CFAR-Based Automatic Ship Detection Exploiting Polarimetric Correlation Descriptors

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ABSTRACT

Synthetic Aperture Radar (SAR) provides a reliable remote sensing solution for detecting ships over vast oceanic regions under all-weather and day-night conditions. However, the normalized radar cross-section (NRCS) often encounters ambiguities that hinder accurate detection. To address this, we utilized the polarimetric correlation of SAR channels, including co-, cross-, and dual-polarization, to effectively mitigate or suppress these ambiguities (or clutter). By integrating these polarimetric correlation descriptors with a constant false alarm rate (CFAR) algorithm, we achieve automatic and robust ship detection. Experimental results demonstrate that the proposed approach yields high detection accuracy with minimal root mean square error (RMSE), outperforming conventional manual image interpretation methods. The framework was applied to SAR data for the Mediterranean Sea near Cyprus, showcasing its potential for detecting and monitoring ships, preventing illegal fishing, and addressing maritime security challenges.

Keywords: CFAR, Ship detection, SAR, Marine Security

1. INTRODUCTION

Ship detection plays a crucial role in ocean remote sensing. In this context, SAR serves as a valuable tool for the detection and monitoring of moving ships in coastal areas. SAR-based ship detection is an emerging research topic, with significant advancements made in recent years.[1,2] Commercial applications include cargo monitoring, fishing operations, and the tracking of specific ships. SAR has garnered considerable interest due to its unique capability to operate under all-weather conditions, irrespective of day or night. Although optical data offers high-resolution imagery, its applicability is limited due to susceptibility to cloud cover and low-light conditions, as noted in.[2]

SAR systems collect backscattering data along the radar trajectory at various positions and azimuth angles. The contrast between targets and the surrounding environment in SAR images can be enhanced through polarimetric correlation, achieving high azimuth resolution. To identify specific targets, different descriptors, such as dual or quad-pol Eigen descriptors and dual-pol complex coherence, are employed.[3] These techniques are effective in detecting coastlines, mangroves, vessels, and other prominent features in the vicinity of the ocean. CFAR detectors have been applied using empirical distributions of polarimetric combinations, including co-, cross-, and dual-polarization correlations.[4]

Co-polarization detection utilizes SAR imagery to distinguish bright, point-like target signatures from the ocean clutter background. Multi-polarization or subaperture decomposition algorithms for SAR imagery have been explored to enhance ship detection using advanced SAR capabilities.[5] Additionally, both Doppler and coherence-based approaches require a method that combines uniformity features with an averaged image, providing a straightforward way to address textural characteristics.[6] Furthermore, comparing target detection results with ground truth with different resolution images, such as optical and SAR images, presents a challenge, as the target canopy cannot be directly overlapped without adaptation of each other resolutions. Consequently, the Sentinel-2 image requires additional co-registration, with the information in the SAR image specifically adjusted to match the same resolution.

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Eleventh International Conference on Remote Sensing and Geoinformation of the Environment (RSCy2025), edited by Andreas Christofi, et al., Proc. of SPIE Vol. 13816 · · doi: 10.1117/12.3070193

The bimodal and statistical distributions of SAR data for target detection, such as ship detection, have gained significant importance, providing valuable support for deploying the CFAR method in our case.[7] Polarimetric correlation enhances the target-to-clutter ratio (TCR) and reduces speckles. Furthermore, utilizing multiple polarization channels in a SAR detection system improves both the accuracy and comprehensiveness of the detection process. As a result, the adapted co-, cross-, and dual-pol correlation descriptors optimize ship detection performance. The results are compared to the "SPAN" descriptor, which represents total backscattering. The CFAR method is directly applied to the components of the scattering matrix to determine the threshold value. The accuracy of ship size estimation can be influenced by various factors, including the resolution and scattering mechanisms of the SAR data, the edge recognition technique, and the presence of noise or clutter in the image. The proposed method operates at full resolution with minimal loss due to the spatial averaging operation using a box-car filter.

