A Fast CFAR Algorithm Based on Density-Censoring Operation for Ship Detection in SAR Images

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Abstract—In this letter, we propose a new constant false alarm rate (CFAR) detector to accelerate the existing superpixel (SP)-based CFAR detectors for ship detection in synthetic aperture radar (SAR) images. In our method, we design a new density-censoring operation to rapidly identify background clutter superpixels (BCSPs) with high densities before the local CFAR detection. In this way, a large number of non-informative BCSPs are removed without time-consuming calculation of decision thresholds, and only a few candidate ship target superpixels (STSPs) are retained. This reduces the computational cost of the subsequent local CFAR detection and the number of false alarms produced by it. During the local CFAR detection process for the retained candidate STSPs, we also propose an improved method to define their neighboring clutter regions (for the calculation of decision thresholds) using BCSPs identified by the density-censoring operation. Experiments on measured SAR images validate that the proposed CFAR method reduces the computational cost of commonly used SP-based CFAR methods by 75%-96% with similar or better detection performance.

Index Terms—Density, superpixels, synthetic aperture radar (SAR), ship detection, constant false alarm rate.

I. INTRODUCTION

SHIP DETECTION in synthetic aperture radar (SAR) images plays an important role in various applications, e.g., maritime surveillance and military reconnaissance [1], [2]. The strategy of constant false alarm rate (CFAR) [3] has been widely investigated in the context of pixel-level ship detection in SAR images [4]–[7]. Note that pixel-level CFAR methods cannot identify whether a few adjacent pixels belong to the (same) target or clutter regions.

A superpixel (SP) represents the set of some locally coherent pixels and benefits the extraction of region-based features [10], [13]–[16], [18], [20], which are robust to speckle noise [21] in SAR images. Several SP-based CFAR detectors [8]–[12] have been developed to enhance the performance of pixel-level CFAR versions. In [8]–[10], different SP-based local background windows were developed to reduce the false alarms caused by anomaly background clutter SPs (BCSPs). It is worth emphasizing that the CFAR methods in [8]–[10] require the calculation of decision thresholds for all SPs in SAR images based on the slide-window operation. Since the calculation of decision threshold for each SP often contains the time-consuming SP clustering or iterative parameter estimation (to obtain the clutter model), it is difficult to achieve fast detection in a global SAR image using the SP-based CFAR detectors in [8]–[10]. In [11], [12], two-stage CFAR detectors were proposed to accelerate the one-stage ones in [8]–[10]. In two-stage CFAR detectors, the global detection stage is firstly performed throughout the SAR image to rapidly remove a few BCSPs based on the global clutter model and a global FAR. Then, the global detection results are elaborately refined in the local detection stage. However, the CFAR detectors in [11], [12] show limited acceleration in the detection process since they allocate excessive computational resources for non-sparse BCSPs in spatiality and do not consider the fact the number of ship target SPs (STSPs) in SAR images is much fewer than that of BCSPs [22].

The density feature of a data point reflects the aggregation level of other data points around it in feature space [17]. The main contribution of the letter is that we propose a new density-censoring (DC)-based CFAR approach for ship detection in SAR images to accelerate existing SP-based CFAR algorithms [8]–[12]. In the DC-based CFAR method, the spatial sparsity degree of SPs is measured by its density value, where non-sparse BCSPs have much higher densities than sparse STSPs. We propose a new DC operation before the local CFAR detection to rapidly filter out BCSPs with high densities and retain only a small number of candidate STSPs in the SAR image via an unsupervised nearest neighbor classifier (NNC). Accordingly, this operation significantly reduces the computational burden and the number of false alarms in the subsequent CFAR detection stage. In addition, the enhanced versions of the CFAR detectors in [8], [10] are presented to calculate the decision thresholds of (retained) candidate STSPs, where their neighboring clutter regions for the estimation of clutter model are refined using the BCSPs identified by DC. Experiments on Gaofen-3 SAR data
show that the proposed method provides higher computation efficiency than existing commonly used CFAR detectors with similar or better detection accuracy.

We also note that deep learning methods have been recently proposed for the task of target detection [24], [29], [30]. Note that deep learning-based methods require a lot of labeled training data. In this letter, the proposed CFAR approach considers the task of target detection without labeled training data, like [1], [10], [12], [19].

II. PROPOSED DC OPERATION

In this section, we introduce the proposed DC approach to accelerate the subsequent SP-based local CFAR detection process and suppress the false alarms. Here, SP segmentation of SAR images before the DC operation is conducted by using the classical simple linear iterative clustering (SLIC) approach [16] owing to its effectiveness and simplicity. Existing faster [31] or more elaborate segmentation algorithms [25]–[28], [32] than SLIC can also be used here.

