Research on CFAR Detection Technology for Ship Targets in SAR Images

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Abstract

Among various SAR (Synthetic Aperture Radar) image ship target detection methods, the most widely used and important is the CFAR (Constant False Alarm Rate) detector with adaptive threshold. To improve the detection performance of ship targets in SAR images, researchers have attempted to statistically model the clutter background in SAR images using various statistical distribution models, such as Gamma, K-distribution, log-normal distribution, G0 distribution, alpha-stable distribution, etc., and then implement ship target detection using CFAR detectors based on the corresponding statistical distribution models and various sample screening techniques. In modern radar systems, CFAR detection technology needs to control the actual false alarm rate at a low level in unknown, time-varying, and non-homogeneous clutter backgrounds, while maximizing the probability of target detection. The clutter background in SAR images is complex and variable; when the actual clutter background mismatches the assumed statistical distribution, the performance of parametric CFAR detectors deteriorates, and non-parametric CFAR detectors demonstrate advantages. This paper proposes a novel approach based on the Wilcoxon non-parametric detector for detecting ship targets in SAR images, and compares it with several typical parametric CFAR detection methods on measured data from Radarsat-2, ICEYE-X6, and Gaofen-3 satellites. Experimental results demonstrate that the Wilcoxon non-parametric detection method can achieve strong false alarm control capability on these three measured datasets, can also improve weak target detection performance, and features fast computational speed and easy hardware implementation.

Full Text

Study on CFAR Detection Technique for Ship Targets in SAR Images

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Abstract: Among the various methods for detecting ship targets in Synthetic Aperture Radar (SAR) images, the Constant False Alarm Rate (CFAR) detector with an adaptive threshold is the most extensively used and important approach. To improve the detection performance of ships in SAR images, researchers have attempted to statistically model the clutter background using various statistical distributions, such as Gamma, K, log-normal, G0, alpha-stable distributions, etc., and then implement CFAR detection of ship targets through the corresponding statistical models combined with various sample screening techniques. In modern radar systems, CFAR detection technology must maintain the actual false alarm rate at a suitably low level in a priori unknown, time-varying, and spatially nonhomogeneous clutter backgrounds while maximizing the detection probability. The clutter background in SAR images is complex and variable. When the actual clutter background deviates from the assumed statistical distribution, the performance of parametric CFAR detectors deteriorates, while nonparametric CFAR detectors demonstrate their advantages. This paper proposes a novel approach for detecting ship targets in SAR images based on the Wilcoxon nonparametric detector. Through comparison with several typical parametric CFAR methods on real measured data from Radarsat-2, ICEYE-X6, and Gaofen-3 satellites, experimental results demonstrate that the Wilcoxon nonparametric detection method can achieve strong false alarm control capability across these three datasets, improve weak target detection performance, and features fast computational speed and ease of hardware implementation.

Keywords: radar; SAR image; target detection; constant false alarm rate; nonparametric;

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Synthetic Aperture Radar (SAR) is an active microwave coherent imaging radar with all-weather, all-day, wide-area, and long-range data acquisition capabilities, offering tremendous advantages for monitoring and surveillance of targets of interest on land and sea. The most widely and deeply applied method for automatic detection of targets of interest in SAR images is the Constant False Alarm Rate (CFAR) detection technology with adaptive thresholds [1]. The most classic among these is the two-parameter CFAR detection method adopted by the Lincoln Laboratory SAR ATR system [2]. Two-parameter CFAR can maintain a constant false alarm probability in Gaussian clutter backgrounds, but as radar resolution improves, the clutter background in SAR images deviates from Gaussian distribution. To enhance detector performance for ship targets in SAR images, researchers have attempted to accurately model the clutter in SAR images based on various statistical distributions, such as K-distribution [3], alpha-stable distribution [4], G0 distribution [5], log-normal distribution [6,7], Gamma distribution [8], Gaussian distribution [9], negative exponential distribution [10], Rayleigh distribution [11], etc., and then set detection thresholds by estimating the parameters of these statistical distributions through some clutter sample selection or screening techniques. These parametric CFAR detection methods based on specific statistical distribution models are applicable to certain scenarios; however, various natural or artificial uncontrollable factors often cause mismatch between the actual clutter background statistics and the assumed distribution, leading to performance degradation.

