Multi-target CFAR Detection Based on SAR Imagery of Complex Background

Yingying Kong, Chunxia Nie, Fen Ge, Shiyu Xing, Henry Leung, Fellow, IEEE

Abstract—**Aiming at the wide application of constant false alarm rate (CFAR) algorithm in target detection of synthetic aperture radar (SAR) image, CFAR algorithm is analyzed and used for multi-target detection of complex background SAR images. Firstly, iteration algorithm is used to improve the automatic censoring detector. Secondly, combine with the priori knowledge of background to detect the desired targets. Finally, use decision fusion (or operation) to get multi-target detection image. Experiments show that the algorithm proposed in the paper can not only detect multi-targets in complex background, but also make the detection rate reach more than 80%.**

Index Terms—**Synthetic aperture radar (SAR), constant false alarm rate (CFAR), complex background, multi-target detection.**

I. Introduction

Target detection is one of the core applications of synthetic aperture radar (SAR) remote sensing [1], [2]. Because of its constant false alarm probability and adaptive threshold, constant false alarm rate (CFAR) detection is one of the most widely used algorithms for ship detection in SAR images [3], [4]. A CFAR detector determines a detection threshold by estimating the local background noise power level from the references cells and multiplying it by a scaling factor. Several types of CFAR detector have been suggested in the literature. The commonly used CFAR detection algorithms include the cell averaging CFAR (CA-CFAR) [5], greatest of CFAR (GO-CFAR), smallest of CFAR (SO-CFAR) [6], order statistic CFAR (OS-CFAR) [7], etc. Each of them has its advantages, disadvantages, and situations of potential application. No single detector performs well in all kinds of scenes. Two-parameter CFAR is the earliest proposed, its background statistical model adopts Gaussian distribution, and the detection performance is well in the background of uniform clutter. Later, many scholars have improved the two-parameter CFAR detector. Salazar proposed CFAR detector based on beta-prime distribution. Blacknell proposed CFAR detector based on the relevant Gaussian distribution. However, these methods have limitations for multi-target detection in complex background. Yuan et al. proposed a method based on the stepwise cumulation CA-CFAR (SCCA-CFAR) detection, which detects the multi-target by interfering with the target sample point automatic deletion scheme and has achieved good Detect performance, but very time consuming. An automatic censoring detector is proposed for target detection in high-resolution SAR images [8]. It adopts G0 distribution as the statistical model of clutter. Cui et al. proposed an iterative CFAR detection for the influence of other target samples in the local CFAR window [2]. An et al. improved the detector by adding a new initialization and clutter suppression method [9], but lacking the background prior knowledge.

In this paper, the background prior knowledge and iterative algorithm are used to automatic censoring detector. Experiments show that it can effectively detect multi-targets in complex background SAR images. The proposed scheme is introduced in Section II, experimental results are given in Section III. Section IV is the conclusion.

II. Iterative CFAR Detection

The sliding reference window shown in Fig. 1 is used for CFAR detection. The window is partitioned into three parts. At the center is the cell under test; in the middle is the guard area for preventing possible spills of distributed target into the clutter area; at the outermost part of the window is the clutter area used for clutter estimation. In practical applications, when the clutter parameter is estimated, target two is likely to be mixed into the clutter area. If mixed with a strong target, the detection area of the weak target is likely to be missed. Take the Gamma distribution as an example.

$$p(x)=\frac{1}{\Gamma(n)}\left(\frac{n}{\sigma}\right)^{n}x^{n-1}\exp\left(-\frac{n}{\sigma}x\right),\qquad x>0 \tag{1}$$

Where n is the image view and σ is the average energy of the image.

If the clutter distribution is Gamma distribution, σ is the parameter to be estimated. The maximum likelihood estimation of the clutter power σ is

$$\hat{\sigma}=\frac{1}{N}\sum_{i=1}^{N}I_i \tag{2}$$

Where I_i is the sample in clutter area.

