Modified cell averaging CFAR detector based on Grubbs criterion in multiple-target scenario

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***Abstract*—Constant false alarm rate (CFAR) is the desired property for automatic target detection in unknown and non-stationary background. In this paper, a modified cell averaging CFAR detector based on Grubbs criterion (CAG-CFAR) is proposed for multiple-target scenario, which is encountered when two or more targets are displayed closely in the range domain. The CFAR property of the proposed method with respect to the distribution parameter in exponential-distributed background is verified via Monte Carlo simulations. The CAG-CFAR detector does not require a priori knowledge of the number of interfering targets, achieving a robust detection performance with a low computational burden. Comparisons of the detection performance of the CAG-CFAR detector with several relevant competitors verify the effectiveness and superiority of the proposed method in multiple-target situation with an unknown number of the interfering targets.**

Keywords—target detection; Grubbs criterion; CFAR; multiple targets

I. INTRODUCTION

As an adaptive threshold technique, constant false alarm rate (CFAR) detector is widely used for radar automatic detection in an unknown clutter environment. Given the lack of a priori knowledge of the practical clutter background, target detection with a fixed threshold suffers an excessive increase in the false alarm rate and an intolerable decrease in the detection performance. As a cure, CFAR detector sets a threshold dynamically by estimating the mean power of the local background, and multiplying it by a multiplication factor which depends on the desired false alarm rate and the statistical characteristics of the background. Consequently, the potential targets can be detected correctly in different clutter backgrounds with a constant false alarm rate, which is important in modern radar system application and receiving popularity in recent years [1]–[11].

Cell-averaging CFAR (CA-CFAR) [12], [13] is the earliest type of CFAR detector, of which the detection performance has been demonstrated to approach the ideal Neyman-Pearson detector with an increase of the reference cell in homogenous exponential environment. However, CA-CFAR suffers significant performance degradation in multiple-target scenario owing to the masking effect, and the false alarm will increase at the clutter edge [14]. The greatest of selection CFAR (GO-CFAR) provides excellent performance in maintaining CFAR property in the case of clutter edge [15]. However, the severe masking effect limits the detection performance in multiple-target scenario, and the CFAR loss will increase in a homogenous background. The ordered statistic CFAR (OS-CFAR) [16] is advantageous for target detection in multiple-target scenario. This method selects the k th sample of the amplitude rank-ordered reference cells to represent the mean power of the local clutter, exhibiting a more robust detection performance compared to CA-CFAR and GO-CFAR in multiple-target situation. However, it still suffers an excessive false alarm rate in the clutter edges [17]. Furthermore, the censored-class CFAR detectors, such as censored mean-level detector (CMLD) [18] and trimmed mean CFAR (TM-CFAR) detector [14], are proposed for target detection in multiple-target scenario with an acceptable CFAR loss in homogenous background. The outliers and potential targets in the reference window of the CFAR processor will be eliminated for an accurate estimation of the background level. However, the number of interfering targets is required to be *priori* known, which is generally impossible in practical scenario. To eliminate the dependence on the number of interfering targets, the generalised CMLD and automatic CMLD are respectively introduced in [19] and [20], while the corresponding computational burden is heavy owing to the iteration in outlier rejection and estimation of background level.

In this paper, a modified CA-CFAR detector based on Grubbs criterion (CAG-CFAR) is proposed in exponential background, which is commonly utilised to describe the clutter power distribution in coherent low range-resolution radar. The Grubbs criterion is applied to prevent the influence on the background level estimation introduced by the outliers and potential targets in the reference window of CFAR processor. The proposed detector is demonstrated to maintain CFAR property with respect to the distribution parameter in exponential-distributed background. Simulation results show that the CAG-CFAR detector does not require *a priori* knowledge of the number of interfering targets, achieving a robust detection performance with a low computational burden. The effectiveness and superiority of the proposed method in multiple-target scenario with an unknown number of the

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interfering targets are verified by performance comparisons with relevant CFAR detectors.