Section 2 describes the CFAR methodology and the descriptors utilized in this work, along with their statistical distributions. Section 3 presents detailed results and findings for each step, while Section 4 concludes the paper and discusses the effectiveness of the proposed method.

2. METHODOLOGY

Microwave remote sensing is very effective for studying ocean applications. The Sentinel-1 sensors are positioned at angles between 29° and 46°.

2.1 Bragg Scattering Theory

At these angles, the sea surface looks rough, and this roughness helps in the process called Bragg scattering. Bragg scattering is important because it helps explain how microwave signals, or electromagnetic waves, reflect off the ocean. The way these signals bounce back, also known as the backscattered signal, is influenced by the polarization of the waves we send out. When dual co-polarization is used, the strength of the returning radar signal is strongly related to something called the normalized radar cross-section (NRCS). The NRCS provides important details about the ocean surface and other oceanographic characteristics. Ocean waters have a high dielectric constant, which makes radio wave penetration at microwave frequency negligible. The roughness of the scattering surface is the main driver defining the observed radar return and may impact ship detection. For a plane electromagnetic wave, polarization refers to the behavior of the electric field vector in time observed at a fixed point in space. Therefore, the basic concept of CFAR is to identify pixels that do not fit the statistical properties of sea clutter, keeping constant the probability of false alarms along the input image.

2.2 SAR Polarimetric Correlation Descriptors

The ship detection and its canopy extraction are carried out using the metrics, which include correlation between co-, cross-, and dual-polarized channels. Such correlations basically improve the TCR. We exploited three correlation descriptors, given as:

$$\sigma_{\mathrm{VV}} = \langle |S_{\mathrm{VV}}|^2 \rangle,\ \sigma_{\mathrm{VH}} = \langle |S_{\mathrm{VH}}|^2 \rangle,\ r = \langle |S_{\mathrm{VH}}| \cdot |S_{\mathrm{VV}}| \rangle \tag{1}$$

where $\langle \cdot \rangle$ is ensamble averaging carried out by using $N \times N$ box-car filter to refine the SAR scene, and $|\ |$ is absolute value in case complex SAR channels are adapted.
The result of ship contour is compared with SPAN which is a detector that can be regarded as the synthetic power of all channels. Past investigation has shown that a lower noise level and a higher TCR can be obtained by this detector so that the targets can be more easily discriminated from the clutter, compared with that only arbitrary single-channel information is used. SPAN is given as:

$$\mathrm{SPAN} = \langle |S_{\mathrm{VV}}|^2 \rangle + \langle |S_{\mathrm{VH}}|^2 \rangle \tag{2}$$

The SPAN detector is a widely used processor that is a noncoherent sum of all polarimetric channels and only makes use of image intensities.[8]

2.3 Workflow and Detection Mechanism for Ship

The workflow for the autonomous ship detection is depicted in Figure 1(a). The polarimetric combination metric undergoes an ensemble averaging process, following which the CFAR technique is used to obtain the logical binary image for distinguishing between target and non-target entities. Subsequently, an image processing block is employed to precisely quantify the boundaries or edges of the desired targets. Finally, superimpose the SAR image over the extracted contours to showcase ship detection. The polarimetric approach utilizes the inherent properties of SAR incoherent polarimetric imaging mode combined with a tailored scattering model to effectively distinguish targets from clutter. Following this, continuous target regions are quantitatively analyzed using standard technique, as shown in Figure 1(b), via a generic CFAR system. In this figure, the amplitude of the cell under test, positioned at the center of the CFAR window, is denoted by X. Surrounding the cell under test, a predefined number of resolution cells are designated as guard cells to prevent interference from nearby targets.

2.4 Statistical Distribution Analysis for CFAR Thresholding

The detection threshold, represented by 'T', is determined using the method outlined in Figure 1(c). The empirical distribution of sea water pixels for each correlation descriptor is checked against the theoretical distribution.