For CA-CFAR, assuming that the detection area has only one test pixel, its pixel value is I, if

Manuscript received March 6th, 2017; revised March 23th, 2017. This work was supported National Natural Science Foundation of China (No. 61501228), Natural Science Foundation of Jiangsu (No. SBK2014043002), Aeronautical Science Foundation of China (No. 20152052029)..

Y.Kong Author is with the Electronic and Information Engineering Department,Nanjing University of Aeronautics and astronautics, NUAA,China(e-mail:yayako_zy@nuaa.edu.cn).

C.Nie Author is with the Electronic and Information Engineering Department,Nanjing University of Aeronautics and astronautics, NUAA,China(e-mail:interstice@163.com).

F.Ge Author is with the Electronic and Information Engineering Department,Nanjing University of Aeronautics and astronautics, NUAA,China(e-mail:gefen@nuaa.edu.cn).

S.Xing Author is with the Department of Electronic and Computer Engineering, University of Calgary, UC, Canada (e-mail: shiyu.xing@yahoo.ca).

H.Leung Author is with the Department of Electronic and Computer Engineering, University of Calgary, UC, Canada (e-mail: Leungh@ucalgry.ca).

ISBN: 978-988-14047-4-9
ISSN: 2078-0958 (Print); ISSN: 2078-0966 (Online)

$$\frac{I}{\hat{\sigma}} > T \qquad (3)$$

It is determined as the target, where T is the detection threshold. From equation (3), if other target samples are mixed in the clutter area, it will lead to a higher estimation of σ , some weak targets may be judged as clutter, resulting in missing targets. Aiming at this problem, an iterative CFAR detection algorithm is proposed. Its core is the result of the previous test as the input of this test. Then the sample that is sent to the target in the previous test will be excluded when the parameter is estimated for this test. Excluding the impact of interference targets, parameter estimation is more accurate, and conducive to this test, so repeated, an iterative CFAR detection is formatted. The iteration ends when the result of the previous two tests no longer changes.

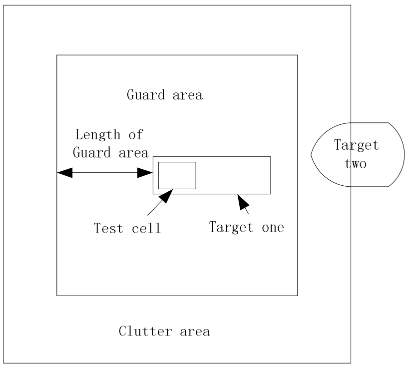


Fig. 1. Reference window for CFAR detection

Suppose that $T_0(x, y)$ is the first test result, it is a binary, where 0 is clutter pixel, 1 is target pixel. The result of this test is a preliminary detection because the target sample mixed into the clutter region is not taken into account. But, this initial test is a good distribution of information about the target in the image. So, $T_0(x, y)$ can be seen as a priori image and $O_1(x, y) = T_0(x, y)$. In the second detection, $O_1(x, y)$ is used to exclude the target sample, and the clutter distribution is corrected. That is mean in second test, any pixel in clutter area of the sliding window is indicated as the target pixel by the $O_1(x, y)$ will be removed. Finally, comparing the detection threshold and the test pixel to obtain a new test result $T_1(x, y)$. In fact, the process of detection can be done all the time to form an iterative process. That is, the detection result $T_i(x, y)$ of the i-th time is taken as the outlier priori image $O_{i+1}(x, y)$ of the $(i + 1)$ th iteration, $O_{i+1}(x, y) = T_i(x, y)$. For the end of the iteration, the differences between the adjacent two iterations are defined as follows

$$\delta(i) = \sum_{x=1}^{m}\sum_{y=1}^{n} T_{i-1}(x, y) \oplus T_i(x, y) \qquad (4)$$

Where m is the number of rows, n is the number of columns, and "$\oplus$" represents the binary XOR operation.

$$\alpha \oplus \beta = \begin{cases} 1, & \alpha \neq \beta \\ 0 & \alpha = \beta \end{cases}, \quad \alpha, \beta \in \{0,1\} \qquad (5)$$

Therefore, the end of the iteration is $\delta(i) = 0$.