The remaining parts of this paper are organized as follows. The traditional CFAR detectors in exponential background are introduced briefly in Section II. The Grubbs criterion and the detection scheme of CAG-CFAR are provided in Section III. In Section IV, the motivations and advantages of the proposed method are verified using simulations. A general conclusion is presented in Section V.

II. TRADITIONAL CFAR DETECTORS

In this section, the schemes of CA-CFAR, GO-CFAR, OS-CFAR, TM-CFAR, and CMLD are introduced. The main purpose of all CFAR processor is to declare the target present or absent by setting an adaptive threshold, which is determined dynamically by the estimated background level and the desired false alarm rate. The target detection is usually performed through the sliding window technique, of which the block diagram is provided in Fig. 1. The in-phase and quadrature signals after pulse compression are first square-law detected, and the successive outputs are stored in a tapped delay line, which consists of the reference window, guard cells and cell under test (CUT). The samples in the reference window P are usually assumed to be statistically independent and identically distributed (IID) random variables in homogenous clutter environment. The local background level is estimated using the samples in the leading and lagging halves of the reference window. The samples in the guard cells are discarded to eliminate the impact of the potential target in the CUT on background level estimation. The adaptive threshold is obtained by multiplying the estimated local power level with a multiplication factor, which is related to the desired false alarm rate. The multiplication factor is also known as scaling factor or normalized factor [15], [16]. If the magnitude of CUT exceeds the adaptive threshold, the target is declared to be present.

Assuming that the samples in the reference window are random variables $X_1, X_2, \cdots, X_N$, N denotes the length of the reference window. The statistical power samples in reference window P satisfy exponential distribution. The probability density function (PDF) of exponential distribution could be expressed as

$$f(x) = 1/2\sigma^2 \exp\left(-x/2\sigma^2\right) \tag{1}$$

where x denotes the power of the clutter sample, σ denotes the distribution parameter. The detection schemes of the referenced CFAR methods are provided as follows.

A. CA-CFAR

In the CA-CFAR detector, the background level is estimated by the mean power of the samples in the reference window, as

$$Z_{CA} = 1/N \sum_{i=1}^{N} X_i \tag{2}$$

B. GO-CFAR

The GO-CFAR method selects the maximum of the two statistical values in the leading and lagging window as the background level estimate, which can be given by

$$Z_{GO} = 2/N \max\left(\sum_{i=1}^{N/2} X_i, \sum_{i=N/2+1}^{N} X_i\right) \tag{3}$$

C. OS-CFAR

The OS-CFAR method uses the estimate of the background level by selecting a sample after a value rank-ordered process. Assuming that the rank-ordered sequence is

$$X_{(1)} \le X_{(2)} \le \cdots \le X_{(N)} \tag{4}$$

where $X_{(1)}$ denotes the minimum and $X_{(N)}$ denotes the maximum value in the reference window. By selecting a certain order k, the representational average background level is

$$Z_{OS} = X_{(k)}, k \in \{1, 2, \cdots, N\} \tag{5}$$

The noise level representative rank k is determined by the pre-assigned false alarm rate and the length of the reference window.

D. CMLD

In CMLD, the n largest ranks of the rank-ordered sequence given in (4) are discarded from the estimation of background level, which can be given as

$$Z_{CMLD(n)} = \sum_{i=1}^{N-n} X_{(i)} \Big/ (N-n) \tag{6}$$

Obviously, CMLD works well when the number of interfering targets is no greater than n.