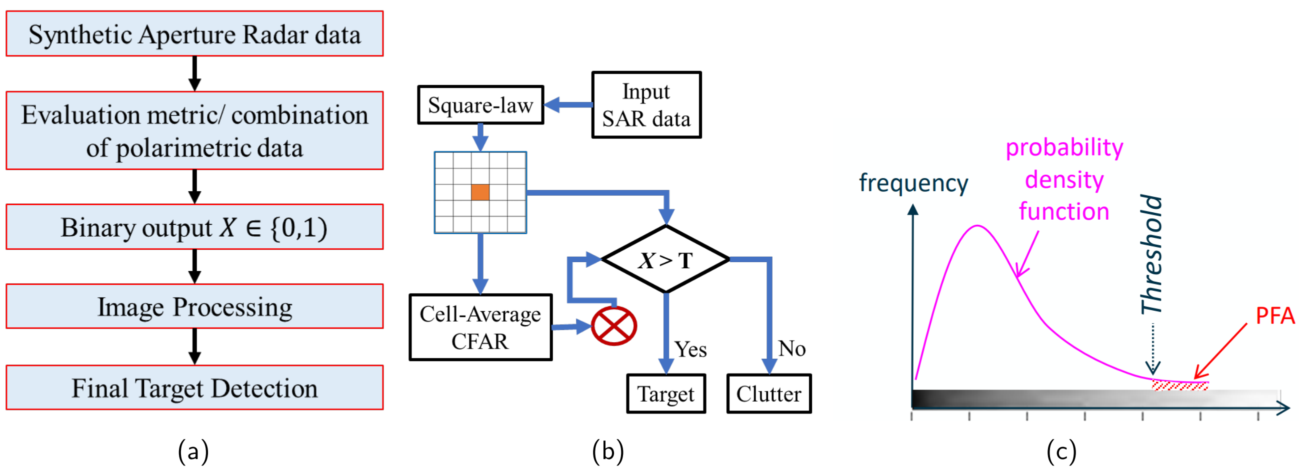

Figure 1: (a) Block diagram illustrating the target detection process; (b) CA-CFAR technique applied for target identification; (c) Statistical method employed for decision-making to detect targets with a well-regulated probability of false alarm (PFA).

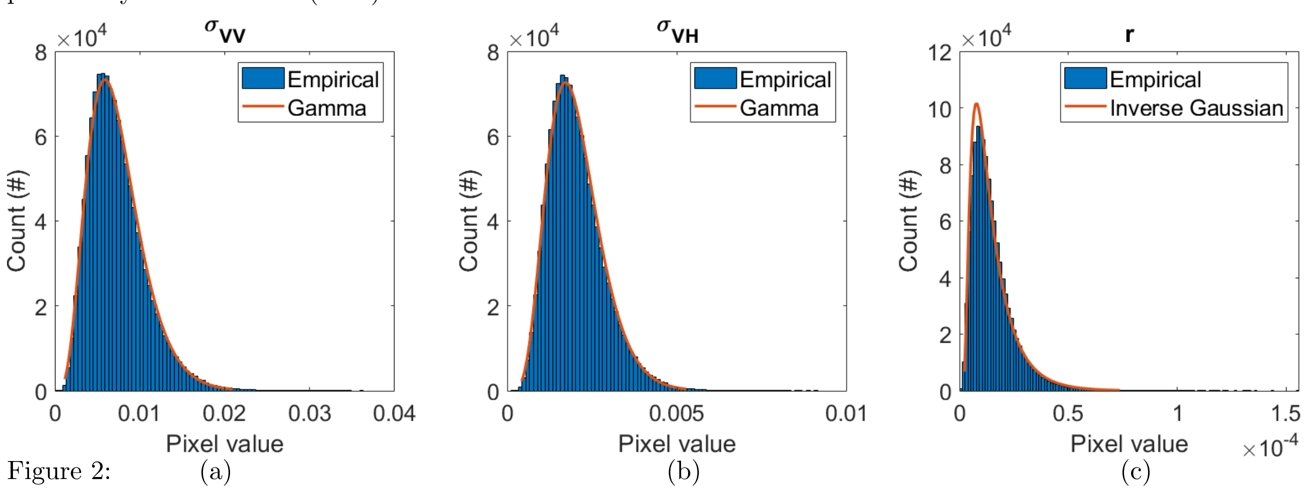

Figure 2: Empirical distribution of (a) σ_{VV} and (b) σ_{VH} overlapped with Gamma, while (c) r overlapped the theoretical inverse Gaussian distribution.