Radar target CFAR detection techniques can be divided into two categories based on whether they require assuming a statistical distribution for the clutter background: parametric CFAR detection methods [12–15] and nonparametric CFAR detection methods. The false alarm probability of nonparametric detectors in a homogeneous background is independent of the specific functional form of the clutter background statistical distribution. When parametric CFAR detection methods based on specific statistical distributions mismatch the actual clutter conditions, nonparametric CFAR detectors demonstrate their advantages. This paper proposes a novel approach for detecting ship targets in SAR images based on the Wilcoxon nonparametric detector. The following sections first introduce the detection principle and model of the Wilcoxon nonparametric detector, derive the analytical expression for its false alarm probability; then, compare and analyze the Wilcoxon nonparametric detection method with other typical parametric CFAR detection methods on real measured data from Radarsat-2, ICEYE-X6, and Gaofen-3 satellites; finally, summarize and discuss the conclusions drawn from this study.

2 Wilcoxon Nonparametric Detector Description and Model

In traditional radar target CFAR detection systems, detection is typically implemented using a reference sliding window across range resolution cells. Clutter samples falling within the reference sliding window are used to compute a decision threshold according to some algorithm, which is then used to determine the presence or absence of a target in the test cell. For ship target detection in SAR images, the Wilcoxon nonparametric detection method employs a two-dimensional sliding window as shown in Figure 1 [Figure 1: see original paper]. The red central portion of the window is the $t \times t$ test cell used to determine target presence. The green surrounding area consists of reference cells, with guard cells between the test cell and reference cells to prevent target energy leakage from the test cell into the reference cells. Let $Y_1, \cdots, Y_n$ represent the clutter samples in the reference cells, and $X_1, \cdots, X_m$ represent the test samples in the test cell.

Assume that $X_1, \cdots, X_m$ and $Y_1, \cdots, Y_n$ are statistically independent and identically distributed random variables with probability density functions $f(x)$ and $g(x)$, respectively. Under the null hypothesis H_0, the test samples $X_1, \cdots, X_m$ and reference samples $Y_1, \cdots, Y_n$ are mutually independent and identically distributed.

Assuming these two sample sets come from continuous distributions eliminates the need to consider ties. By combining the test samples $X_1, \cdots, X_m$ and reference samples $Y_1, \cdots, Y_n$ according to their magnitudes, we obtain a new pooled sample set of size $N = m + n$. Sorting this pooled sample set $X_1, \cdots, X_N$ by magnitude yields the following ordered sequence:

$$X_{(1)} \leq X_{(2)} \leq \cdots \leq X_{(N)}$$

The sequence $(X_{(1)}, \cdots, X_{(N)})$ in Equation (1) is called the order statistics, with the indices in parentheses representing the rank values of the ordered samples. Let R_i $(i = 1, \cdots, m)$ denote the rank of sample X_i in the order statistics. Thus, $R_1, \cdots, R_m$ are the ranks of the test samples $X_1, \cdots, X_m$ in the pooled sample set.

To decide whether a target signal exists in the test cell, the Wilcoxon nonparametric detector employs the following test statistic:

$$S_{m,n} = \sum_{i=1}^{m} R_i$$

If the test statistic $S_{m,n}$ exceeds the decision threshold T_W, a target signal is declared present in the test cell. If it is less than T_W, no target exists. For ship target detection in SAR images, the key is to derive the analytical expression for the detector' s false alarm probability P_{FA}, which allows determination of the detection threshold based on a preset false alarm probability. The following derives the analytical relationship between the false alarm probability P_{FA} and the decision threshold T_W for the Wilcoxon nonparametric detector.