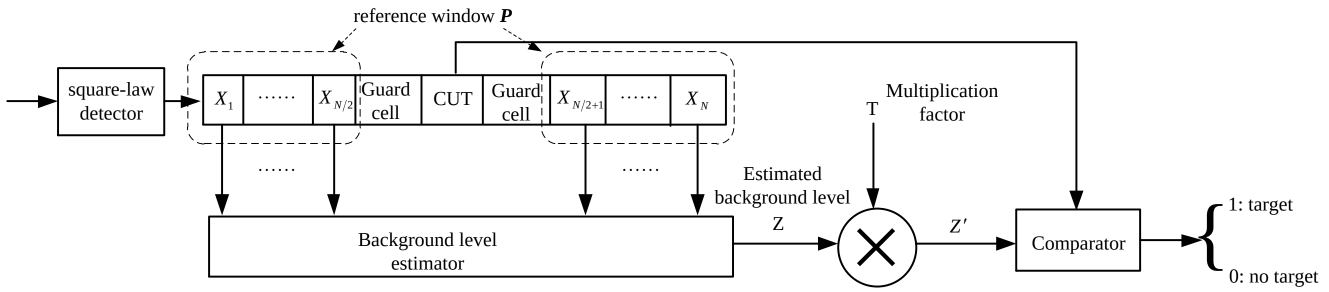


Fig. 1. Block diagram of sliding window technique.

E. TM-CFAR

The TM-CFAR detector is often regarded as a generalisation of the OS-CFAR. In this detector, the references samples are sorted firstly, as provided in (4). The background level is estimated as a linear combination of the rank-ordered samples, replacing the sample selected by a certain order k . In addition, a total of T_1 samples from the lowest ranks and T_2 samples from the largest ranks are discarded from the estimation of background level. This process is advantageous for outlier rejection. It's worth mentioning that, however, the number of interfering targets is also required to be *priori* known, showing a similarity to CMLD. The background level of TM-CFAR is

$$Z_{TM(T_1,T_2)} = \sum_{i=T_1+1}^{N-T_2} X_{(i)} \Big/ \left(N - T_1 - T_2\right) \tag{7}$$

In addition, it's obvious that the CA-CFAR, OS-CFAR, and CMLD methods are special cases of the TM-CFAR method.

III. The CAG-CFAR processor

In this section, the principle of CAG-CFAR detector is provided. This method consists of two procedures: outlier rejection with Grubbs criterion and detection threshold estimation.

A. Outlier rejection with Grubbs criterion

The existence of outliers, sea spikes, interfering targets in the reference window of CFAR detector may lead to an unavoidable bias in the estimation of background level, which will greatly affect the detection performance. Thus, outlier rejection is essential for detection threshold estimation in radar system.

Typical criterions for outlier rejection in raw data consists of Lomnaofski norm (Student's t test), Grubbs criterion, Dixon criterion, and 3σ criterion [21]. In this paper, the Grubbs criterion is utilised for outlier rejection, wherein two reasons are considered: 1) Grubbs criterion is feasible when the sample size is small and 2) the critical value is only related to the sample size and significant level. Given the clutter background is unknown in practical scenario and the size of reference cells is usually limited, Grubbs criterion is more appropriate in radar application when compared to the others.

Assume the elements in a set of measurements sequence $S_1, S_2, \cdots, S_N$ satisfy normal distribution. We form a statistic as

$$\mu = \max_{1 \le i \le N} \left| S_i - \bar{S} \right| \tag{8}$$

where $\bar{S} = 1/N \sum_{i=1}^{N} S_i$ denotes the mean value of the raw data. For convenience, we assume that $\mu = \left| S_j - \bar{S} \right|$ from (8). Thus, the sample S_j should be discarded in the original measurement set for data processing if the following inequality is satisfied, as

$$\mu \ge g\left(N, \alpha/2\right) \hat{\sigma} \tag{9}$$

where $\hat{\sigma} = \sqrt{1 \Big/ \left(N-1\right) \sum_{i=1}^{N} \left(S_i - \bar{S}\right)^2}$ denotes the estimated standard derivation of the raw data, $g\left(N, \alpha/2\right)$ is the critical value which is determined by the sample size and significant level α . Critical values with several typical parameters are listed in TABLE I. The outlier rejection with Grubbs criterion will be repeated on the rest of $N-1$ samples until no outlier is declared.

