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A novel method based on comparison using threshold scale for CFAR detectors under environments with conditions of electromagnetic interference

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Abstract: Detection of a noisy signal is a complex process. Many radar systems are working in an environment where the signal processing parts cannot overcome the effects of interference sources due to their high power. These sources of conflict may completely erode the signal or may make a mistake in deciding. It may make the return of the echoes of the goals difficult. To solve this problem, the detector processor can use a new algorithm to estimate noise power and then can set the threshold in different positions of the cell under test. The proposed algorithm, by differentiating between homogeneous and interference environments in a multitarget structure, selects a set of reference cells that surround the cell under test to estimate the unknown noise/clutter and determine the effective threshold. Then, to evaluate the performance of cell averaging of constant false alarm rate (CA-CFAR), censored mean level detector CFAR (CMLD-CFAR), and excision CFAR (EX-CFAR) detectors, we compared threshold, false alarm, and detection probability in terms of different correlation coefficients. The values were obtained using simulation by MATLAB software. The simulation results show that the excision parameter, by adding to the window of the reference cells that surround the cell under test, reduces the effects of background noise on the received signal. We conclude from the proposed method that the hybrid detector not only has higher quality detection interactions in heterogeneous environments but also has relatively less computational complexity than CA-CFAR, CMLD-CFAR, and EX-CFAR detectors.

Key words: CA-CFAR, CMLD-CFAR, excision-CFAR, excision parameter, cell under test

1. Introduction

The accurate detection of targets in the presence of clutter is an issue of importance to radar systems, which is, in fact, the most important destructive factor in detecting moving targets. Constant false alarm rate (CFAR) is a significant issue in radar receivers. With the help of the CFAR detector, one can design an algorithm for decision-making that can be determined by the presence or absence of a target. CFAR processors are suitable for detecting targets in environments where the parameters of interfacing statistics are unspecified. The conventional method for using CFAR theory is to estimate the range of ambient interference with range cells and to determine the threshold level for detecting false alarm probability. Several algorithms have been proposed for false alarm rates in different environmental conditions, including in the presence of interference targets. These algorithms can be considered in two areas of CFAR detectors with a target and CFAR detectors with multiple targets in similar and interference environments with a different distribution. The CFAR detectors are two-dimensional processors that use each cell for ranging themselves from multiple-pulsed samples for detection. In this paper, after modeling the received data as a vector, the parameters of these generalized two-dimensional

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detectors are computed by analytical application, and then their performance in an interference environment using computer simulation is investigated. In modern radar systems, target detection is automatically based on dual decisions, in which the hypothesis of the presence and absence of the target is represented by symbols H_1 and H_0, respectively. It is examined under the specific Neyman–Pearson criterion [1]. In the presence of noise/clutter, these assumptions use a threshold that improves reliability in detecting the probability of false alarm (P_{fa}). In noise-free environments, CFAR is one of the best means of detecting targets [2–4]. Since the performance of these detectors in the presence of multiple targets causes problems in detecting, various methods can be used to improve the accuracy of target detection. Many researchers have used upgraded CFAR algorithms to evaluate CFAR detector performance in specific conditions, such as multitarget locations and interference environments.