Theorem 1 [16]: For sample sets $X_1, \cdots, X_m$ and $Y_1, \cdots, Y_n$, let $S_{m,n}$ be the two-sample Wilcoxon test statistic. Under hypothesis H_0, the probability that $S_{m,n} = k$ is:

$$P(S_{m,n} = k) = \frac{\pi_{m,n}(k)}{\binom{m+n}{m}}$$

where $\pi_{m,n}(k)$ represents the number of ways to select m numbers from $\{1, 2, \cdots, m+n\}$ whose sum equals exactly k. The function $\pi_{m,n}(k)$ satisfies the recursion formula:

$$\pi_{m,n}(k) = \pi_{m,n-1}(k) + \pi_{m-1,n}(k - (m+n))$$

with initial and boundary conditions:

$$\pi_{0,n}(0) = 1; \quad \pi_{0,n}(k) = 0 \text{ for } k \neq 0$$

$$\pi_{m,n}(k) = 0 \text{ for } k < 0 \text{ or } k > \frac{(m+n)(m+n+1)}{2}$$

For readability, the proof of Theorem 1 from reference [16] is excerpted here. $\pi_{m,n}(k)$ represents the number of ways to select m numbers from $\{1, 2, \cdots, m+n\}$ whose sum equals exactly k, making Equation (3) obvious. The proof of Equation (4) can be obtained by removing the sample $X_{(m+n)}$ from the pooled sample. In fact, if $X_{(m+n)}$ is some Y_j, we obtain $\pi_{m,n-1}(k)$; if $X_{(m+n)}$ is some X_i, we obtain $\pi_{m-1,n}(k-(m+n))$. This completes the proof.

Under hypothesis H_0, a false alarm occurs if the Wilcoxon nonparametric detector' s test statistic $S_{m,n}$ exceeds the detection threshold T_W. Therefore, the false alarm probability for the Wilcoxon nonparametric detector when applied to ship target detection in SAR images is:

$$P_{FA} = \sum_{k=T_W+1}^{\frac{(m+n)(m+n+1)}{2}} \frac{\pi_{m,n}(k)}{\binom{m+n}{m}}$$

It can be seen that the derivation of the Wilcoxon nonparametric detector' s false alarm probability P_{FA} is independent of the statistical distribution of the SAR image clutter background. Consequently, when using the Wilcoxon nonparametric detector for ship target detection in SAR images, a constant false alarm probability can be maintained regardless of the specific functional form of the clutter background statistical distribution. This is the distribution-free characteristic of nonparametric detectors.

Since the Mann-Whitney nonparametric detector is equivalent to the Wilcoxon nonparametric detector [17], and the Mann-Whitney nonparametric detector is easier to implement, this paper uses the Mann-Whitney nonparametric detector instead of the Wilcoxon nonparametric detector for analysis and research. The Mann-Whitney nonparametric detector' s test statistic is defined as:

$$R_{WM} = \sum_{i=1}^{m} \sum_{j=1}^{n} u(Y_j - X_i)$$

where $u(t)$ is the unit step function. If the Mann-Whitney nonparametric detector' s test statistic R_{WM} exceeds the detection threshold T_{MW}, a target is declared present; otherwise, no target exists. The relationship between the Wilcoxon nonparametric detector' s test statistic and the Mann-Whitney nonparametric detector' s test statistic is $R_{WM} = S_{m,n} - \frac{m(m+1)}{2}$. For a preset false alarm probability P_{FA}, the Mann-Whitney nonparametric detector' s detection threshold T_{MW} can still be obtained through Equation (9) and the relationship $T_{MW} = T_W + \frac{mn}{2}$.

3 Experimental Results and Performance Analysis

CFAR technology in radar target detection must maintain the actual false alarm rate at a suitably low level in unknown, time-varying, and nonhomogeneous clutter backgrounds while maximizing the detection probability. Sea clutter in SAR images varies with radar operating frequency, incidence angle, resolution, polarization, wind speed, ocean currents, and other factors, making it complex and variable. Therefore, when comparing the performance of various CFAR detection methods for ship targets in SAR images, two aspects must be considered: first, measuring their false alarm control capability in various clutter environments, and second, comparing detection performance under the same or similar actual false alarm probabilities. For clarity, the false alarm probability derived from the analytical expression or used to determine the detection threshold is referred to as the theoretical false alarm probability P_{FA}, while the false alarm probability actually produced during detection is called the actual false alarm probability P_{fa}. This section uses real measured SAR image data from Radarsat-2, ICEYE-X6, and Gaofen-3 satellites to validate and analyze the detection performance of the Wilcoxon nonparametric detector, with two-parameter CFAR [2], Weibull CFAR [18], TS-CFAR [8], and AIS-RCFAR [11] selected as reference methods.