B. Detection scheme of CAG-CFAR

In CAG-CFAR, the background level is estimated by the sample processed by Grubbs criterion in the reference window. Note that the Grubbs criterion is established based on the assumption the samples satisfy normal distribution. In exponential-distributed background, the in-phase (I) and quadrature (Q) samples of the complex radar returns are known to satisfy normal distribution with zero mean and constant variance σ^2 , thus, the requirement for the application of Grubbs criterion is satisfied. It is reasonable to believe that if the I or Q sample of a complex radar return appears to be an outlier, the resultant amplitude or power after envelope- or square-law detection will also behave as an outlier. This is the main motivation of the design of CAG-CFAR detector. The background level will be estimated accurately by applying Grubbs criterion to the outlier rejection in the I and Q samples which locate in the reference window before square-law detection, respectively.

The simplified block diagram of CAG-CFAR is illustrated in Fig. 2. Comparing to Fig. 1, this detector contains an additional reference windows *C*, and the rest parts of the CAG-CFAR are identical to those in Fig. 1. The reference window *C* in Fig. 2 contains the complex radar returns with the same order of Fig. 1 before square-law detection, wherein the I and Q signals of each sample are available and stored in the sub-reference window marked by *CI*, and *CQ*. This indicates that $X_i = I_i^2 + Q_i^2, i = 1, 2, \cdots, N$. The detailed scheme for background level estimation of CAG-CFAR detector is as follows:

1) Outlier index recording: By applying Grubbs criterion to the I and Q signals of reference samples in reference window *C*, respectively, the indexes of the potential outliers in corresponding sub-reference windows *CI* and *CQ* are recorded.

2) Outlier rejection: The main purpose is to discover and eliminate the outlier in the reference window *P* for a relatively accurate estimation of background level. Given the indexes of the potential outliers in I and Q signals of reference samples

TABLE I. Critical values of Grubbs criterion

sample size	**significance level**	
	0.05	***0.01***
16	2.585	2.852
32	2.938	3.270
64	3.224	3.586

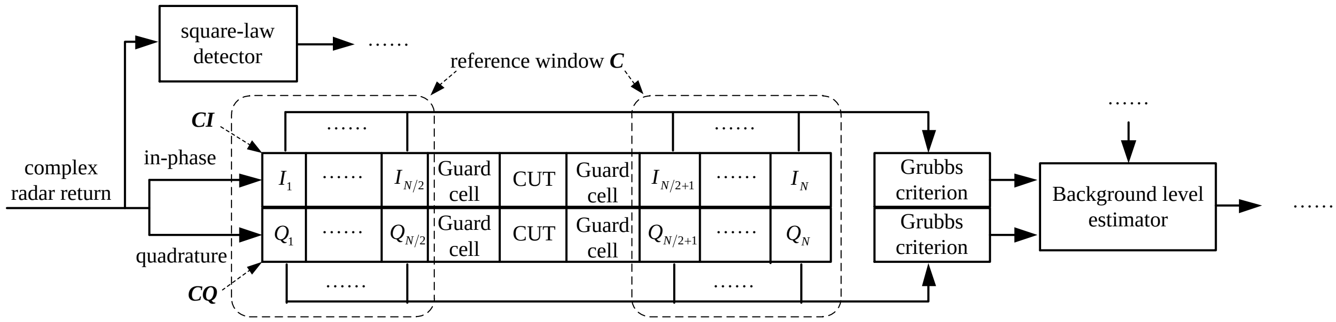


Fig. 2. Simplified block diagram of CAG-CFAR processor (omitted parts are identical to Fig. 1).

are available after step 1), the samples which have the same indexes in reference window P are discarded from the background level estimation.

3) Background level estimation: Assume that a total of M samples in reference P should be discarded, the background level is estimated as the mean value of the rest of $N-M$ samples.