Some researchers use the greatest of CFAR (GO-CFAR) [5–7] and smallest of (SO-CFAR) algorithms [8, 9] as modified cell averaging of CAFR (CA-CFAR) detectors [10, 11]. The GO-CFAR algorithm at the edge of the clutter can maintain the function of the probability of a false alarm. However, this method causes a shielding phenomenon in multitarget conditions. When the intruder targets are located just before or after the reference cell, the SO-CFAR algorithm is a good solution in detecting multiple targets, but the false alarm control function is not ideal. Rohling introduced order statistical CFAR (OS-CFAR) [12], which processes samples sorted in a test cell. In multitarget environments, the OS-CFAR detector is superior to the maximum likelihood (ML-CFAR) detector. This method eliminates some of the disturbing target signals from reference samples to a certain degree. Therefore, this method can reduce the probability of detecting disturbing signals in noise estimation. According to this theory, researchers have used new CFAR techniques. For example, Farrouki introduced the greatest of statistical CFAR (GS-CFAR) method based on an automatic censoring technique [13]. Another group of researchers combined the benefits of different approaches to obtain a better assessment function [14–16]. They used a few methods to estimate the noise and clutter power and then run CFAR processing. In [17], CA, GO, and SO algorithms were selected appropriately. According to [18], the goodness-of-fit test was used to determine the characteristics of clutter in an interference environment. This test combines an innovative solution with the OS called cell index CFAR (CI-CFAR). In this combination method, the probability of false alarms and the likelihood of a change is altered when the number of disturbing signals changes randomly. This results in noise/clutter deviation from the actual value. Therefore, the estimation of false alarms cannot be done correctly and may even affect the accuracy of the test results. Therefore, the use of an appropriate assessment algorithm is necessary to make a proper decision with specific circumstances. The signal received in the range is sampled by high-quality cells, and the threshold is obtained by scaling the noise level estimation by constant T to obtain a suitable false alarm probability. In [19] detection was introduced as the generalized version of OS-CFAR and CMLD-CFAR. This detector censors the cells from the beginning and the end of the reference window and balances the remaining cells to estimate unknown parameters [20, 21]. In [22], the CMLD-CFAR detector was introduced, which does not require any prior knowledge in detecting intruder targets with any number. In [5, 23], the authors introduced the automatic CMLD detector (ACMLD) and the general two-level CMLD detector (GTL-CMLD). In [24], Srinivasan introduced the ensemble-CFAR (E-CFAR) detector. The variable index-CFAR (VI-CFAR) was presented in [25, 26]. The upgraded version of the detector, called IVI-CFAR, was analyzed in [27]. These detectors are changed to CA, SO, GO, or OS-CFAR based on the results obtained from VI and the dynamic mean hypothesis test. In [13], Farrouki and Barkat introduced a modified detector autocensored cell average of CFAR (ACCA-CFAR). It uses the censors of cells corresponding to the second target, and then the threshold estimation through the CA-CFAR algorithm is used. In [28], a new CFAR detector, which is the cell average, was introduced. This detector does not require any prior knowledge of clutter detection. This detector uses the reference window to estimate and to censor unwanted samples. Also, in the estimation of new variables, false alarms have been proposed and analyzed statistically by CFAR (S-CFAR). The S-CFAR algorithm chooses the CFAR reference cell using the sample size in the test cell. In [29], Meng recommended the use of a rating theorem to estimate the false alarm level of the S-CFAR.

The rest of this paper is organized as follows. In Section 2, CFAR detector modeling is introduced. Implementation of the proposed detector is described in Section 3. Simulation results and conclusions are presented in Sections 4, and 5, respectively.

2. CFAR detector modeling

Detector design and modeling are difficult when the noise/clutter parameter is unknown and constant. The usual solution is to determine the threshold by estimating noise power. The detector performance in the noise should be independent of the power of noise to achieve a CFAR. In a homogeneous environment, due to the use of a small number of samples, the detection accuracy decreases significantly compared to the optical detector. To resolve this problem, the number of processing samples should be increased. Increasing the number of processing samples increases the probability of occurrence of interference conditions in reference cells. The main reasons for the loss of similar conditions are the interference goals and the edge of the clutter [30]. The received signals from the targets increase the threshold and thus reduce the probability of detection (P_d). This indicates that there is a balance between maintaining similar conditions and reducing the number of processing cells. It thereby reduces the detection loss by increasing the number of samples. Several nonlinear estimation mechanisms have been proposed by various researchers to solve this problem. The CMLD will have an appropriate estimation of the uncertain noise level and has good performance in detecting large targets [31]. This detector provides good noise power after removing a certain number of specimens larger than a specific surface. A newer technique is the EX-CFAR detector that solves the heterogeneity problem by separating larger reference cell samples [25]. In the EX-CFAR, an excision parameter (β) is used. The separation operation ensures that the detection threshold limit is calculated based on a set of cells that do not contain interference goals. Thus, it displays the noise level in better resolution. In this detector, large samples are separated, and only samples that are smaller than β are not segregated [25, 26].

2.1. CA-CFAR detector

The CA-detector reference data are $Z_{CA} = \sum_{i=1}^{N_R} Z_i$, and when the cell value under the Z test exceeds $\mathrm{T}_{CA}\mathrm{Z}_{CA}$, it is alarming [32]. Consequently, under the H_0 hypothesis, which only contains noise, the probability of false alarms for CA is obtained. Figure 1 shows a block diagram of a CA-CFAR detector.

2.2. EX-CFAR detector

In the EX-CFAR detector method, the mean probability density function of the samples is used and depends on the ratio of the cut-off threshold of BE [33]. Use the same techniques, a false alarm may result, depending on the scale factor for the detection limit setting. The threshold can be shown again with a relationship that depends on it and must be known. Suppose there are only noises in the reference cells, so small values are effective in reducing the function of the detector. If α is too large, the scale factor will be proportional to $\gamma_D = T_{CA}N_R$,