3.1 Detection of Medium/Large Ships in Relatively Calm Sea Conditions

The SAR image used here is a scene acquired by the C-band Radarsat-2 satellite on March 8, 2010, near Tokyo Port, Japan. The polarization mode is HH, with azimuth and range resolution of 3 meters, in SLC format, covering approximately a 20 km × 20 km area. The SAR image shown in Figure 2 Figure 2: see original paper is a chip from this scene, with size 1001 × 901 pixels, containing 4 ships. Speckle in the SAR image and sidelobe effects caused by strong ship reflections are clearly visible. The Wilcoxon nonparametric detector uses a reference sliding window of size $\lambda \times \lambda = 68 \times 68$ as shown in Figure 1 [Figure 1: see original paper]. The red central portion is the $t \times t = 2 \times 2$ test cell for determining target presence. The green surrounding area consists of reference cells, with guard cells between the test and reference cells to prevent target energy leakage. To avoid leakage of target energy from the test cell into reference cells, the guard window width must exceed the maximum ship length in the image. Here, the Wilcoxon nonparametric detector selects $q = 3$ layers of clutter samples from the edge of the reference sliding window as reference cells, resulting in a total of $n = 780$ reference cells and $m = 4$ test cells. The Wilcoxon nonparametric detector moves 2 pixels at a time during detection.

The two-parameter CFAR, Weibull CFAR, TS-CFAR, and AIS-RCFAR methods detect by moving one pixel at a time. The two-parameter CFAR, Weibull CFAR, and TS-CFAR use the same guard window width as the Wilcoxon nonparametric detector ($g = 30$). They use $q = 1$ layer of samples from the reference sliding window periphery as reference cells, with a reference sliding window size of $\lambda \times \lambda = 63 \times 63$, providing 248 clutter samples for estimating the detection threshold. This number is sufficient for maximum likelihood estimation of clutter distribution parameters. TS-CFAR uses the Equivalent Number of Looks (ENL) to replace shape parameter estimation, with a truncation depth [8] of 10%. AIS-RCFAR uses a reference sliding window size of $\lambda \times \lambda = 63 \times 63$, does not use a guard window, and employs adaptive censoring to remove strong clutter samples, with parameter $\lambda = 2.0$ as recommended in [11].

The two-parameter CFAR assumes a Gaussian clutter background, estimates the mean and variance via maximum likelihood, and sets the detection threshold according to a theoretical false alarm probability $P_{FA} = 10^{-7}$. Its detection result for the SAR image in Figure 2(a) is shown in Figure 2(b). Weibull CFAR assumes a Weibull clutter background, estimates the scale and shape parameters via maximum likelihood, and sets the detection threshold according to $P_{FA} = 3 \times 10^{-5}$. Its detection result is shown in Figure 2(c). Although the two-parameter CFAR and Weibull CFAR have different theoretical false alarm probabilities, they produce similar actual false alarm performance. This occurs because the detection threshold is a scalar, and both methods use all reference samples for parameter estimation. The two-parameter CFAR threshold could be approximated by Weibull CFAR at another theoretical false alarm probability, resulting in similar actual false alarm performance under different P_{FA} values. In modern radar systems, CFAR detection technology must control actual false alarms at a low level in unknown, time-varying, nonhomogeneous clutter. Comparing different CFAR detectors at the same theoretical P_{FA} is feasible when they assume the same distribution type. However, comparing CFAR detectors assuming different distributions at the same theoretical P_{FA} is unfair; comparison should be made under the same or similar actual false alarm probabilities for greater practical significance.