In addition, some comments are provided based on step 2). The sample in reference window P should be discarded if the corresponding I or Q signal in reference window C is declared to be a potential outlier by Grubbs criterion. The outlier declarations in both I and Q signals are not required. This indicates that the indexes of outliers in reference window P is given by

$$p = \{p_{CI}\} \cup \{p_{CQ}\} \tag{10}$$

where $\{p_{CI}\}$ and $\{p_{CQ}\}$ denotes the indexes of outliers in CI and CQ of reference C, and $\{p_{CI}\} \subseteq \{1, 2, \cdots, N\}$, $\{p_{CQ}\} \subseteq \{1, 2, \cdots, N\}$. For example, if the 3, 6, and 9-th samples in CI and the 4 and 6-th samples in CQ of reference window C are declared to be outliers, the 3, 4, 6, and 9-th samples in reference window P should be discarded from the background level estimation.

IV. PERFORMANCEN ASSESSMENT

In this section, the detection performance of the referenced CFAR detectors in multiple-target scenario is investigated. We assume that the primary target, namely the target of interest, is located in the CUT while multiple interfering targets appear in the reference window simultaneously. The Marcum (nonfluctuating) target is generated to evaluate the detection performance of the relevant CFAR detectors in exponential-distributed clutter without the additional interference introduced by the target fluctuation. Two representative scenarios – two or more interfering targets with the interference-to-clutter ratio (ICR) of 20 dB, two or more interfering target with same power of the primary target – are considered.

A. Proof of CFAR property

In this subsection, the CFAR property of CAG-CFAR detector in exponential-distributed background is investigated. Owing to the outlier rejection by Grubbs criterion, the analytical expression of the PDF of the estimated background level and the corresponding false alarm rate of CAG-CFAR detector are also difficult to be obtained. Consequently, the P_{fa} is preferred to be estimated by Monte-Carlo method. The false alarm rates of CAG-CFAR versus multiplication factors for different distribution parameters σ are illustrated in Fig. 3. The length of reference window is 32 and the guard cell size is 3. Three options of σ, such as 1, 10, and 100, are considered. The significant level for Grubbs criterion is 0.05. A total of 10^9 Monte Carlo trials are performed for any combination of the distribution parameter and multiplication factor. Results in Fig. 3 show that the proposed method maintains CFAR property with respect to σ since the curves of P_{fa} with different distribution parameters coincide. A locally enlarged subfigure is provided for better visual effect. The minor differences between the results with different parameters are due to the limited precision of the Monte Carlo simulation and can be neglected.

B. Detection performance in multiple-target scenario

In this subsection, the detection performances of CAG-

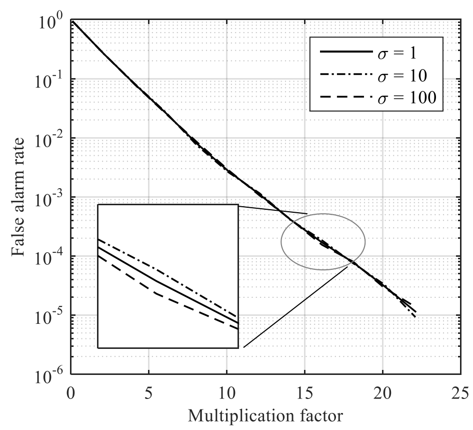
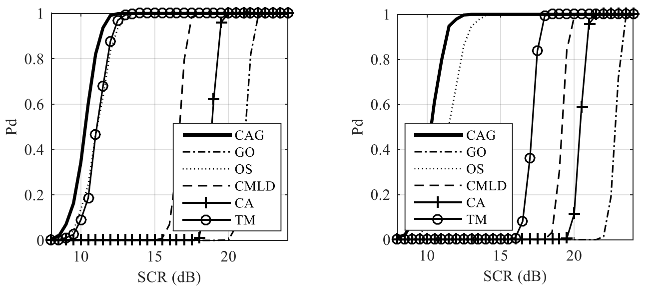
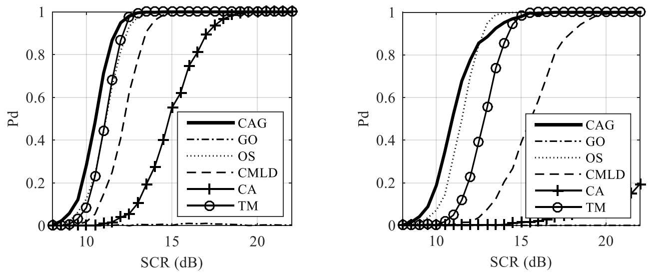


Fig. 3. False alarm rates of CAG-CFAR for different σ in exponential-distributed background.