A. Calculation of Density-Based Features

In this subsection, we introduce two density-based features to discriminate BCSPs and STSPs.

Density Feature: The density of a data point denotes its similarity degree to other points in feature space [17], [23], i.e., its sparsity degree in the data set. Let \( \mu_i \) denote the mean value of pixel intensities within the \( i \)-th SP in the SAR image, where \( i = 1, 2, \ldots, I \) and \( I \) is the number of SPs in the image. \( \mu_i \) can also be called by the reflectivity [11] of the \( i \)-th SP. The density of the \( i \)-th SP is defined as

\[
\rho_i = \sum_{j \in \{1, 2, \ldots, I\} / i} \exp \left[ -\left( \frac{D_{i,j}}{D_c} \right)^2 \right], \tag{1}
\]

where \( D_{i,j} = |\mu_i - \mu_j| \) is the distance between the \( i \)-th and the \( j \)-th SP reflectivities, \( D_c = \alpha \times \max_{\forall i,j} \{ D_{i,j} \} \) represents the cutoff distance, and \( \alpha \in (0, 1) \) denotes the scale factor. The spatial sparsity of STSPs [22] implies that for a specific STSP, the number of other SPs with similar reflectivities to it in the global SAR image is very small. Accordingly, STSPs have lower densities based on the definition in (1). On the contrary, BCSPs share high densities since they often occupy majority regions in SAR images.

Density-Based Distance Feature: We define \( \Gamma_i = \{ j | \rho_j < \rho_i, j = 1, 2, \ldots, I, j \neq i \} \) as the index set of SPs which have lower densities than the \( i \)-th SP. Then, the density-based distance feature of the \( i \)-th SP can be calculated as

\[
D_i = \begin{cases} 
\max_{j \in \Gamma_i} \{ D_{i,j} \}, & \text{if } \Gamma_i \neq \emptyset, \\
\min_{j \in \{1, 2, \ldots, I\} / i} \{ D_{i,j} \}, & \text{if } \Gamma_i = \emptyset. \tag{2}
\end{cases}
\]

The above density-based distance feature discriminates BCSPs and STSPs based on the fact that

1) The densities of STSPs are lower than that of BCSPs and there are often large reflectivity differences between BCSPs and STSPs.

2) The reflectivities of STSPs are similar, i.e., an STSP has small reflectivity distances to other STSPs with lower densities. When the \( i \)-th SP has the lowest density value (i.e., \( \Gamma_i = \emptyset \)), \( D_i \) is the minimum value in \( \{ D_{i,j} | \forall i, j \} \).

Therefore, STSPs have significantly smaller values of \( D \) than BCSPs.

B. Density-Censoring Via NNC Throughout the SAR Image

In this subsection, DC is performed via an unsupervised NNC for all the SPs in the SAR image based on densities \( \{ \rho_i, \forall i \} \) in (1) and density-based distances \( \{ D_i, \forall i \} \) in (2). Both \( \{ \rho_i, \forall i \} \) and \( \{ D_i, \forall i \} \) are normalized into [01] using the Min-Max normalization, respectively, for fair comparison in the following. Since STSPs/BCSPs have small/large values of \( \{ \rho, D \} \), the “centers” of them are found by

\[
i_{STSP} = \arg \min_{\forall i} f (\rho_i, D_i), \tag{3}
i_{BCSP} = \arg \max_{\forall i} f (\rho_i, D_i), \tag{4}
\]

respectively, where \( f(\cdot, \cdot) \) denotes the fusion rule of \( \{ \rho_i, D_i \} \), e.g., additive, multiplicative, or fuzzy fusion. Here, additive fusion \( f(\rho_i, D_i) = \rho_i + D_i \) is used due to its computational simplicity. Next, NNC is used to censor each SP in the SAR image:

\[
\delta_i = \begin{cases} 
1, & \text{if } \theta_i^{(BCSP)} \geq \theta_i^{(STSP)}, \\
0, & \text{otherwise,}
\end{cases} \tag{5}
\]
where
\[
\begin{align*}
\theta_i^{(BCSP)} &= \sqrt{(\rho_i - \rho_{BCSP})^2 + (D_i - D_{BCSP})^2}, \\
\theta_i^{(STSP)} &= \sqrt{(\rho_i - \rho_{STSP})^2 + (D_i - D_{STSP})^2}.
\end{align*}
\]

In (5), the \(i\)-th SP is a candidate STSP when \(\delta_i = 1\), while it belongs to BCSP areas and will not be meticulously handled in the next local CFAR detection stage when \(\delta_i = 0\). It is worth mentioning that the retained SPs after DC in (5) are called “candidate STSPs” since, besides true STSPs, they may contain a small number of sparse BCSPs in the SAR image.