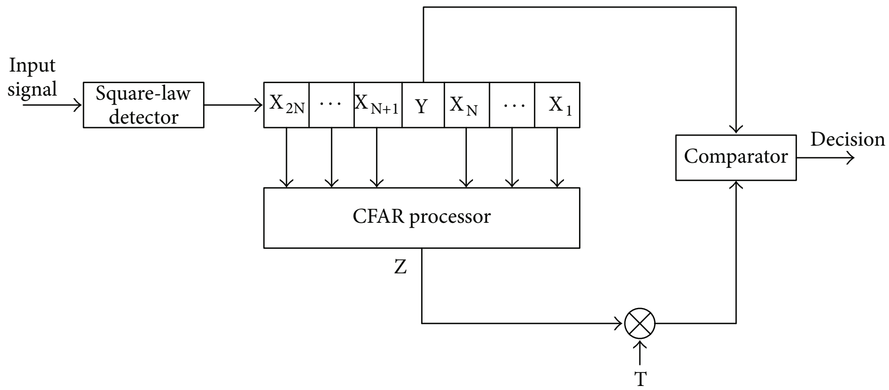

Figure 1. The block diagram of a typical CFAR detector.

where the TCA is conventionally calculated by the CA scaling factor multiplied by NR to calculate the mean instead of the sum. The CA scaling factor is specifically the probability of false alarm required for situations that are very large. In [8], Goldman arrived at the experience of revealing a constant goal, as well as binary integration, to make an offer of choice γ_D based on α infinity. As long as α is large enough, the probability of false alarm will be close to the actual value.

3. Implementation of the proposed detector

In this paper, based on the history of CFAR detectors and the ability to detect targets in the presence of noise/clutter under different conditions, a combined excision algorithm and censored mean level detector used to reference cells and its performance are evaluated in a noisy environment and then compared with the CA-CFAR detector in terms of threshold, false alarms, and detection using correlation coefficients. It can be concluded from the performance of this detector that it can work in any environment with a large number of interference signals in addition to the relatively smooth implementation of hardware and software. Before the averaging of reference cells, first each cell is compared to a threshold level, and if it is larger than the threshold level, that cell is not included in the averaging. The difference between the proposed algorithm and the EX-CFAR in applying β is that before and after the censorship of a certain number of samples larger than the threshold level. Using this algorithm, a better performance than that of the CA-CFAR, CMLD-CFAR, and EX-CFAR detectors is achieved. A flowchart of the proposed algorithm is shown in Figure 2. If there are multiple interference targets in the CFAR reference window, the threshold level will increase significantly and the probability of missed (P_m) smaller targets will increase sharply, which is caused by a sharp drop in P_d. Limit leveling is significant for detecting false alarms because different decision-making targets are dependent on changes in the threshold value. It should be noted that the proposed model is very similar to EX-CFAR in terms of performance and simulation results. The proposed block diagram for the presentation of extra details is shown in Figure 3.

3.1. Algorithm implementation

The CFAR detector refers to a typical pattern in using endowed algorithms to detect targets in the presence of noise/clutter. If the threshold is too high, the targets will be less clear, but the number of false warnings will be reduced. In most CFAR detection algorithms, threshold levels are obtained by estimating the noise level around the cell under test (CUT). To avoid distortion in estimating the noise level, the cells around the cell

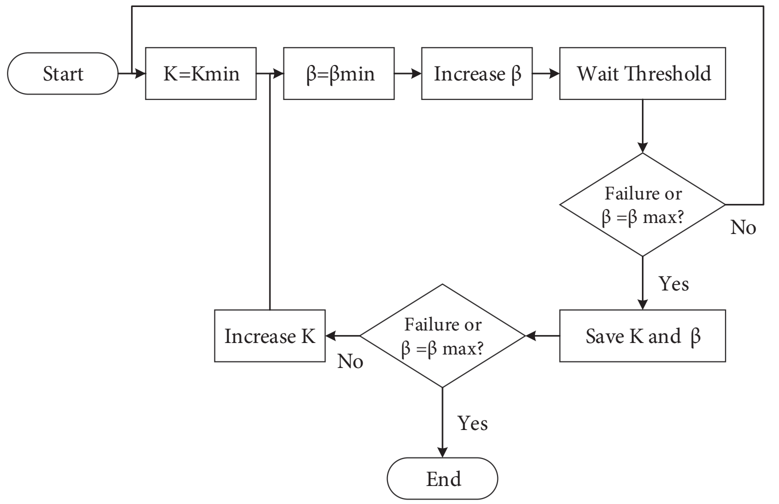

Figure 2. Flowchart of the proposed algorithm's steps.