In this paper, the automatic censoring detector is improved as shown in Fig. 2, background statistical modeling and iterative detection are added.

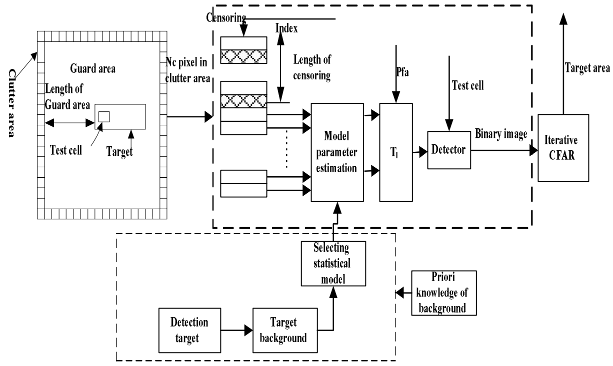


Fig. 2. Proposed method

To sum up, the proposed method can be described as follows.

Step 1) Find the global threshold, generate an initial target detection image $O_0(x, y)$ according to the global threshold.

Step 2) According to different detection targets, select different background statistical model. Use statistical model to calculate the local threshold T_1 with censoring length.

Step 3) Traverse the whole image, binarize the image and then get the first iterative image.

Step 4) When the i-th iterative detection, excluding the last detection of the target pixel in clutter area, with the remaining pixels for clutter parameter estimation. According to the theory of background statistical modeling, the detection threshold T under the given false alarm probability is obtained, and comparing the test cell and threshold. If it is target , the pixel is 1, if not, the pixel is 0, iterative result $T_i(x, y)$ is get.

Step 5) Suppose that $O_{i+1}(x, y) = T_i(x, y)$, then repeat step 2 for the $i + 1$ iteration until the iteration ends.

Step 6) $T_i(x, y)$ is clustered as the final result.

Using the flow of Fig. 2 to deal with complex images, according to the desired target to choose the appropriate background statistical model, and finally in the decision-making, use or operation to get multi-target detection, the flow of multi-target detection is shown in Fig. 3.

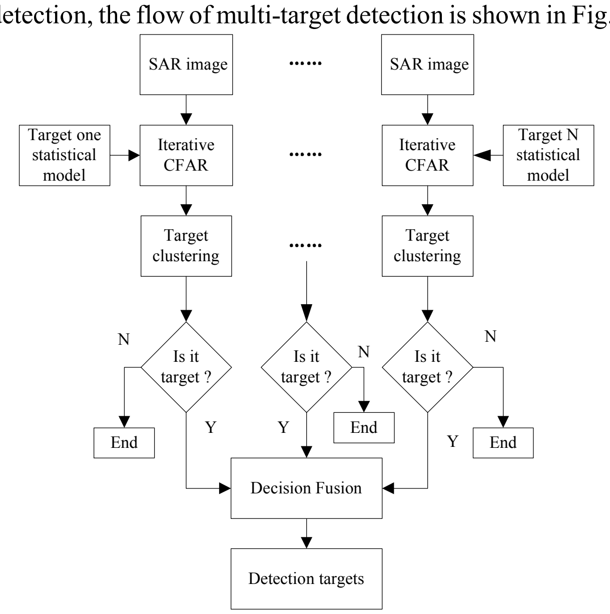
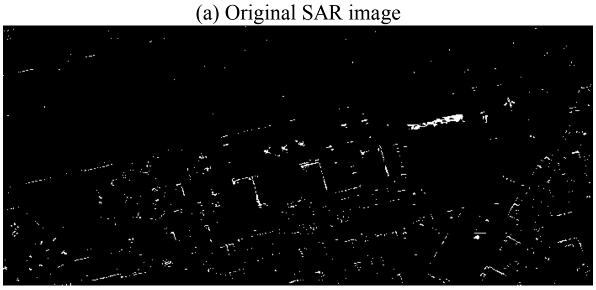