This comparison helps them match accurately so that the correct threshold value can be identified. The next step is to generate the logical images to better visualize the ship and water pixels to be separated. The histograms are evaluated to analyze the empirical distribution that is well approximated for each polarimetric combination and then adapt the relevant threshold, which is then applied to r, σ_{VH}, and σ_{VV}, images that provide logical binary outputs in a robust manner.
For the given three combinations, the region of interest (ROI) from calm sea water indicates that the empirical distribution of σ_{VV} and σ_{VH} follows a gamma distribution, whereas r follows an inverse Gaussian distribution, as shown in Figure 2(a)–(c). Once CFAR is computed for these distributions, a threshold value is obtained to classify pixels as either water or ship. The threshold value may vary across different combinations and SAR analogies. Upon that,[9,10] provided the relationship between the probability of false alarm and CFAR threshold for inverse Gaussian and Gamma distributions. Once the 'T' values are obtained over a smooth water region, the logical binary outputs are obtained to distinguish sea and ship easily. 'T' values of r, σ_{VH}, and σ_{VV} over the ROI are varying for each distribution.

2.5 Quantitative Analysis of Ship Detection Accuracy

The root mean square error (RMSE) is calculated to evaluate the accuracy of water and ship pixel classification compared to the ground truth (Water: 60%, Ship: 40%).[11] The results for each dataset are summarized in Table 1 below.

$$\mathrm{RMSE} = \sqrt{\frac{1}{2}\left[(\mathrm{Water}_{\mathrm{predicted}} - \mathrm{Water}_{\mathrm{actual}})^2 + (\mathrm{Ship}_{\mathrm{predicted}} - \mathrm{Ship}_{\mathrm{actual}})^2\right]} \tag{3}$$

The actual target pixels are identified based on the SPAN detector, which represents the total backscattered power. A well-designed detector should inherently improve the Target-to-Clutter Ratio (TCR) by enhancing the target signal while suppressing clutter. The choice of 60% and 40% is intended to reduce the number of target pixels and retain more clutter pixels, thereby making the system more robust for automatic detection in scenarios where clutter is dominant.

3. EXPERIMENTAL RESULTS

In this paper, we make use of well-calibrated ground range detected (GRD) data from Sentinel-1 IW mode over the Mediterranean Sea, acquired on $2024-04-10$. The resolution loss of the polarimetric correlation mode may result in the loss of some targets, but this drawback is mitigated by the availability of different polarization modes. Figure 3(a)–(c) show ship backscattering for co-, cross-, and dual-polarization combinations, respectively. To automatically extract ships, the detection scheme used here is based on a local process algorithm called CFAR, which identifies image samples with brightness values statistically higher than the surrounding ocean clutter. However, detection fails when the background statistics are corrupted by the presence of nearby ships.

The reflection symmetry approach was tested using a heat map to estimate the weights of σ_{VV}, σ_{VH}, and r. Compared to single SAR channels, the given correlation descriptors effectively suppress clutter. The ship detection scheme utilizes a moving window that computes the local amplitude, as shown in Figure 4(a)–(c). In the CFAR algorithm, at each step, if the central pixel has a value smaller than the calculated threshold, a "zero" value is inserted at its original position. Conversely, if the pixel value is equal to or higher than the threshold,