The actual false alarm probability during detection is defined as:

$$P_{fa} = \frac{N_{fa}}{N_c} = \frac{N_{fa}}{\text{Image length} \times \text{Image width} - \text{Number of ship pixels}}$$

where N_{fa} is the number of false alarms, counted as the number of independent bright spots in the clutter background, mathematically the number of non-adjacent connected regions. N_c is the number of clutter background pixels, calculated as the total SAR image pixels (image length $\times$ width) minus the sum of ship region pixel counts. Here, ellipses are fitted to the 4 ships in Figure 2(a) to estimate the major axis a and minor axis b of each ship, with ship pixel count calculated using the ellipse area formula $\pi ab/4$. The clutter background pixel count in the SAR image chip shown in Figure 2(a) is

$N_c = 1001 \times 901 - 1583 = 900318$. Table 1 lists N_{fa}, N_c, P_{fa}, and P_{FA} for the two-parameter CFAR, Weibull CFAR, TS-CFAR, AIS-RCFAR, and Wilcoxon nonparametric detector when applied to the SAR image chip in Figure 2(a). These detectors produce similar actual false alarm probabilities P_{fa} under different theoretical P_{FA} values. Figure 3 [Figure 3: see original paper] shows enlarged views of the detection results for the ship target circled in white in Figure 2(a). For such strong targets (medium/large ships) in Figure 2(a), all detectors can detect most ship pixels at similar actual false alarm probabilities around $P_{fa} = 10^{-4}$. However, TS-CFAR and AIS-RCFAR produce more false alarms in the sidelobe regions of ships, while the Wilcoxon nonparametric detector significantly suppresses false alarms caused by ship sidelobes, primarily because it uses a $t \times t = 2 \times 2$ test cell structure that suppresses linear false alarms caused by sidelobes.

Computation time is an important aspect of CFAR detector performance. The CFAR detection schemes discussed in this paper are implemented in Matlab and run on a PC with an Intel E7500 CPU at 2.93 GHz and 8 GB of memory. Table 1 also provides the computation time T_s for each detector when processing the SAR image in Figure 2(a). The Wilcoxon nonparametric detector has the shortest runtime, approximately half that of two-parameter CFAR, while TS-CFAR has the longest runtime.

3.2 Detection of Medium/Large Ships in Rough Sea Conditions

The SAR image shown in Figure 4(a) is a chip from data acquired by the X-band ICEYE-X6 satellite on the night of June 24, 2022, near Maharashtra, India [19]. The polarization mode is VV, using scanning mode with resolution greater than 15 meters, in GRD format. The image size is 1455 × 1707 pixels, containing 6 ships. Wave-induced ripples make the image appear very rough. The Wilcoxon nonparametric detector uses a test cell size of $t \times t = 2 \times 2$, guard window width $g = 60$, and selects $q = 3$ layers of clutter samples from the reference sliding window edge as reference cells, yielding a total of $n = 1500$ reference cells. The Wilcoxon nonparametric detector moves 2 pixels at a time during detection. The two-parameter CFAR, Weibull CFAR, and TS-CFAR use the same guard window width ($g = 60$) and $q = 1$ layer of samples from the reference sliding window periphery as reference cells, with 488 reference samples total. TS-CFAR uses a truncation depth [8] of 10%. AIS-RCFAR uses a reference sliding window size of $\lambda \times \lambda = 123 \times 123$, with parameter $\lambda = 2.0$.

The detection results for the SAR image chip in Figure 4(a) using two-parameter CFAR, Weibull CFAR, TS-CFAR, AIS-RCFAR, and Wilcoxon nonparametric detector are shown in Figures 4(b), 4(c), 4(d), 4(e), and 4(f), respectively. The N_{fa}, N_c, P_{fa}, and P_{FA} values are given in Table 1. Figure 5 [Figure 5: see original paper] shows enlarged views of the detection results for the ship target circled in white in Figure 4(a). For strong targets (medium/large ships) in Figure 4(a), all detectors detect most ship pixels at similar actual false alarm probabilities. The Wilcoxon nonparametric detector' s suppression of false alarms caused by ship sidelobes is also evident here. The computation times for these detectors on the Figure 4(a) SAR image are similar to those for Figure 2(a).