Fig. 3. Flow of muti-target detection

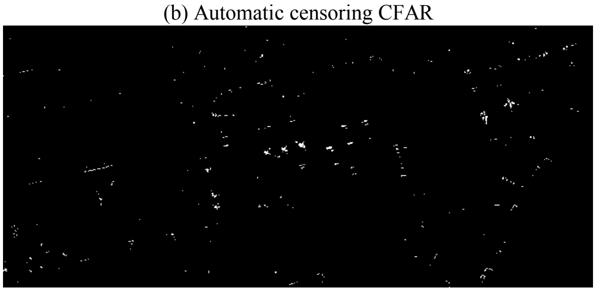
III. EXPERIMENTAL RESULTS

Fig. 4 (a) is the SAR image of the Air Force Base. In the image, there are nine aircrafts and eight cars, which are interested targets. Automatic censoring detector, two-parameter CFAR detector and the proposed method are used to detect nine aircrafts and eight cars in Fig. 4 (a). The logarithmic normal distribution is selected according to the background statistical model. The false alarm probability is 10^{-2}, and the detection results are shown in Fig. 4 (b), Fig. 4 (c) and Fig. 4 (d). Fig. 4 (b) is the result of automatic censoring CFAR. Fig. 4 (c) is the two-parameter CFAR. Fig. 4 (d) is the proposed method.

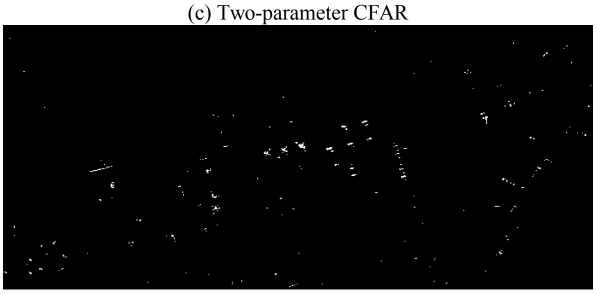
(a) Original SAR image



(b) Automatic censoring CFAR



(c) Two-parameter CFAR

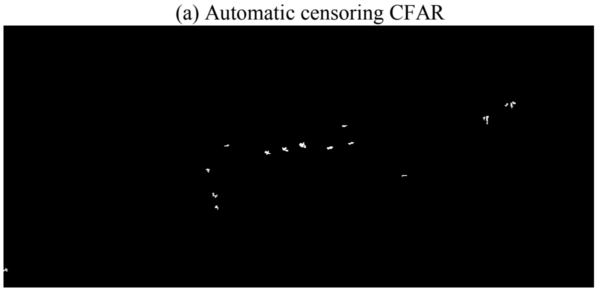


(d) Proposed method

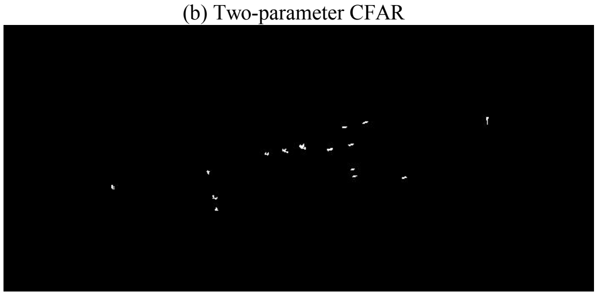
Fig. 4. Air force base image

Fig. 5 is their target clustering images. Fig. 5 (a) is automatic censoring CFAR detection, Fig. 5 (b) is two-parameter CFAR detection, Fig. 5 (c) is the proposed method detection.