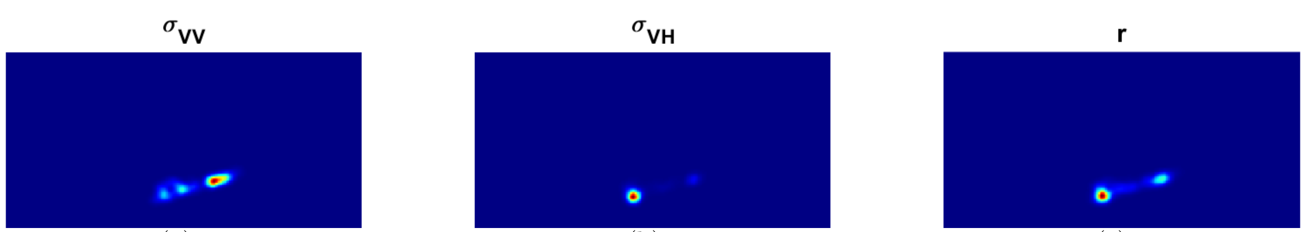

Figure 3: (a) (b) (c)
Ship signature of total backscattering from (a) co-pol, (b) cross-pol, and (c) dual-pol correlation descriptors.

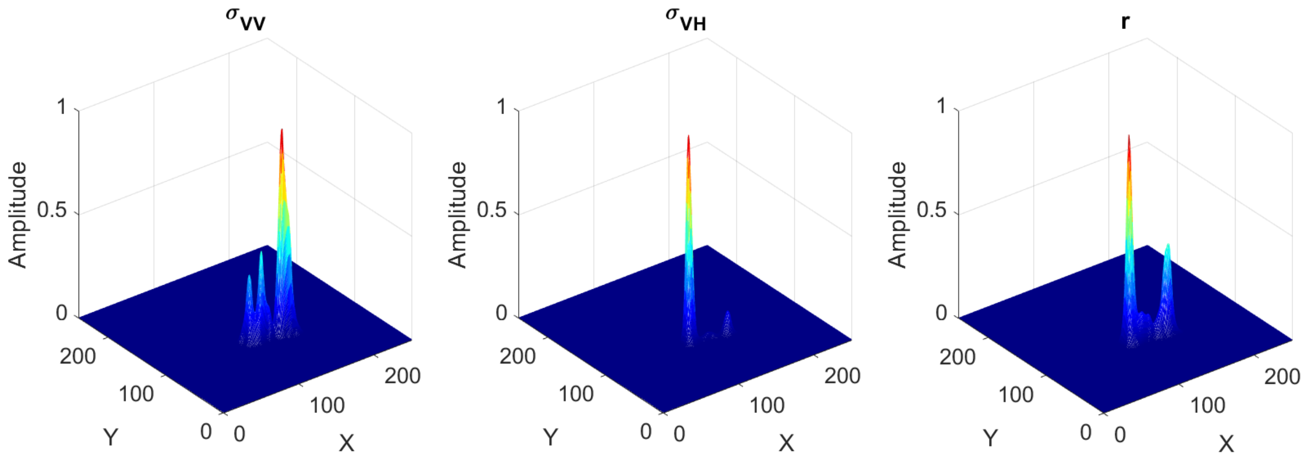

Figure 4: (a) (b) (c)
Heat maps for weights of (a) co-pol, (b) cross-pol, and (c) dual-pol correlation with the suppressed clutter.

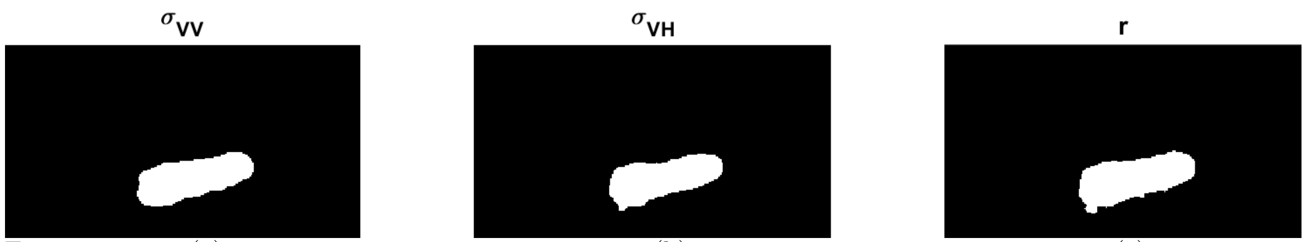

Figure 5: (a) (b) (c)
Binary images for ship and sea-water discrimination based on CFAR threshold values. Black pixels valued 0, and white pixels valued 1. (a) σ_{VV}, (b) σ_{VH}, and r.

the original pixel value is retained in the image. The processed image will display a black background, where bright pixels correspond to either true targets or false alarms.

