TELKOMNIKA, Vol. 11, No. 6, June 2013, pp. 3298 ~ 3303
e-ISSN: 2087-278X

A New CFAR Detector based on Automatic Censoring Cell Averaging and Cell Averaging

Yuhua Qin*[1,2], Huili Gong[1], Ting Liu[1]
[1]College of Information Science and Engineering, China Ocean University, No. 238 Songling Road, Qingdao 266100, China
[2]College of Information Science and Technology, Qingdao University of Science and Technology, No. 69 Songling Road, Qingdao 266061, China
*Corresponding author, e-mail: yuu71@163.com

Abstract

In order to improve the interference immunity of the detector, a new CFAR detector (ACGCA-CFAR) based on automatic censoring cell averaging (ACCA) and cell averaging (CA) is presented in this paper. It takes the greatest value of ACCA and CA local estimation as the noise power estimation. Under swerling II assumption, the analytic expressions of P_{fa} *in homogeneous background are derived. In contrast to other detectors, the ACGCA-CFAR detector has higher detection performance both in homogeneous and nonhomogeneous backgrounds, while the sample sorting time of ACGCA is only quarter that of OS and ACCA.*

Keywords: *detection, constant false alarm rate (CFAR), automatic censoring cell averaging (ACCA), ordered data variability (ODV)*

1. Introduction

Constant false alarm rate (CFAR) detection refers to a common form of adaptive algorithm used in radar systems to detect target returns against a background of noise, clutter and interference. In most radar detectors, the threshold is set in order to achieve a required probability of false alarm. However, in most fielded systems, unwanted clutter and interference sources mean that the noise level changes both spatially and temporally. In this case, a changing threshold can be used, where the threshold level is raised and lowered to maintain a constant probability of false alarm. This is known as constant false alarm rate (CFAR) detection. The earliest CFAR detection scheme is called cell averaging (CA) [1] CFAR. Later, other conventional detection schemes such as the greatest of (GO) [2], the smallest of (SO) [3], the order statistics (OS) [4] and the censored mean (CM) [5] CFAR have been proposed one after the other. Because of the GO logic has better false alarm performance in the presence of clutter edges, it is commonly used for the adaptive setting of a radar detection threshold. In [6], in order to enhance the detection performance in a homogeneous background, a generalization of OS and GO, known as OSGO has been proposed. In [7], the authors presented OSCAGO algorithm based on the OS, CA and GO CFAR schemes. Also in [8], the authors proposed CMCAGO algorithm which combines the advantages of the CM, CA and GO. However, the censoring points of CM and order value of OS are fixed, they can not make full use of all the valid cells in the reference window. Also the sample sorting time is relative long. In [9], the authors proposed an automatic censored cell averaging (ACCA) CFAR detector based on ordered data variability (ODV) for nonhomogeneous background environments. The ACCA-ODV detector selects dynamically, by doing successive hypothesis tests, a suitable set of ranked cells is determined to estimate the unknown background level. This enhanced the detection ability of the CFAR detector. However, its drawback is that it suffers from excessive probability of false alarm (P_{fa}) in clutter transitions. According to these, a new robust CFAR detector (ACGCA-CFAR) which combines the advantages of the CA, ACCA and GO is presented in this paper. It takes the greatest value of ACCA and CA local estimations as noise power estimation. Under Swerling II and the Gaussian distribution assumption, the analytic expressions of P_{fa} in homogeneous

Received January 17, 2013; Revised April 12, 2013; Accepted April 24, 2013

background are derived. In contrast to other detectors, the ACGCA-CFAR detector has higher detection performance both in homogeneous and nonhomogeneous backgrounds.

2. ACCA-CFAR Detector

Assume $\{q_i\}$ is the reference cells, they are ranked to form the ordered samples $\{q_{(1)} <= \cdots <= q_{(p)} <= \cdots q_{(N)}\}$. The basic idea of ACCA algorithm is to consider that the p lowest cells represent the initial estimation of the background level. Next, perform the ODV-based successive hypothesis tests and get the estimated number of censored cells $\hat{i}$, then utilize the sum of $N-\hat{i}$ lowest cells to estimate the noise level.