(a) Automatic censoring CFAR



(b) Two-parameter CFAR



(c) Proposed method

Fig. 5. Target clustering

Table I
Comparison of Three Algorithms

Detection methods	Pd	Pf	FOM
Automatic censoring	64.7%	22.7%	0.5
Two-parameter	70.6%	10.5%	0.632
Proposed method	82.4%	5.6%	0.778

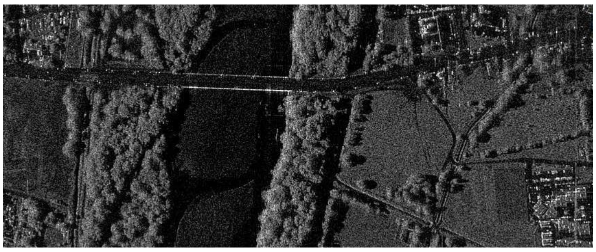
From the above study, it is found that the detection rate of automatic censoring detector is the lowest among the three detectors because the statistical model used in the automatic censoring detector is G0 distribution. G0 distribution is not the best statistical model for the air base image. In the two-parameter CFAR detection, the detection rate can reach 70.6% because the logarithmic normal distribution has good modeling effect on the air base image. The proposed method not only takes the logarithmic normal distribution as the background model, but also uses iterative CFAR detection. Compared with other two detectors, the detection rate is greatly improved. In the three detectors, the algorithm proposed in this paper is the best, the probability of detection (Pd), the probability of false alarm (Pf) and figure of merit (FOM) are more accurate than the above two detectors. For complex scenes in multi-target detection, detection rate of more than 80%.

For the Grand River Bridge image in Fig. 6 (a), the Grand River Bridge is detected by the method this paper proposed. Firstly, it needs to know the background distribution in Fig. 6 (a). The target is the bridge, then all objects except the bridge

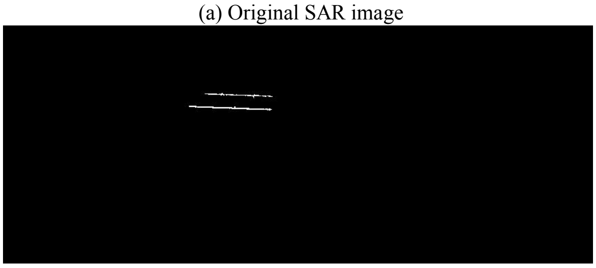
ISBN: 978-988-14047-4-9
ISSN: 2078-0958 (Print); ISSN: 2078-0966 (Online)

are clutters, including farmland, woods, cement and so on. The background is mainly composed of farmland and woods, belonging to the natural vegetation area. From the statistical model knowledge, the best statistical model of farmland and forest is Weibull distribution. Therefore, the background statistical model is Weibull distribution. The probability of false alarm is set to 10^{-3}. Fig. 6 (b) shows the result of the detection.

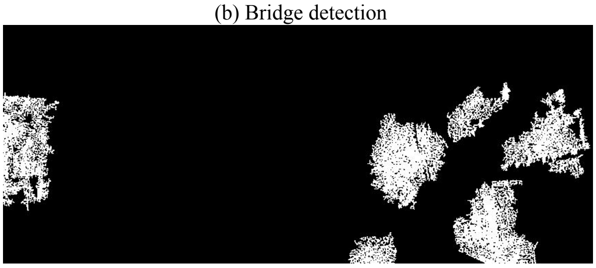
With the development of science and technology, the application of SAR technology in agricultural production is more and more, and the detection of farmland in large SAR images can help farmers understand the growth of crops. For the image of Fig. 6 (a), if the target of interest is not the bridge in the image, but the farmland, then except the bridge, there are high vegetation, river, building, etc. They are belonging to non-uniform areas or extremely non-uniform areas. Use the G0 distribution as background model, the probability of false alarm is set to 10^{-3}, the detection of farmland is shown as Fig. 6 (c). According to the flow of multi-target detection in Fig. 3, the bridge and farmland in Fig. 6 (a) are tested. The test results are shown in Fig. 6 (d).