3.3 Detection of Weak Targets in Complex Backgrounds

This SAR image chip comes from the SAR image ship target detection dataset: AIR-SARShip-1.0 [20]. AIR-SARShip-1.0 was collected by China’ s Gaofen-3 satellite, which is China’ s first C-band multi-polarization high-resolution synthetic aperture radar satellite. The SAR image shown in Figure 6(a) has size 1201 × 1101 pixels, 3-meter resolution, sea state 4, and is in TIFF format. In addition to two clearly visible medium/large ships, Figure 6(a) contains a weak ship target in the red circle, used here to test detector performance. The two-parameter CFAR, Weibull CFAR, and TS-CFAR use guard window width $g = 60$ and $q = 1$ layer of samples from the reference sliding window periphery as reference cells, with 488 reference samples for threshold setting. AIS-RCFAR uses a reference sliding window size of $\lambda \times \lambda = 123 \times 123$ with parameter $\lambda = 2.0$. The Wilcoxon nonparametric detector uses test cell $t \times t = 2 \times 2$, guard window width $g = 60$, selects $q = 3$ layers of clutter samples from the reference sliding window edge as reference cells, with $n = 1500$ reference cells total.

The detection results for the SAR image chip in Figure 6(a) using two-parameter CFAR, Weibull CFAR, TS-CFAR, AIS-RCFAR, and Wilcoxon nonparametric detector are shown in Figures 6(b), 6(c), 6(d), 6(e), and 6(f), respectively. The N_{fa}, N_c, P_{fa}, and P_{FA} values are given in Table 1. Figure 7 [Figure 7: see original paper] shows the detection results for the weak ship target in Figure 6(a). The Wilcoxon nonparametric detector detects more ship pixels of the weak target than the other parametric CFAR detectors. Here, the Wilcoxon nonparametric detector’ s runtime is about twice that of two-parameter CFAR because it moves one pixel at a time to detect more detailed ship target information.

3.4 Discussion of False Alarm and Detection Performance

In the previous sections, two-parameter CFAR, Weibull CFAR, TS-CFAR, AIS-RCFAR, and Wilcoxon nonparametric detector were applied to ship target detection in SAR image chips from Radarsat-2, ICEYE-X6, and Gaofen-3 satellites. The results show differences between the theoretical and actual false alarm probabilities for these detectors. In modern radar systems, CFAR detection technology must control actual false alarms at a low level in unknown, time-varying, nonhomogeneous clutter. Therefore, performance comparison and analysis must be conducted under the same or similar actual false alarm probabilities.

Table 1 shows that when two-parameter CFAR and Weibull CFAR detect ship targets in SAR image chips from Radarsat-2, ICEYE-X6, and Gaofen-3 satellites at actual false alarm probabilities around $P_{fa} = 10^{-4}$, their theoretical false alarm probabilities P_{FA} vary by 4 and 3 orders of magnitude, respectively. In other words, if the theoretical P_{FA} remains fixed, their actual false alarm performance would severely degrade when the actual clutter background changes.

However, TS-CFAR and AIS-RCFAR show only about 1 order of magnitude variation in theoretical P_{FA}, with TS-CFAR' s theoretical value particularly close to the actual value, indicating that TS-CFAR' s assumed Gamma distribution matches the actual SAR image sea clutter distribution well. The Wilcoxon nonparametric detector can control the actual false alarm probability within 10^{-4} for all three SAR image scenes at the same theoretical $P_{FA} = 10^{-8}$, demonstrating strong false alarm control capability because its false alarm probability does not depend on the specific statistical distribution of the clutter. The large difference between theoretical and actual P_{FA} for Wilcoxon occurs because sea clutter in SAR images appears patchy and fluffy, and the detector' s $t \times t = 2 \times 2$ test cell structure is prone to false alarms, requiring a higher detection threshold (corresponding to lower theoretical P_{FA}) to suppress false alarms during detection.