Choose the ranked ordered subset $E_x = \{q_{(1)}, q_{(2)}, \cdots, q_{(p)}, x\}$ of length $p+1$, the ODV statistics can be written as:

$$ODV(x) = \frac{\mu_p + x^2}{(\sigma_p + x)^2}, \text{ Where } \sigma_p = \sum_{i=1}^{p} q_{(i)}, \ \mu_p = \sum_{i=1}^{p} q_{(i)}{}^2 \tag{1}$$

$ODV(x)$ increases for x varying in the interval under investigation $[q_{(p+1)}, q_{(N)}]$. Define the sequence V_k as:

$$V_k = ODV(x)|_{x=q(N-k)}, \ k = 0,1,\cdots,N-p-1 \tag{2}$$

Since V_k decreases for $k = 0,1,\cdots,N-p-1$, we can do successive hypothesis tests until the kth subset $E_x|_{x=q(N-k)}$ is declared to be homogeneous or $k = N-p$.

At the kth step, the ODV-based hypothesis test is:

$$V_k \underset{H_h}{\overset{H_{nh}}{\gtrless}} S_k \tag{3}$$

Where S_k is the ODV threshold corresponds to V_k. Increasing S_k results in a higher probability of detecting homogeneous environments. However, there is a significant decrease in sensitivity to make correct decisions when the successive subsets are nonhomogeneous. Assume α_k is the probability of hypothesis test error in a homogeneous environment, we define this probability, at each step k, as:

$$a_k = \Pr(V_k > S_k \mid E_{x=q(N-k) \text{ is homogeneous}}) \tag{4}$$

Hence, the values of S_k are determined by setting:

$$\alpha_0 = \alpha_1 = \cdots = \alpha_{N-p-1} = P_{fc} \tag{5}$$

Where P_{fc} is the desired probability of false censoring. Because an analytic expression for the probability density function(pdf) of V_k is not available, the Monte Carlo simulations are used to estimate S_k. Table 1 gives the thresholds S_k obtained in a homogenous background.

3. ACGCA-CFAR Detector

The ACGCA-CFAR detector block diagram is shown in Figure 1. The test cell is D. The lengths of leading and lagging window are both N. The data available in the leading and lagging window are processed by using ACCA and CA methods respectively to obtain two local estimations X and Y. Thus the estimation of the total noise power Z is obtained as $Z=\max(X,Y)$. The adaptive threshold is obtained according to the hypothesis test $D \underset{H_0}{\overset{H_1}{\gtrless}} T_{\hat{i}}Z$. Where $T_{\hat{i}}$ is a scale factor that is determined by the estimated number of censored samples $\hat{i}$ and the designed false alarm probability. H_1 denotes the presence of a target in the cell and H_0 denotes the absence of a target in the cell. The shift controller[10] and shift register for the reference cells in Figure 1 are used to select and censor the target sample. This makes the target sample can not enter the lagging reference window, which will enhance the interference immunity of the detectors in multiple target situations.

Table1. The ODV Threshold in Homogenous Background

(N,p)	P_{fc}	S_0	S_1	S_2	S_3
(8,6)	10^{-2}	0.565	0.389		
	10^{-3}	0.693	0.511		
(16,12)	10^{-2}	0.356	0.246	0.199	0.173
	10^{-3}	0.456	0.320	0.246	0.206

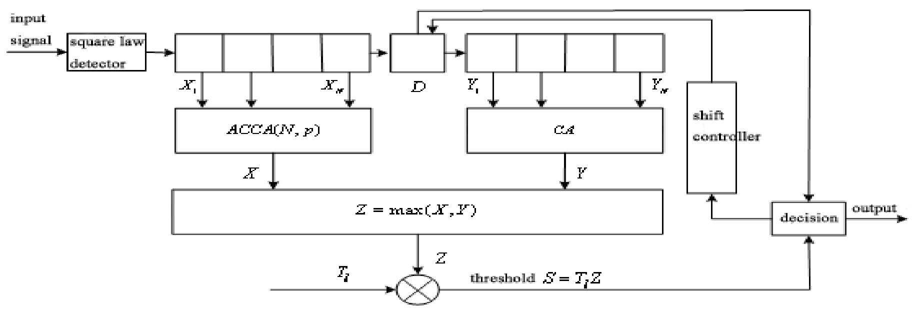

Figure 1. Block Diagram of ACGCA-CFAR Detector

The probability of false alarm (P_{fa}) of this CFAR detector is:

$$P_{fa} = P(H_1 \mid H_0) = \int_0^{\infty} f_Z(z)\int_{Tz}^{\infty}\frac{1}{\mu}e^{-x/\mu}dxdz$$
$$= \int_0^{\infty} e^{-Tz/\mu} f_Z(z)dz = E\left[e^{-uz}\right]|_{u=T/\mu} = M_z(u)|_{u=T/\mu} \tag{6}$$