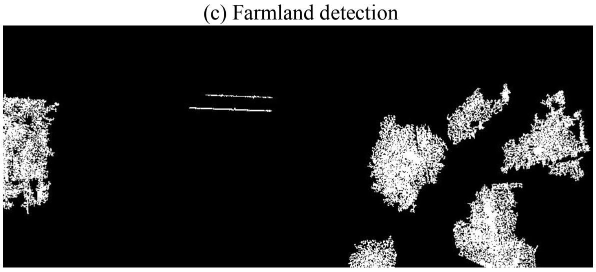
(a) Original SAR image



(b) Bridge detection



(c) Farmland detection



(d) Bridge and farmland detection

Fig. 6. Grand River Bridge image

IV. CONCLUSION

In this paper, the multi-target CFAR detection in complex background is studied. Add the prior knowledge of the background statistical model to the local sliding window to improve the existing automatic censoring CFAR detector. Considering the mutual interference of adjacent targets, adopt the iterative method to update the clutter area constantly, and make the parameter estimation more accurate. Compared with the original automatic censoring detector and the two-parameter CFAR detector, the algorithm proposed in this paper has a higher Pd and FOM, and the Pd is attached more than 80% of the multi-target detection in complex background. From the detection image of the Grande River, the algorithm of this paper can achieve the purpose of on-demand detection and can detect many kinds of targets in the image.

REFERENCES

[1] Liao, Mingsheng, et al. "Using SAR Images to Detect Ships From Sea Clutter." *IEEE Geoscience & Remote Sensing Letters*, vol. 5, no. 2, pp. 194-198, 2008.

[2] Cui, Yi, et al. "On the Iterative Censoring for Target Detection in SAR Images." *IEEE Geoscience & Remote Sensing Letters*, vol. 8, no. 4, pp. 641-645, 2011.

[3] Hwang, Seong In, and K. Ouchi. "On a Novel Approach Using MLCC and CFAR for the Improvement of Ship Detection by Synthetic Aperture Radar." *IEEE Geoscience & Remote Sensing Letters*, vol. 7, no. 2, pp. 391-395, 2010.

[4] Leng, X, et al. "A Bilateral CFAR Algorithm for Ship Detection in SAR Images." *IEEE Geoscience & Remote Sensing Letters*, vol. 12, no. 7, pp. 1-5, 2015.

[5] Steenson, Bernard O. "Detection Performance of a Mean-Level Threshold." *Aerospace & Electronic Systems IEEE Transactions on*, vol. 4, no. 4, pp. 529-534, 1968.

[6] Gandhi, P. P., and S. A. Kassam. "Analysis of CFAR processors in homogeneous background." *Aerospace & Electronic Systems IEEE Transactions on*, vol. 24, no. 4, pp. 427-445, 1988.

[7] Novak, L. M., and S. R. Hesse. "On the performance of order-statistics CFAR detectors." *Asilomar Conference on IEEE*, vol. 2, pp. 835-840, 1991.

[8] Gao, Gui, et al. "An Adaptive and Fast CFAR Algorithm Based on Automatic Censoring for Target Detection in High-Resolution SAR Images." *IEEE Transactions on Geoscience & Remote Sensing*, vol. 47, no. 6, pp. 1685-1697, 2009.

[9] An, Wentao, C. Xie, and X. Yuan. "An Improved Iterative Censoring Scheme for CFAR Ship Detection With SAR Imagery." *Geoscience & Remote Sensing IEEE Transactions on*, vol. 52, no.8, pp. 4585-4595, 2014.

ISBN: 978-988-14047-4-9
ISSN: 2078-0958 (Print); ISSN: 2078-0966 (Online)