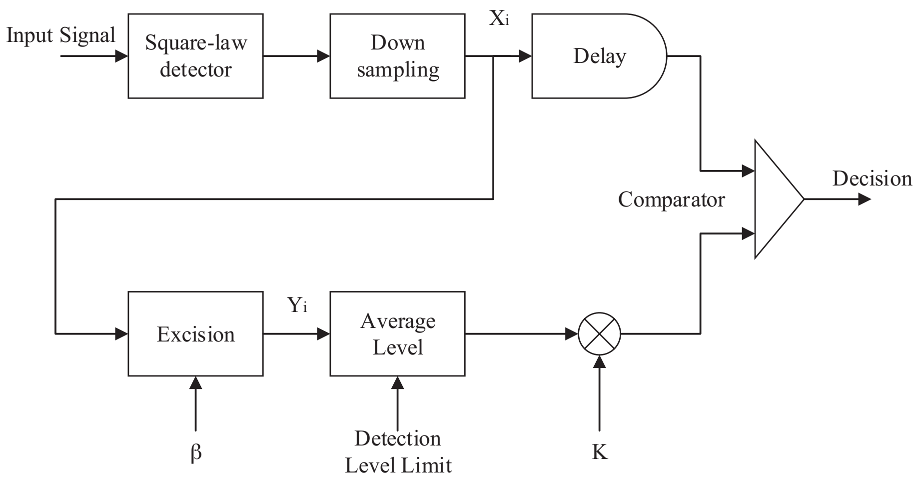

Figure 3. The block diagram of the proposed detector.

under test are typically ignored (guard cells). To determine the threshold level, the overall noise power estimate is calculated as follows:

$$P_n = \frac{1}{N}\sum_{m=1}^{N} X_m. \tag{1}$$

If the number of spikes is greater than or equal to M, then the target presence hypothesis "1" and the absence of the target "0" are established. The role of the constant false alarm rate is to determine the threshold of noise power. For the threshold setting, it is necessary to consider the probability density function (pdf) of the decision variable under hypothesis H_0. If parameters are unknown, reference samples can be obtained using the threshold. Reference samples are Z_i and i=0,1,..., N_R, where N_R is the number of reference cells. Here, it is assumed that the cells are independent and have a probability density function with exponential distribution:

$$f(z) = \frac{1}{2\lambda} exp\left\{-\frac{z}{2\lambda}\right\},\ z \geq 0, \tag{2}$$

where λ is considered in two general terms:

- If the cell only contains noise Γ, $\lambda = \Gamma$, the noise power, is used as background.
- If the cell contains the signal Γ, $\lambda = \Gamma(1+s)$ is the average signal-to-noise ratio [33].

In the various CFAR methods, the following expression can be expressed as $\int = T_g\,(Z_1, Z_2, ..., Z_{N_R})$, where T is scale factor, and g is represented by the CFAR specification function.

In [34], the g-parameter is the total weight of ordered samples. The threshold is calculated from the approach as $\int = T\sum_{i=1}^{N_R} l_i Z(i)$, where $Z(1) \leq \lambda Z(2) \leq ... \leq \lambda Z(N_R)$, l_i is filtering weight, and T is scale factor. The probability of detection is obtained from Equation (3):

$$P_D = \prod_{i=1}^{N_R} \frac{1}{1 + \dfrac{(T+B)\zeta_i}{1+S}}, \tag{3}$$

where $\zeta_i = \frac{1}{N_R+1-i}\sum_{i=1}^{N_R} l_i$. Therefore, if S = 0 is considered, the probability of false alarms is calculated:

$$P_{fa} = \prod_{i=1}^{N_R} \frac{1}{1+(T+B)\zeta_i}. \tag{4}$$

In CA-CFAR, the amount $\zeta = 1$ and the total amount of reference cells are calculated. By calculating the probability of a false alarm with the formula presented above, we can find the probability of a false alarm as desired ($P_{fa,\ Des}$), where the CA scale factor is calculated as follows:

$$T_{CA} = (P_{fa,Des})^{-\dfrac{1}{N_R}} - 1. \tag{5}$$

Due to choosing a hybrid algorithm and its computational similarity to the CMLD-CFAR, it is necessary to explain this detector. The CMLD uses the following weights:

$$l_i = \begin{cases} 1, & i = 1, 2, ..., K-1 \\ N_R - k + 1, & i = K \\ 0, & otherwise. \end{cases} \tag{6}$$

The scale factor is assumed to be [34]:

$$T_{CMLD} = (P_{fa,Des})^{-\dfrac{1}{K}} - 1. \tag{7}$$

Lops [35] showed that the weighting for a system with (N_{R-k}) deletions is optimal, and reference cells are assumed to contain only noise. For the case where the samples are not removed, an optimal solution is to use the CA-CFAR detector. To implement and simulate the proposed algorithm, it is assumed that the smallest number of cells is constant, and Z(K) is the smallest value of the reference set. Now cell values are used in the range of $(Z(K),\ (1+\nabla)Z(K))$ and are considered as reference sets ∇. The design parameter and threshold for the test cell are the means of the reference set multiplied by the T scale factor. In the simulation, the reference samples of the signal or interference components that are useless are just noises. Here there are at least two methods for comparing the effects of interference. In the first method, some of the largest reference cell values are not considered. In the second method, the number of censored cells is not constant and is based on the actual values of reference cells. In the simulation, the number of reference cells is N_R=32, and the infinite interference is strong. In this case, the interference reduces the size of the reference set, so the values of the largest reference cell are considered.