Having (1)-(5) in mind, we can see that the DC operation does not require time-consuming calculations unlike the CFAR methods in [8]–[11] containing iterative process or traversal search for parameter estimation. Furthermore, non-sparse BCSPs with high densities are removed via the density-driven NNC in (5) and only a small number of candidate STSPs are required to be finely processed.

III. PROPOSED DC-BASED CFAR DETECTOR

The implementation of the proposed DC-based CFAR algorithm is summarized as the flowchart in Fig. 1:

1) Step 2: Determine the neighboring clutter SP region of the current candidate STSP using a square window (see Fig. 2 in [8] or Fig. 1 in [10]). Then, the neighboring clutter SP region (of the current candidate STSP) is refined by only using BCSPs therein identified by the DC operation in (5).
2) Step 3: Estimate the probability density function (PDF) of clutter using the neighboring clutter SP region and then calculate the adaptive decision threshold based on a predefined FAR.
3) Step 4: Compare pixel intensities in the current candidate STSP with the adaptive decision threshold to produce a final decision. If the ratio of the number of detected pixels in a candidate STSP to the total number of pixels therein is larger than a fixed constant (here is 20%), then this candidate STSP is regarded as a true one.

In the above step 3, we select Gaussian [8] and truncated Gamma [10] distributions, respectively, when conducting experiments.

The proposed DC-based CFAR method shows the following two superiorities in comparison with other CFAR methods in [8]–[12]. 1) First and foremost, the DC-based processing in step 1 helps the subsequent local CFAR detection stage not to waste lots of computational times on background clutter regions. 2) In steps 2 and 3, more accurate parameters in the clutter PDF (to determine adaptive decision thresholds in CFAR) are obtained using pure clutter samples identified by the proposed DC operation.

IV. EXPERIMENTAL RESULTS

In this section, we conduct experiments with the proposed DC-based CFAR algorithm on Gaofen-3 SAR images in [19], [33]. The parameters of the SAR image dataset are listed in Table I. The scale factor for the calculation of (1) is \(\alpha = 0.3\). The robustness of the proposed detector on the setting of scale factor \(\alpha\) will be investigated in Fig. 5. The experiments are performed using MATLAB 2019a (with the 64-bit Windows system, Inter R Xeon CPU, and 768-GB RAM).

In Fig. 2, we show an explicit sketch of density-based features \(\rho\) in (1) and \(D\) in (2). Fig. 2(a) and Fig. 2(b) provide a SAR image with heterogeneous clutter and its SP map, respectively. From Fig. 2(c), we can see that STSPs and BCSPs in Fig. 2(b) are well discriminated based on the above two density-based features. The DC result is shown in Fig. 2(d), where most of BCSPs are removed.

In Fig. 3, we show the binary detection results of SP-clustering-CFAR (SPCCFAR) detector [8], truncated SPCFAR (TSPCFAR) detector [10], two-stage SP-CFAR (TSSPCFAR) detector [12], and the proposed DC-based CFAR detector on a SAR image with crowded ship targets and low target-to-clutter contrast. \(P_{global}\) represents global FAR for the global detection stage in [12]. From Fig. 3, we can see that SPCCFAR and TSSPCFAR suffer from some false alarms. TSPCFAR shows degraded performance with low target-to-clutter contrast in the SAR image. The proposed DC-based CFAR method successfully finds all targets without false alarm.

In Fig. 4, we depict receiver operating characteristic (ROC) curves of different SP-based CFAR detectors using 300 SAR images from [19] to further validate the superiority of the proposed methods. \(S\) denotes the SP size in the SP segmentation task [16], where an SP is expected to have \(S^2\) pixels. Similar to [15], [18], we select \(S^2\) based on a fixed percentage (approximately 60%−100%) of the average number of pixels in the region occupied by a ship target to maintain the shape of ship targets. Fig. 4 shows that the proposed DC-based CFAR detector attains superior detection performance than other detectors in [8], [10], [12] due to the significantly reduced false alarm areas using the DC operation. Especially, the proposed DC-based detector with the clutter model in [8] provides better ROC performance than other detectors. Fig. 4 also shows that the proposed method achieves robust ROC performance versus the SP size in the SP segmentation step.