(a) (b)

Fig. 4. Detection probabilities with (a) two interfering targets and (b) three interfering targets for ICR = 20 dB.



(a) (b)

Fig. 5. Detection probabilities with (a) two interfering targets and (b) three interfering targets for ICR = SCR.

CFAR, GO-CFAR, OS-CFAR, CMLD, CA-CFAR and TM-CFAR are investigated though simulations. The length of reference window is 32 and the guard cell size is 3 for each detector. The desired false alarm rate is 10^{-4}. Without loss of generality, the noise level representative rank k of OS-CFAR is 24, which is well suited for practical applications [16]. The number of censored samples for CMLD is 1 and $T_1 = T_2 = 2$ for TM-CFAR; these configurations reveal that the maximum acceptable numbers of interfering targets for CMLD and TM-CFAR are 1 and 2, respectively. The false alarm rates of the referred competitors have been detailed in the references cited in Section I.

In Fig. 4(a), two Marcum interfering targets with the ICR of 20 dB are simulated. In this condition, CAG-CFAR achieves a similar performance with TM-CFAR, which is demonstrated to outperform the other competitors. OS-CFAR also works well while the CFAR loss is relatively larger. The performance of CMLD is seriously affected since the corresponding maximum acceptable number of interfering targets is only 1. The detection probabilities of the CA and GO detectors decrease significantly owing to the serious masking effect.

If the number of interfering targets is larger than T_2, however, the detection performance of TM-CFAR will also decrease significantly, as shown in Fig. 4(b) wherein the number of interfering target is 3. In this condition, the CAG-CFAR achieves the superior performance when compared to the other competitors owing to its independence to the number of interfering targets. The outliers, which includes the returns of interfering targets, will be discarded adaptively by Grubbs criterion with CAG-CFAR. Given that the interfering target number is unknown in practical scenario, the disadvantages of TM-CFAR, OS-CFAR, and CMLD with pre-assigned configurations will be exhibited obviously.

In Fig. 5, the ICRs of the interfering targets are equal to the signal-to-clutter ratio (SCR) of the primary target. The numbers of interfering targets in Fig. 5(a) and (b) are 2 and 3, respectively. This condition will introduce the most serious masking effect because the powers of the interfering targets are difficult to be averaged unless the length of reference window is sufficiently large, which is usually difficult to be satisfied in practical scenario. Results in Fig. 5 exhibit similarities to Fig. 4, while the CA-CFAR, GO-CFAR detectors are saturated in varying degrees. When the interfering target number reaches 3, the CAG-CFAR is demonstrated to be optimal in these methods. The robustness and effectives of CMLD and TM-CFAR with inappropriate pre-assigned configurations will degraded significantly, as shown in Fig. 5(b). Note that the OS-CFAR works robustly in these scenarios because the corresponding background level is estimated by the k-th sample in the reference window. In this condition, the robustness and the ability of anti-interfering targets of OS-CFAR are enhanced while the CFAR loss will accordingly increase.

C. Results analysis and discussion

TABLE II provides the SCR improvement of the proposed method compared to the OS-CFAR detector, which is demonstrated to work robustly in multiple-target scenario. The results of GO-CFAR, CMLD, CA-CFAR, and TM-CFAR are also provided for better comparison. Without loss of generality, we set the required SCR to satisfy the detection probability of 0.85 as the reference. Four conditions marked by Situation (*Situ.*) 1, 2, 3, and 4 represent the scenarios of Fig. 4(a), Fig. 4(b), Fig. 5(a), and Fig. 5(b), respectively. The results in Table II validate the superiority of the proposed method, especially under the multiple-target scenario.