Where $f_Z(z)$ is the probability density function (PDF) of the estimation Z, $M_Z(u)$ is the moment generating function (MGF) of Z. While $u=\dfrac{T}{\mu(1+\lambda)}$, (6) represents the probability of detection in homogeneous background. It is given by:

$$P_d = P(H_1 \mid H_1) = M_z(u)|_{u=\frac{T}{\mu(1+\lambda)}} \tag{7}$$

Where λ is the average signal-to-noise ratio (SNR) per pulse. In the ACGCA-CFAR processor, the clutter level estimate Z is obtained from the larger of two separate local estimations for the leading and lagging window. The PDF [11] of the estimate Z is given by:

$$f_Z(z) = f_X(z)F_Y(z) + F_X(z)f_Y(z) \tag{8}$$

Where $f_X(z)$, $F_X(z)$, $f_Y(z)$, $F_Y(z)$ are the probability density function (PDF) and the cumulative density function (CDF) respectively of the X and Y. So we can write:

$$\varphi_Z(u) = \int_0^\infty f_X(z)F_Y(z)e^{-uz}dz + \int_0^\infty F_X(z)f_Y(z)e^{-uz}dz = \varphi_1(u) + \varphi_2(u) \tag{9}$$

Assume $\hat{i}_X$ is the number of samples to be censored from the leading window, the analytic expression of P_{fa} for ACGCA-CFAR is derived as following.

1) $\hat{i}_X \neq 0$

The X is obtained by using CM method in the leading window and Y is obtained by using CA method in the lagging window, so the PDF and CDF [5] of X are given by:

$$f_X(x) = \sum_{j=1}^{N-\hat{i}_X} \frac{a_j}{\mu} e^{-\frac{c_j}{\mu}x} \tag{10}$$

$$F_X(x) = \sum_{j=1}^{N-\hat{i}_X} \frac{a_j}{c_j}(1 - e^{-\frac{c_j}{\mu}x}) \tag{11}$$

Where $c_j = \dfrac{(N - j + 1)(N - \hat{i}_X)}{N - \hat{i}_X - j + 1}$

$$a_j = \frac{\prod_{j=1}^{N-i_X} c_j}{\prod_{\substack{l=1 \\ l \neq j}}^{N-i_X} (c_l - c_j)} = \binom{N}{\hat{i}_X}\binom{N - \hat{i}_X}{j-1}(-1)^{j-1}\left(\frac{N - j + 1 - \hat{i}_X}{\hat{i}_X}\right)^{N-\hat{i}_X-1} \tag{12}$$

The PDF and CDF of Y are given by:

$$f_Y(y) = \frac{N^N}{\mu}\left(\frac{y}{\mu}\right)^{N-1} \frac{e^{-Ny/\mu}}{\Gamma(N)} \tag{13}$$

$$F_Y(y) = 1 - e^{-Ny/\mu} \sum_{i=0}^{N-1} \frac{(Ny/\mu)^i}{i!} \tag{14}$$

Therefore:

$$\begin{aligned} \varphi_1(u) &= \int_0^\infty \sum_{i=1}^{N-\hat{i}_X} \frac{a_i}{\mu} e^{-\frac{c_i}{\mu}z} e^{-uz}\left(1 - e^{-Nz/\mu}\sum_{j=0}^{N-1}\frac{(Nz/\mu)^j}{j!}\right)dz \\ &= \sum_{i=1}^{N-\hat{i}_X}\left[\frac{a_i}{c_i + \mu u} - \sum_{j=0}^{N-1}\frac{a_i N^j}{(c_i + N + \mu u)^{j+1}}\right] \end{aligned} \tag{15}$$

$$\begin{aligned} \varphi_2(u) &= \int_0^\infty \sum_{i=1}^{N-\hat{i}_X} \frac{a_i}{c_i}(1 - e^{-\frac{c_i}{\mu}z})e^{-uz} \frac{N^N}{\mu}\left(\frac{z}{\mu}\right)^{N-1}\frac{e^{-Nz/\mu}}{\Gamma(N)}dz \\ &= \sum_{i=1}^{N-\hat{i}_X}\frac{a_i}{c_i}\left[\frac{1}{(\mu u/N + 1)^N} - \frac{1}{((c_i + \mu u)/N + 1)^N}\right] \end{aligned} \tag{16}$$