4. Simulation analysis

In this section, the proposed model outlined in the previous section is implemented using MATLAB software. At first, the number of reference cells should be $Z_1 \leq Z_2 \leq ... \leq Z_{N_R}$ and tested on K. This step is performed and the repetition starts with the K value equal to the size of the smallest assumed set. T_K scaling factors control the characteristics of the censorship process. In many applications, it is important to control the refraction rate of clean samples (P_r) and it also depends on the likelihood of a false alarm. The received detector signals are compared with an adaptive threshold, and CFAR maximizes the detection performance in the noise/clutter environment. The signal is obtained as follows:

$$z = \sum_{i=1}^{2N} x_i,\ P_d = \left(1 + \frac{T}{1+s}\right)^{-2N}. \tag{8}$$

The signal detection in reference cells around the cell under test in the new CFAR hybrid detector is obtained by using the excision parameter as follows:

$$z = x(k),\ P_d = \prod_{i=1}^{k-1} \frac{2N-i}{2N-i+\dfrac{T+B}{1+S}}. \tag{9}$$

To investigate the impact of integration on targets, two scenarios are considered. In the first scenario, simulation is considered without integration. In this case, the simulation of the probability of detection regarding threshold voltage is as in Figure 4. As shown in Figure 4, with the increase of the threshold voltage, the probability of detection is reduced. In the simulation for the various threshold voltages, the probability of detection is calculated for each threshold voltage. Additive Riley distribution noise with a voltage equal to 4 V and one hundred times, based on the number of loads the signal received from the threshold voltage, is calculated. In fact, in practice, it pulses 100 times to the desired target, and the probability of detection is calculated based on how many received pulses are higher than the threshold voltage. In the second scenario, simulation is considered with integration. The calculation of the probability of detection in this case is similar to the previous one. The difference is that instead of the probability of calculating the signal itself, the average values taken from the received signals will be calculated. In fact, instead of sending a pulse each time and looking at the result, we send 10 packets at a time. After receiving the values obtained from the average of each packet, the probability of detection will be calculated. As shown in Figure 5, the probability of detection is approximately zero at a voltage of 4.0 in the previous state, but in this case, by performing an averaging operation of the integration packet, even though the signal box in the mean pack is not necessarily 4 V, it increases nearly 95%.

The probability of false alarm and the probability of detection curves of correlation coefficients are presented in Figure 6 and Figure 7, respectively. Among the solutions for undesirable effects of interfering signals and consequently their effects on detection is the use of a comparative method in which samples of interference signals are replaced by the proportion of the average of the total effective samples in the detection. In these methods, after analytical calculations, the interference signals are eliminated, and, as a result, their

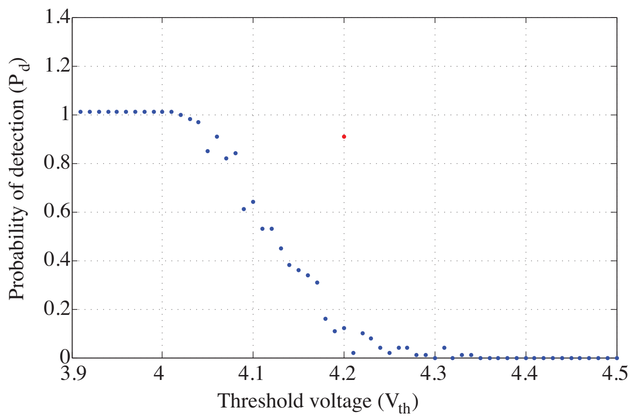

Figure 4. Detection probability diagram based on threshold voltage variations for assumed point.

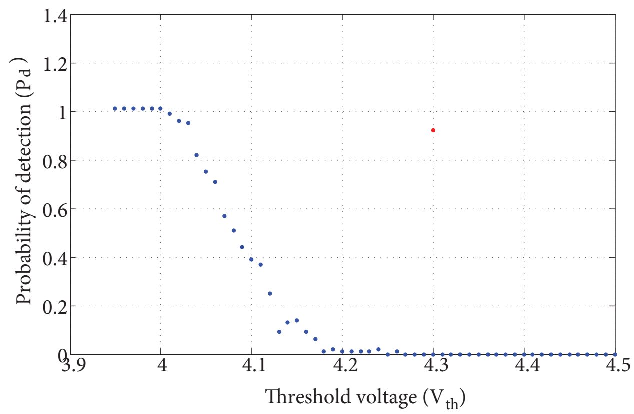

Figure 5. Detection probability diagram in terms of threshold voltage variations for assumed point.

undesirable effects in detection are counteracted. To evaluate the performance of the proposed method, the thresholds of the EX-CFAR detector, CA-CFAR detector, CMLD-CFAR detector, and CA-CFAR detector with the proposed method for the received signal in an interference environment are compared. The results of comparing these detectors with the proposed method can be seen in Figure 8, Figure 9, and Figure 10. In this simulation, a set of reference cells was selected to estimate the unknown noise/clutter area. The threshold value in the proposed detector is then compared with the CA-CFAR detector regarding a threshold. The probability of false alarm and detection in the correlation coefficients is also analyzed. It is clear from the results that the performance of this detector in similar conditions (without interference targets) does not change much compared to the CA-CFAR detector. However, if there are interference goals (interference environment), the performance is far better and more targets can be revealed.