Although no theoretical proofs are provided in this study, the assumptions can be empirically validated. Furthermore, the Gaussian distribution is assumed to remain stable across the image in terms of mean and standard deviation values. However, this assumption may not hold under high sea conditions. The objective of the polarimetric combination is to apply a clutter suppression technique while enhancing target visibility. To quantitatively assess performance, the target-to-clutter ratio (TCR) can be evaluated for the VV and VH channels, as well as for σ_{VV}, σ_{VH}, and r. The TCR values indicate which approach performs best in distinguishing targets from the surrounding sea clutter.

Figure 5 illustrates the binary images obtained after applying threshold values to each polarimetric combination to distinguish between ship and water pixels within the ROI. The primary objective of developing automatic threshold detectors is to control the probability of false alarms while accurately retrieving a binary (logical) image. The selection of the CFAR threshold value is influenced by meteorological conditions and the incidence angle. If the CFAR threshold is improperly chosen, the back-scattering increase beyond its normal threshold, leading to elevated clutter levels.

After obtaining the logical image, the ship target contour is extracted pixel by pixel using the Sobel (yellow) and Canny (red) edge detection algorithms, applied to σ_{VV}, σ_{VH}, and r, respectively, as illustrated in Figures 6(a)–(c). The *Sobel* and *Canny* edge detectors compute the 2-D spatial gradient of the binary image to delineate the ship's edges. Overall, the detected edges closely follow the actual ship contours, with no false detections observed. However, due to the relatively narrow structure of the ship's boundaries, some edge pixels may be missed. Figure 6(d) presents a comparative analysis of all correlation descriptors: σ_{VV} (yellow), σ_{VH} (red), and r (magenta), with SPAN (green). In the absence of optical imagery or ground-truth data (e.g., Sentinel-2), SPAN is used as a reference for evaluation, as it represents the total back-scattered power from all available

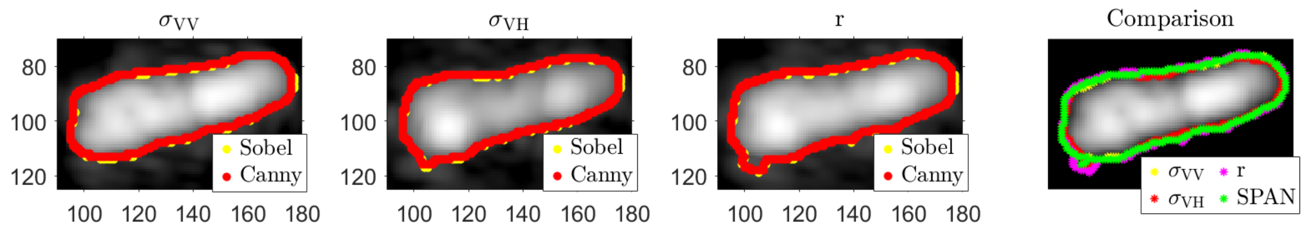

Figure 6: (a) (b) (c) (d)
Ship detection over SAR scene and ship contour extraction by Sobel and Canny edge detectors. (a) σ_{VV}, (b) σ_{VH}, (c) r, and (d) is comparisons of all with SPAN detector.

