.306 & 00.421 & 0 & 0 & 0 & 0 & 0 & 0\\
00.248 & 00.247 & 00.252 & 00.267 & 00.303 & 00.415 & 0 & 0 & 0 & 0 & 0 & 0 & 0\\
00.246 & 00.251 & 00.265 & 00.300 & 00.411 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0\\
00.250 & 00.264 & 00.298 & 00.407 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0\\
00.263 & 00.297 & 00.230 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0\\
00.296 & 00.227 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0\\
00.403 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0
\end{pmatrix}$$

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