In addition, the computational costs of the referenced detectors are investigated quantitatively, as shown in TALBE III. Without loss of generality, the processor cycle count, which

TABLE II. SCR IMPROVEMENT OF REFERRED CFAR METHODS WITH RESPECT TO OS-CFAR

SCR improvement (dB)	**Situation**			
	Situ. 1	***Situ. 2***	***Situ. 3***	***Situ. 4***
CAG	1.0	1.2	0.5	0.1
GO	-5.4	-11	-inf[a]	-inf
CMLD	-3	-7.3	-1.2	-4.1
CA	-6.2	-8.5	-4.3	-inf
TM	0.1	-5.4	0.1	-1.3

a. ‘inf’ denotes the infinite, namely the corresponding target is miss-detected.

TABLE III. COMPUTATIONAL COMPLEXITIES OF REFERRED CFAR DETECTORS

Processor cycle count[b]					
CA	GO	OS	CMLD	TM	CAG
7091	7081	23291	30496	31411	8309

b. The processor cycle count is calculated based on the TigerSHARC architecture of Analog Devices, Inc.

is directly related to the computational burden of a certain algorithm, is calculated based on the TigerSHARC digital signal processor (DSP) produced by Analog Devices, Inc. The processor cycle count is able to provide an objective evaluation of the computational complexity owing to its independence of the speed of DSP chip. Results show that the result of CAG-CFAR is similar to those of CA-CFAR and GO-CFAR. This result reveals that the CAG-CFAR achieves high efficiency when compared to others owing to the relatively small processor cycle count. Concluding, the CAG-CFAR outperforms the rest of the competitors by taking the detection performance into consideration.

V. CONCLUSION

In this study, the authors propose a modified cell averaging CFAR detector for multiple-target scenario based on Grubbs criterion. The outliers in the reference window are discarded automatically by Grubbs criterion, thus, the background level is able to be estimated accurately. The CAG-CFAR detector is demonstrated to maintain CFAR property with respect to the distribution parameter in exponential-distributed background via Monte Carlo simulations. The proposed method does not require *a priori* knowledge of the number of interfering targets, achieving a robust detection performance with a low computational burden. Quantitative performance evaluations verify the effectiveness and superiority of the proposed method when compared to several relevant competitors in multiple-target scenario with an unknown number of interfering targets. Given the complexities of unknown interfering targets, such as number and magnitude, the CAG-CFAR detector is predicted to be feasible and advantageous in practical scenario, such as sea clutter where the sea spikes occur. Future study is required to investigate the performance of CAG-CFAR detector in situations of clutter edges.

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REFERENCES

[1] G. V. Weinberg, “Noncoherent Radar Detection in Correlated Pareto Distributed Clutter”, *IEEE Trans. Aerosp. Electron. Syst.*, vol. 53, no. 5, pp. 2628–2636, Oct. 2017.

[2] S. Gong, M. Pan, W. Long, and H. Huang, “Distributed fuzzy maximum-censored mean level detector-constant false alarm rate detector based on voting fuzzy fusion rule”, *IET Radar Sonar Navig.*, vol. 9, no. 8, pp. 1055–1062, Sep. 2015.

[3] Y. Xu, S. Yan, X. Ma, and C. Hou, “Fuzzy soft decision CFAR detector for the K distribution data”, *IEEE Trans. Aerosp. Electron. Syst.*, vol. 51, no. 4, pp. 3001–3013, Oct. 2015.

[4] Y. Xu, C. Hou, S. Yan, J. Li, and C. Hao, “Fuzzy statistical normalization CFAR detector for non-Rayleigh data”, *IEEE Trans. Aerosp. Electron. Syst.*, vol. 51, no. 1, pp. 383–396, Jan. 2015.

[5] P. Shui, M. Liu, and S. Xu, “Shape-parameter-dependent coherent radar target detection in K-distributed clutter”, *IEEE Trans. Aerosp. Electron. Syst.*, vol. 52, no. 1, pp. 451–465, Feb. 2016.