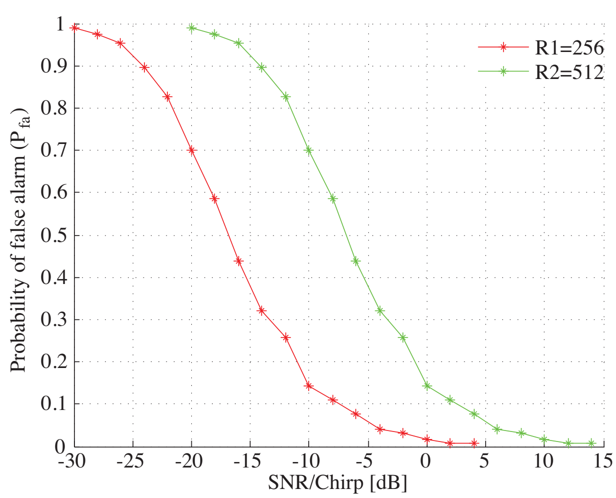

Figure 6. P_{fa} curve in no-noise mode under conditions of correlation coefficients of 256 and 512.

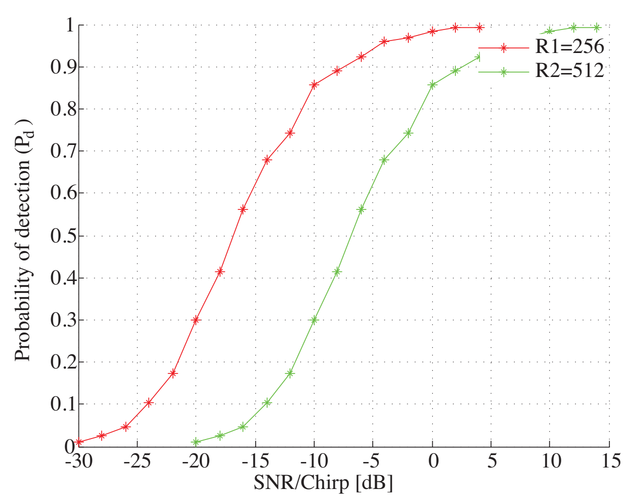

Figure 7. P_d curve in terms of correlation coefficients of 256 and 512.

The created parameter has been used to determine the standard for the censoring of abnormal values in the reference cell. The noise detector plays an essential role in determining the simulation parameters. The

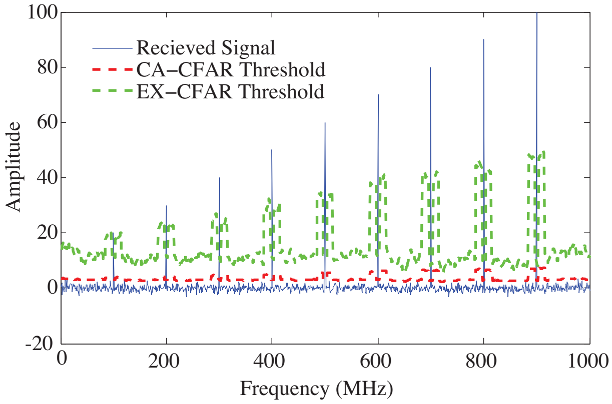

Figure 8. Comparison of the threshold of the EX-CFAR detector and the CA-CFAR compared to the received signal in an interference environment.

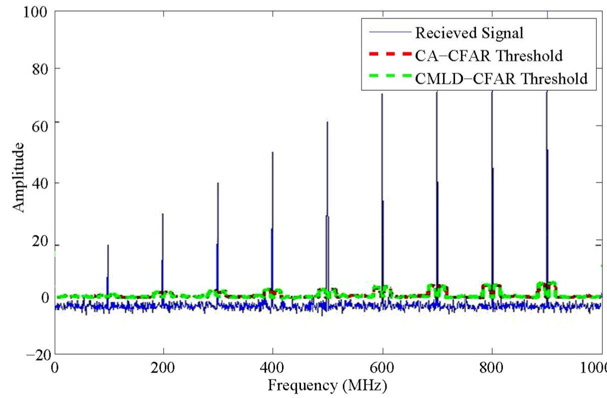

Figure 9. Comparison of CMLD-CFAR and CA-CFAR detector thresholds with the received signal in an interference environment.