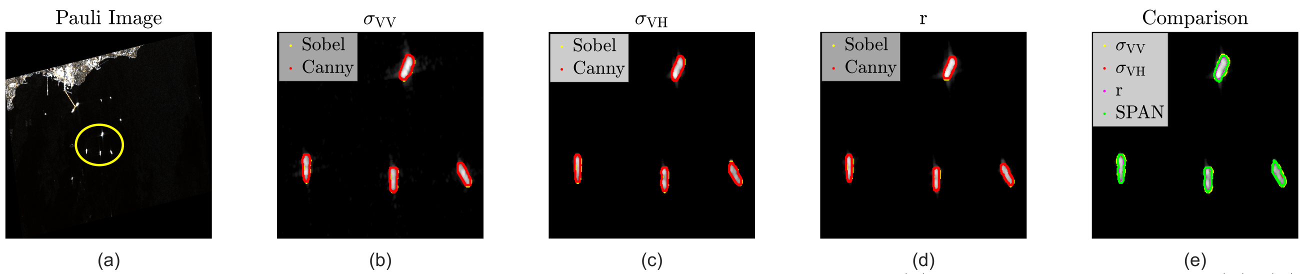

Figure 7: Overview of ship detection performance over a large SAR scene. (a) Limassol Marina Port; (b)–(d) show results using given descriptors and (e) presents a comparative analysis based on Figure 6.

Table 1: Statistics for Ship Detection with 60% water and 40% ship target pixels.

Descriptor	**Water Pixel** [%]	**Ship Pixel** [%]	**RMSE** [%]
$\sigma_{\mathtt{VV}}$	61.32	38.68	1.0976
$\sigma_{\mathtt{VH}}$	62.77	37.23	2.6646
r	58.91	41.09	1.4847

polarization channels.

To demonstrate ship detection over a large SAR scene, a subset of the SAR image covering Limassol Marina is extracted, as shown in Figure 7(a), to highlight the detection of multiple ships with varying sizes and velocities. Figures 7(b–e) present a comparative analysis corresponding to Figure 6, extended to a larger SAR scale. These results confirm that polarimetric descriptors combined with CFAR have the potential to effectively detect multiple moving objects at sea.

Quantitative results for ship and water pixel identification accuracy are presented in Table 1. The overall accuracy (OA)[11] for each class (i.e., ship and water pixels) is computed as the product of the marginal proportions for each category. The root mean square error (RMSE) values are minimal: 1.09%, 2.66%, and 1.48% for σ_{VV}, σ_{VH}, and r, respectively. These results indicate that well-calibrated SAR channel correlation descriptors are effective for ship detection, with a low probability of false alarm (PFA). As part of future work, we aim to extend this approach by incorporating convolution neural network (CNN) techniques to identify ships causing oil spill to enhance maritime surveillance capabilities. This advancement is expected to significantly contribute to detecting and preventing illegal activities in maritime operations, thereby bolstering overall maritime security and safety.[12]

4. DISCUSSION AND CONCLUSION

Ship detection and monitoring are critical for ensuring marine safety and security. Optical imaging solutions, while commonly used, are inherently limited under adverse conditions such as fog, cloud cover, and low light. SAR, due to its all-weather, day-and-night imaging capabilities, offers a reliable alternative for ship detection and monitoring. In this study, we utilized well-calibrated SAR data to perform ship detection using co-polarized, cross-polarized, and dual-polarization correlation descriptors, integrated with the widely recognized

CFAR method. We demonstrated the efficacy of automatic CFAR-based ship detection in maintaining a regulated PFA. The detection results were quantitatively compared with the "SPAN" metric, where the RMSE was found to be negligible. This validates the robustness of correlation descriptors in conjunction with CFAR as a promising framework for automated ship detection in SAR imagery.

ACKNOWLEDGMENTS

The 'EXCELSIOR' project has received funding from the European Union's Horizon 2020 research and innovation programme under Grant Agreement No 857510, from the Government of the Republic of Cyprus through the Directorate General for the European Programmes, Coordination and Development, and the Cyprus University of Technology. The authors also acknowledge the 'EXCELSIOR': ERATOSTHENES: Excellence Research Centre for Earth Surveillance and Space-Based Monitoring of the Environment H2020 Widespread Teaming project (www.excelsior2020.eu), in which the Eratosthenes CoE has been established.

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