[6] W. Zhou, J. Xie, G. Li, and Y. Du, “Robust CFAR Detector With Weighted Amplitude Iteration in Nonhomogeneous Sea Clutter”, *IEEE Trans. Aerosp. Electron. Syst.*, vol. 53, no. 3, pp. 1520–1535, Jun. 2017.

[7] V. A. Aalo, K. P. Peppas, and G. Efthymoglou, “Performance of CA-CFAR detectors in nonhomogeneous positive alpha-stable clutter”, *IEEE Trans. Aerosp. Electron. Syst.*, vol. 51, no. 3, pp. 2027–2038, Jul. 2015.

[8] G. Gao and G. Shi, “CFAR Ship Detection in Nonhomogeneous Sea Clutter Using Polarimetric SAR Data Based on the Notch Filter”, *IEEE Trans. Geosci. Remote Sens.*, vol. 55, no. 8, pp. 4811–4824, Aug. 2017.

[9] S.-N. Shi and P.-L. Shui, “Optimum coherent detection in homogenous K-distributed clutter”, *IET Radar Sonar Navig.*, vol. 10, no. 8, pp. 1477–1484, Oct. 2016.

[10] D. Tao, S. N. Anfinsen, and C. Brekke, “Robust CFAR Detector Based on Truncated Statistics in Multiple-Target Situations”, *IEEE Trans. Geosci. Remote Sens.*, vol. 54, no. 1, pp. 117–134, Jan. 2016.

[11] Y. Wang, W. Xia, and Z. He, “CFAR Knowledge-Aided Radar Detection With Heterogeneous Samples”, *IEEE Signal Process. Lett.*, vol. 24, no. 5, pp. 693–697, May 2017.

[12] H. M. Finn and R. S. Johnson, “Adaptive Detection Mode with Threshold Control as a Function of Spatially Sampled Clutter-Level Estimates”, in *RCA Review*, 1968.

[13] M. Weiss, “Analysis of Some Modified Cell-Averaging CFAR Processors in Multiple-Target Situations”, *IEEE Trans. Aerosp. Electron. Syst.*, vol. AES-18, no. 1, pp. 102–114, Jan. 1982.

[14] P. P. Gandhi and S. A. Kassam, “Analysis of CFAR processors in non-homogeneous background”, *IEEE Trans. Aerosp. Electron. Syst.*, vol. 24, no. 4, pp. 427–445, Jul. 1988.

[15] V. Hansen, “Detectability Loss Due to Greatest Of Selection in a Cell-Averaging CFAR”, *IEEE Trans. Aerosp. Electron. Syst.*, vol. AES-16, no. 1, pp. 115–118, Jan. 1980.

[16] H. Rohling, “Radar CFAR Thresholding in Clutter and Multiple Target Situations”, *IEEE Trans. Aerosp. Electron. Syst.*, vol. 19, no. 4, pp. 608–621, Jul. 1983.

[17] P. P. Gandhi and S. A. Kassam, “An adaptive order statistic constant false alarm rate detector”, in *IEEE International Conference on Systems Engineering*, 1989, pp. 85–88.

[18] J. Ritcey, “Performance Analysis of the Censored Mean-Level Detector”, *IEEE Trans. Aerosp. Electron. Syst.*, vol. AES-22, no. 4, pp. 443–454, Jul. 1986..

[19] M. Barkat, S. D. Himonas, and P. K. Varshney, “CFAR detection for multiple target situations”, *Radar Signal Process. IEE Proc. F*, vol. 136, no. 5, pp. 193–209, Oct. 1989.

[20] S. D. Himonas and M. Barkat, “Automatic censored CFAR detection for nonhomogeneous environments”, *IEEE Trans. Aerosp. Electron. Syst.*, vol. 28, no. 1, pp. 286–304, Jan. 1992.

[21] R. N. McDonough, A. D. Whalen, and A. D. Whalen, *Detection of signals in noise*, 2nd ed. San Diego: Academic Press, 1995.