2) $\hat{i}_X = 0$

The X and Y are both obtained by using CA method in the leading and lagging window. ACGCA scheme becomes GO. Therefore:

$$P_{fa}(\hat{i}_X = 0) = 2\left(1+T_0\right)^{-N} - 2\sum_{i=0}^{N-1}\binom{N+i-1}{i}\left(2+T_0\right)^{-(N+i)} \tag{17}$$

$$P_d(\hat{i}_X = 0) = 2\left(1+\frac{T_0}{1+\lambda}\right)^{-N} - 2\sum_{i=0}^{N-1}\binom{N+i-1}{i}\left(2+\frac{T_0}{1+\lambda}\right)^{-(N+i)} \tag{18}$$

For a designed P_{fa}, the threshold multipliers $T_{\hat{i}_x}$ can be computed by numerical method from the expression (18). Since $\hat{i}_X$ is assumed to be random variable, thus the overall detection probability of the ACGAC can be written as:

$$P_d = \sum_{l=0}^{p} \Pr(\hat{i}_X = l) P_d(\hat{i}_X) \tag{19}$$

Where $\Pr(\hat{i}_X = l)$ denotes the probabilities of $\hat{i}_X = l$ in a homogeneous background.

4. Performance of the ACGCA Detector

We used Monte-Carlo simulations to analysis the performance of the ACGCA-CFAR detector and the detection performance is compared to those of the other detectors. The number of the reference cells is $2N = 32$, interfering targets are SwerlingII model, and a designed $P_{fa} = 10^{-4}$. For the ACGCA-CFAR, $p = 12$, $P_{fc} = 10^{-2}$. For the OSCAGO-CFAR, the order value of the left sub window is $k = 12$. For the OS-CFAR, $kos = 28$ and for the CMCAGO-CFAR, the censoring point of the left sub window is $r = 12$. Therefore, they all have the ability to counteract the influence of four interfering targets in the leading window.

Table 2 shows the CFAR loss of four detectors in a homogeneous background. It is can be seen that the ACGCA-CFAR acts like the CA-CFAR in a homogeneous background and has better performance than the CMCAGO-CFAR and OSCAGO-CFAR.

Table 2. CFAR Loss (dB) of Four Detectors in Homogenous Background for $P_d = 0.5$

CA	ACGCA	OSCAGO	CMCAGO
0.638	0.736	1.0354	1.199

The CFAR loss of four detectors in a multiple target situations are shown in Table 3. We observe that the ACGCA-CFAR and the CMCAGO-CFAR have the similar CFAR loss, which is much less than that of OS-CFAR and OSCAGO-CFAR. When the number of interfering targets in the leading window is less than the number of censoring samples of CMCAGO, the CFAR loss of ACGCA is less than the CMCAGO. While the number of the interfering targets in the leading window is equal to the number of censoring samples of CMCAGO, the ACGCA and CMCAGO exhibit the same CFAR loss. These show the higher performance of the ACCA method.

The false alarm rate performance is much more affected by the clutter edge environment. We consider that when the leading window cells and the test cell are immersed in the high clutter region, while the lagging window cells are still in the low clutter region. This results in a sharp transition from a lower power level to a high power level in the ranked window and the worst P_{fa} regulation for many CFAR detectors [12, 13]. Table 4 shows the comparison of the rise of P_{fa} of four detectors in the case of clutter edge power transition $\gamma = 30\text{dB}$. It is can be seen that the P_{fa} regulation of the ACGCA is slightly less than that of the CMCAGO, and is much better than that of the OSCAGO and OS.

Table 3. CFAR Loss (dB) of Four Detectors in Multiple Target Situations for $P_d = 0.5$

IL, IR	1,0	2,0	3,0	4,0
ACGCA	1.020	1.197	1.361	1.698
CMCAGO	1.102	1.208	1.379	1.698
OS	1.427	2.004	2.816	3.954
OSCAGO	1.522	2.207	3.089	4.659

Table 4. Comparison of the Rise of P_{fa} of Four Detectors Against Clutter Edges Background ($\times 10^{-4}$)

γ(dB)	CFAR Detectors	ACGCA	CMCAGO	OS	OSCAGO
30		5.35	1.72	33.1	9.72

5. Conclusion

This paper presents a novel ACGCA CFAR detector based on ACCA and CA. The performance of the ACGCA CFAR detector has been examined in details and then compared with those of the OS, OSCAGO and CMCAGO CFAR detectors. From the simulation results we could see that the novel ACGCA has a better detection performance in both homogeneous background and multiple target situations. In the clutter edge environment, the ACGCA detector also performs robustly, while the sample sorting time of ACGCA is only quarter that of OS and ACCA. It is also easy for engineering implementation.

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