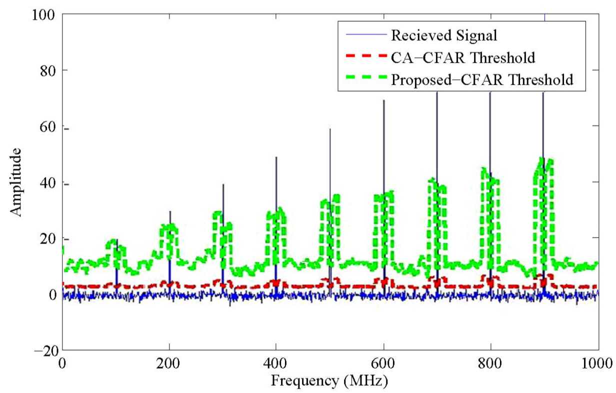

Figure 10. Comparison of suggested detector threshold with the CA-CFAR detector relative to the received signal in an interference environment.

results show that the excision parameter, by adding in the window, reduces the effects of background noise on the received signal from the reference cells that contain the test cell. It is concluded that the combined detector is not resistant to interference signals, but it is also relatively less computational than conventional detectors. Also, with integration, the threshold voltage can be increased so that the probability of detection is not reduced.

5. Conclusion

Among the solutions to the undesirable effects of interfering signals is the use of a comparative method in which samples of interference signals are replaced by the proportion of the average of the total effective samples in the detection. In these methods, after analytical calculations, the interference signals are eliminated, and as a result, undesirable effects can be detected. In this simulation, a set of reference cells was selected to estimate the unknown noise/clutter area. The threshold value in the proposed detector was compared with the CA-CFAR detector regarding a threshold. The probability of false alarm and detection in the correlation coefficients was also compared. It is clear from the results that the performance of this detector in similar conditions (without interference targets) does not change a lot compared to the CA-CFAR detector. However, if there are interference goals (interference environment), performance is far better and more targets can be revealed. The created parameter has been used to determine the standard for the censoring of abnormal values in the reference cell. The noise detector plays an essential role in determining the simulation parameters. The results show that the excision parameter, by adding in the window, reduces the effects of background noise on the received signal from the reference cells that contain the test cell. From the proposed method, it is concluded that the combined detector is not resistant to interference signals and leads to improved detection quality. Besides, it is relatively less computational than conventional detectors. In addition, with integration, the threshold voltage range can be increased so that the probability of detection is not reduced.

References

[1] Abbadi A, Abbane A, Bencheikh M, Soltani F. A new adaptive CFAR processor in multiple target situations. In: Seminar on Detection Systems Architectures and Technologies; Algiers, Algeria; 2017. pp. 1-5.

[2] Farrouki A, Barkat M. Automatic censoring CFAR detector based on ordered data variability for nonhomogeneous environments. IEEE Proceedings on Radar, Sonar and Navigation 2005; 152: 43–51.

[3] Verma A. Variability index constant false alarm rate (VI-CFAR) for sonar target detection. In: International Conference on Signal Processing, Communications and Networking; Chennai, India; 2008. pp. 138–141.

[4] Zaimbashi A. An adaptive cell averaging-based CFAR detector for interfering targets and clutter-edge situations. Digital Signal Processing 2014; 31: 59–68.

[5] Zaimbashi A, Norouzi Y. Automatic dual censoring cell-averaging CFAR detector in non-homogenous environments. Signal Processing 2008; 88: 2611–2621.

[6] Wu F, Wu N, Wu M. A fast and slow time combined CFAR detection algorithm used in through-the-wall radar. In: IEEE Electrical Design of Advanced Packaging and Systems Symposium; Haining, China; 2014. pp. 1-3.

[7] Trunk GV. Range resolution of targets using automatic detectors. IEEE Transactions on Aerospace and Electronic Systems 1978; 14 (5): 750–755.

[8] Goldman H, Bar-David I. Analysis and application of the excision CFAR detector. IEEE Proceedings on Communications, Radar and Signal Processing 1988; 135: 563–575.

[9] Rohling H. Radar CFAR thresholding in clutter and multiple target situations. IEEE Transactions on Aerospace and Electronic Systems 1983; 19 (4): 608–621.

[10] Song H, Lu S, Yi W, Kong L. CFAR detector based on clutter partition in heterogeneous background. In: IEEE China Summit and International Conference on Signal and Information Processing; Chengdu, China; 2015. pp. 288-291.

[11] Ritcey JA. Performance analysis of the censored mean-level detector. IEEE Transactions on Aerospace and Electronic Systems 1986; 22 (4): 443–454.

[12] Lehtomaki JJ, Juntti M. Analysis of energy based signal detection. University of Oulu 2005; 68 (1): 1-102.