In Table II, the corresponding average running times of aforementioned detectors using 300 SAR images are provided, where the proposed DC-based CFAR detector is more computationally efficient than their original versions in [8], [10], benefiting from fast deletion of a large number of BCSPs before the local CFAR.
Crowded targets:

Low contrast:

Fig. 3. First line: SAR image (256×256) with crowded targets [19]. Second line: SAR image (1000×1000) with the low contrast [33]. (a) Original SAR image. (b) SP map. Binary detection results of (c) SPCCFAR [8], (d) TSPCFAR [10], (e) TSSPCFAR [12] with \( P_{\text{global}} = 0.1 \), (f) TSSPCFAR [12] with \( P_{\text{global}} = 0.2 \), (g) TSSPCFAR [12] with \( P_{\text{global}} = 0.3 \), (h) proposed DC-based CFAR, where the clutter model in [8] is used, and (i) proposed DC-based CFAR, where the clutter model in [10] is used. The (local) FARs for detectors in [8], [10], [12], and the proposed detectors are 0.1 and 0.06 for the first and second lines, respectively. The proposed DC-based CFAR method shows better or comparable detection performance in comparison with other methods.

Fig. 4. ROC curves of CFAR detectors using 300 Gaofen-3 SAR images in [19] with different SP sizes \( S \), where \( P_d \) and \( P_{fa} \) are the probability of detection and probability of false alarm, respectively. (a) \( S = 24 \), (b) \( S = 28 \), and (c) \( S = 32 \). The proposed DC-based CFAR method outperforms other CFAR methods in terms of ROC curves with different SP sizes.

Fig. 5. Investigation of performance robustness: the average ratios of the number of removed BCSPs to the total number of SPs in 300 SAR images [19] versus the hyper-parameters of (a) \( P_{\text{global}} \) in the global detection stage of [12] and (b) \( \alpha \) in the proposed DC operation. More robust censoring performance is provided by the proposed DC operation.

V. CONCLUSION

In this letter, we proposed a new DC-based CFAR approach for SAR ship detection, where the DC operation is innovatively designed to filter out BCSPs with high densities before the local CFAR detection stage. This alleviates the computational burden in the subsequent local CFAR detection stage and leads to a more accurate clutter model to determine adaptive decision thresholds in CFAR. Experiments with Gaofen-3 data show the proposed method only requires 4%-25% computation time of the state-of-the-art TSSPCFAR detector with \( P_{\text{global}} = 0.1 \).

Table II

<table>
<thead>
<tr>
<th>Method</th>
<th>Running Time</th>
</tr>
</thead>
<tbody>
<tr>
<td>SPCCFAR [8]</td>
<td>3.45</td>
</tr>
<tr>
<td>Proposed DC-based CFAR with the clutter model in [8]</td>
<td>0.19</td>
</tr>
<tr>
<td>TSSPCFAR [10]</td>
<td>0.52</td>
</tr>
<tr>
<td>Proposed DC-based CFAR with the clutter model in [10]</td>
<td>0.02</td>
</tr>
<tr>
<td>TSSPCFAR [12] ((P_{\text{global}} = 0.1))</td>
<td>0.08</td>
</tr>
<tr>
<td>TSSPCFAR [12] ((P_{\text{global}} = 0.2))</td>
<td>0.10</td>
</tr>
<tr>
<td>TSSPCFAR [12] ((P_{\text{global}} = 0.3))</td>
<td>0.12</td>
</tr>
<tr>
<td>Global detection stage in [12]</td>
<td>0.06</td>
</tr>
<tr>
<td>Proposed DC operation</td>
<td>0.01</td>
</tr>
</tbody>
</table>

stage. Quantitively, only 6% and 4% running times are required by the DC-based CFAR detector in comparison with the detectors in [8], [10], respectively. Note that the clutter model of [8] contains a time-consuming SP clustering task, while that of [12] does not. Therefore, compared with the method in [12], more computational time is required by the proposed DC-based CFAR detector with the clutter model in [8]. As shown in Table II, only 17% computation time is required by the proposed DC operation compared with the global detection stage in [12]. The proposed DC-based CFAR detector with the clutter model in [10] has the minimum running time, which is 25% of that of the state-of-the-art TSSPCFAR detector with \( P_{\text{global}} = 0.1 \).

In Fig. 5, we investigate the censoring performance of the proposed DC operation and the global detection stage in [12]. We can see that the global detection stage in [12] shows the deteriorative censoring performance with the increase of \( P_{\text{global}} \), while the DC operation provides robust censoring performance versus the scale factor \( \alpha \) in (1). This is because the performance of the DC operation is mainly determined by the relative magnitudes of density-based features (in a SAR image) instead of the value of hyper-parameter \( \alpha \).

REFERENCES