Figures 3, 5, and 7 show that at similar actual false alarm probabilities, all discussed detectors can detect most ship pixels for strong targets (medium/large ships). However, for weak ship target detection, performance differences emerge. To quantitatively analyze weak target detection performance, detection probability P_d is defined as:

$$P_d = \frac{\text{Number of detected ship pixels}}{\text{Total number of ship target pixels}}$$

Ellipses are fitted to weak ship targets to estimate major and minor axes, with total ship pixels N_s calculated from the ellipse area. For the Gaofen-3 SAR image chip in Figure 6(a), different theoretical false alarm probabilities P_{FA} are given to determine detection thresholds, and the actual false alarm probability P_{fa} and detection probability P_d for the weak ship target are statistically analyzed. Figure 8 [Figure 8: see original paper] plots the Receiver Operating Characteristic (ROC) curves for the weak ship target detection. At the same or similar actual false alarm probabilities P_{fa}, the parametric CFAR detectors show similar weak target detection capability, while the Wilcoxon nonparametric detector demonstrates clear advantages.

4 Conclusion

The most widely and deeply applied method for automatic detection of targets of interest in SAR images is CFAR detection technology with adaptive thresholds. Sea clutter in SAR images is complex and variable. When the statistical distribution assumed by a CFAR detection algorithm mismatches the actual clutter background, the algorithm' s theoretical false alarm probability deviates significantly from the actual value. Therefore, detector performance evaluation must consider: first, measuring false alarm control capability across different scenes, and second, comparing detection performance under the same or similar actual false alarm probabilities. Since the Wilcoxon nonparametric detector' s false alarm probability does not depend on the specific clutter distribution type, this paper proposes using the Wilcoxon nonparametric detector for ship target detection in SAR images and derives its false alarm probability analytical expression. Performance validation and analysis were conducted on real measured data from Radarsat-2, ICEYE-X6, and Gaofen-3 satellites, with comparisons to typical parametric CFAR detectors including two-parameter CFAR, Weibull CFAR, TS-CFAR, and AIS-RCFAR.

The results show that to achieve acceptable actual false alarm probabilities around $P_{fa} = 10^{-4}$ when detecting ship targets in SAR image chips from Radarsat-2, ICEYE-X6, and Gaofen-3, the theoretical false alarm probabilities P_{FA} of two-parameter CFAR and Weibull CFAR vary by 4 and 3 orders of magnitude, respectively. In other words, if their theoretical P_{FA} remained fixed, their actual false alarm probabilities would severely degrade across different SAR image backgrounds because their assumed Gaussian and Weibull distributions significantly deviate from actual SAR image statistics. To reach the actual $P_{fa} = 10^{-4}$ level, TS-CFAR and AIS-RCFAR show about 1 order of magnitude variation in theoretical P_{FA}, with TS-CFAR' s theoretical value particularly close to the actual value, indicating its assumed Gamma distribution matches the actual SAR image sea clutter background well. The Wilcoxon nonparametric detector can control the actual false alarm probability within 10^{-4} for all three SAR image scenes at the same theoretical $P_{FA} = 10^{-8}$, demonstrating strong false alarm control capability. At similar actual false alarm probabilities $P_{fa} = 10^{-4}$, all discussed detectors can detect most ship pixels for strong targets, but the Wilcoxon nonparametric detector shows clear advantages for weak target detection. Notably, this does not mean parametric CFAR detectors assuming different distributions have consistent performance; their false alarm control capabilities differ significantly across different clutter backgrounds. Additionally, the Wilcoxon nonparametric detector has hardware implementation advantages, requiring only $m \times n$ comparators and one accumulator. By not assuming a statistical distribution for SAR image clutter background, it avoids the extensive computation time required for parameter estimation. Therefore, the Wilcoxon nonparametric detector is a recommended solution for ship target detection in SAR images.

To enhance the robustness of the Wilcoxon nonparametric detector in nonhomogeneous backgrounds caused by multiple targets and clutter edges, this paper proposes adopting adaptive censoring techniques such as the Ordered Data Variable (ODV) method, sub-window selection techniques like Greatest-Of (GO), Smallest-Of (SO), and Variable Index (VI) methods, as well as superpixel-level techniques to improve the Wilcoxon nonparametric detector. These will be the focus of our future research.

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Note: Figure translations are in progress. See original paper for figures.