[13] Jiang W, Huang Y, Yang J. Automatic censoring CFAR detector based on ordered data difference for low-flying helicopter safety. Sensors 2016; 16: 1-21.

[14] Yong HK, Sungshin K, Hye-Young H, Bok-Haeng H, Cheol-Hwan Y. Real-time detection and filtering of chaff clutter from single-polarization Doppler Radar Data. Journal of Atmosphere Ocean Technology 2013; 30 (5): 873–895.

[15] Luo J, Han Y, Fan L. Underwater acoustic target tracking: a review. Sensors 2018; 18 (1): 1-37.

[16] Lops M. Hybrid clutter-map/L-CFAR procedure for clutter rejection in nonhomogeneous environment. IEEE Proceedings on Radar, Sonar and Navigation 1996; 143: 239–245.

[17] Xiangwei M, Jian G, You H. A generalized smallest of selection CFAR algorithm [radar signal processing]. In: Proceedings of the International Conference on Radar; Adelaide, Australia; 2003. pp. 130-132.

[18] Xiangwei M, You H. Quasi best weighted order statistics CFAR detector. In: International Conference on Signal Processing; Beijing, China; 1998. pp. 145-147.

[19] Messali Z, Soltani F, Sahmoudi M. Robust radar detection of CA, GO and SO CFAR in Pearson measurements based on a non linear compression procedure for clutter reduction. Signal, Image and Video Processing 2008; 2: 169-176.

[20] Nouar N, Farrouki A. CFAR detection of spatially distributed targets in k-distributed clutter with unknown parameters. In: 22nd European Signal Processing Conference; Lisbon, Portugal; 2014. pp. 1731–1735.

[21] Pace E, Taylor L. False alarm analysis of the envelope detection GO-CFAR processor. IEEE Transactions on Aerospace and Electronic Systems 1994; 30 (3): 848–864.

[22] Srinivasan R. Robust radar detection using ensemble CFAR processing. IEEE Proceedings on Radar, Sonar and Navigation 2000; 147 (6): 291–297.

[23] Srinivasan R. Fast simulation of smallest-of and geometric-mean CFAR detectors. IEEE Proceedings on Radar, Sonar and Navigation 2001; 148 (3): 186–191.

[24] Zhang R, Sheng W, Xiaofeng M. Improved switching CFAR detector for non-homogeneous environments. Signal Processing 2013; 93 (1): 35–48.

[25] Richards MA, Scheer JA, Holm WA. Principles of Modern Radar: Basic Principles. Raleigh, NC, USA: SciTech Publishing, 2010.

[26] Himonas DS. Adaptive censored greatest-of CFAR detection. IEEE Proceedings on Radar and Signal Processing 1992; 139 (3): 247–255.

[27] Himonas DS, Barkat M. Automatic censored CFAR detection for nonhomogeneous environments. IEEE Transactions on Aerospace and Electronic Systems 1992; 28 (1): 286–304.

[28] Yan S, Hao C, Hou C. Performance analysis of two modified censored mean-level CFAR detectors in Pearson distributed reverberation. In: 4th International Conference on Systems and Informatics; Hangzhou, China; 2017. pp. 1114–1119.

[29] Miftahushudur T, Kurniawan D, Putra AR. Summed area table for optimizing of processing time on CA CFAR algorithm. In: International Conference on Radar, Antenna, Microwave, Electronics and Telecommunications; Bandung, Indonesia; 2015. pp. 109–113.

[30] Aalo V, Peppas K, Efthymoglou G. Performance of CA-CFAR detectors in nonhomogeneous positive alpha-stable clutter. IEEE Transactions on Aerospace and Electronic Systems 2015; 51 (3): 2027–2038.

[31] Han YI, Kim T. Performance of excision GO-CFAR detectors in nonhomogeneous environments. IEE Proceedings on Radar, Sonar and Navigation 1996; 143: 105–112.

[32] Li Y, Wu L, Zhang N. A CFAR detector based on a robust combined method with spatial information and sparsity regularization in non-homogeneous Weibull clutter. IEEE Access 2018; 6: 16279–16293.

[33] Zhang Y, Gao M, Li Y. Performance analysis of typical mean-level CFAR detectors in the interfering target background. In: 9th IEEE Conference on Industrial Electronics and Applications; Hangzhou, China; 2014. pp. 1045–1048.

[34] Ling-Zhi Y, Wei-Ping L, Zhi-Rong L, Gen-Ping W. Study on consistent CFAR detection of a linear signal with unknown parameters. In: Fifth World Congress on Intelligent Control and Automation; Hangzhou, China; 2004. pp. 3886–3890.

[35] Likai Z, Sen L, Guangzhao H. An improved VI-CFAR detector based on GOS. In: Seventh International Conference on Mechatronics and Manufacturing; Singapore; 2016. pp. 1-5.