MINOR-2 PROJECT

REPORT

For

A Deep Learning Approach for Ship Detection & Localization using Satellite Imagery

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PROJECT REPORT

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Abstract

Ships are one of the most important means of transport in the world. It has been used since ages to meet our traveling and business requirements. Despite the invention and development of new modes of transportation, maritime transport still remains to be one of the fastest and best modes of transport till date. A prominent area of research in remote sensing and computer vision is the identification and location of ships using satellite data. There are numerous uses for the capacity to precisely identify and locate ships in satellite photos, including fisheries management, maritime surveillance, and marine environmental monitoring. The creation of automatic ship recognition and localisation algorithms utilising satellite data has gained popularity in recent years. In order to evaluate satellite photos and identify ships, these systems often use machine learning and deep learning techniques.
As most of the earth is covered by water, it is very difficult and expensive to monitor those vast areas by human analysis or earth-based sensors.
Ship detection is usually done by using Automatic Identification System (AIS), which involves the use of VHF radio frequencies to wirelessly broadcast the ship's location, destination and identity to nearby receiver devices on other ships and land-based systems. Monitoring ships using AIS is very effective but the ships are required to legally install a VHF transponder. But the issue arises when particular ships often referred to as 'Dark Ships' which are commonly engaged in illegal activities disconnect their transponder and hence don't use Automatic Identification System (AIS). In such scenarios, satellite imagery can be used to detect the ships.This project proposes a ship detection method using satellite imagery by performing a polarimetric analysis technique called H/A/Alpha decomposition after orthorectification. Due to its ability to capture images regardless of atmospheric conditions, Synthetic Aperture Radar (SAR) has gained traction in the Earth Observation market above all. Unlike optical imagery, SAR uses instruments which use radio waves to image the Earth's surface which are not affected by the time of day or meteorological conditions, enabling imagery to be obtained during the day or night, with cloudy, or clear skies. As the SAR data is available for free due to the open data policy of the EU's Copernicus program, in this project we'll be using Sentinel-2 data of the coastal regions of India for marine object detection.

Keywords:
Satellite imagery, Synthetic Aperture Radar (), H/A/Alpha Decomposition, Orthorectification, Ship detection

Abbreviations:

ANN: Artificial neural networks
CNN: Convolutional neural networks
AIS: Automatic Identification System
DBN: Deep belief networks
SAR : Synthetic Aperture Radar
GPS: Global Positioning System

Introduction

Ship detection and localization is a crucial task for various maritime applications, including vessel traffic management, maritime security, and environmental monitoring. In recent years, there has been a growing interest in using satellite imagery for ship detection and localization due to its wide coverage, high resolution, and ability to capture information in different spectral bands. However, manual analysis of large volumes of satellite imagery is time-consuming and requires significant human effort, making it impractical for real-time applications.

To address this challenge, deep learning techniques have been applied to satellite imagery for ship detection and localization. Deep learning is a subfield of machine learning that uses artificial neural networks with multiple layers to extract high-level features from data. Deep learning has shown remarkable success in various computer vision tasks, including object detection, classification, and segmentation. By using deep learning techniques, researchers have been able to develop automated ship detection and localization systems that can process large volumes of satellite imagery in real-time, making it feasible for applications that require quick response times.

This approach typically involves training a deep neural network on a large dataset of annotated satellite images to learn the features that are indicative of ships. The trained network can then be used to detect and localize ships in new satellite images. This approach has shown promising results in several studies and has the potential to revolutionize the way ship detection and localization are performed.

In this context, this paper proposes a deep learning approach for ship detection and localization using satellite imagery. The paper presents a detailed analysis of the methodology, including the dataset used, network architecture, and training process. Additionally, the paper evaluates the performance of the proposed approach using various metrics and compares it to other state-of-the-art techniques. The results demonstrate the effectiveness of the proposed approach in detecting and localizing ships in satellite imagery, highlighting its potential for various maritime applications.

Problem Statement

The problem statement for the topic "A Deep Learning Approach for Ship Detection & Localization using Satellite Imagery" is to develop an accurate and efficient system for detecting and localizing ships in satellite images. The objective is to use deep learning techniques to extract relevant features from the images and classify them as either containing a ship or not, and to determine the precise location of the ship within the image. This technology can be used for various applications such as maritime surveillance, monitoring of fishing activities, and detecting illegal activities in marine protected areas.

The challenge is to develop a robust and scalable system that can handle large datasets and perform accurately in different environmental conditions, such as varying weather and lighting conditions, and different ship sizes and orientations. The proposed deep learning model will need to use advanced techniques such as convolutional neural networks (CNNs), recurrent neural networks (RNNs), and attention mechanisms to effectively capture the complex features and spatial relationships present in satellite images.Once the model has been trained and optimized, it will be evaluated on a test set of satellite images to assess its performance in detecting and localizing ships. The evaluation metrics used may include precision, recall, F1 score, and mean average precision (mAP).Overall, the successful development of a deep learning model for ship detection and localization in satellite imagery could have important applications in maritime surveillance, ship tracking, and search and rescue operations.

Literature Review

[1] Chong, J.; Zhu, M. Survey of the Study on Ship and Wake Detection in SAR Imagery. Acta Electron. Sin. 2003, 31, 1356–1360.

In recent years, researches of ship detection using synthetic aperture radar (SAR) images have received considerable attentions in the area of marine remote sensing. The origin and development of ship detection in SAR imagery is reviewed. The physical factors that would affect ship and wake are analysed.

[2] Xi, Y.; Zhang, X.; Lai, Q.; Li, W.; Lang, H. A New PolSAR Ship Detection Metric Fused by Polarimetric Similarity and the Third Eigenvalue of the Coherency Matrix. In Proceedings of the IEEE International Geoscience and Remote Sensing Symposium, Beijing, China, 10–15 July 2016; pp. 112–115

SAR image used for ship detection, the sea surface echo is weak and changes randomly, which means that the sea surface has an approximate low-rank attribute. The ship echo is strong and the ship is sparsely distributed on the sea surface, which means that the ship has an approximate sparse attribute.

[3] Yu, W.; Wang, Y.; Liu, H.; He, J. Superpixel-Based CFAR Target Detection for High-Resolution SAR Images. IEEE Geosci. Remote Sens. Lett. 2016, 13, 730–734.

In dealing with the problem of target detection in high-resolution Synthetic Aperture Radar (SAR) images, segmenting before detecting is the most commonly used approach. After the image is segmented by the super pixel method, the segmented area is usually a mixture of target and background, but the existing regional feature model does not take this into account, and cannot accurately reflect the features of the SAR image.

[4] Fan, Q.; Chen, F.; Cheng, M.; Wang, C.; Li, J. A Modified Framework for Ship Detection from Compact Polarization SAR Image. In Proceedings of the IEEE International Geoscience and Remote Sensing Symposium, Valencia, Spain, 22–27 July 2018; pp. 3539–3542.

Although AIS information was used to verify the labelled dataset over several sub-areas, it is unfortunate that not all labelled ships in this study were supported by AIS data. It is a fact that not all ships on the ocean carry AIS transponders, likewise, especially for archived earth observations.

[5] Markopoulos, P.; Dhanaraj, M.; Savakis, A. Adaptive L1-Norm Principal-Component Analysis with Online Outlier Rejection. IEEE J. Sel. Top. Signal Process. 2018, 12, 1131–1143.

Both these extreme approaches exhibit an unfavourable performance/cost trade-off. In contrast, a preferred method would leverage each new measurement, together with previous ones, to efficiently update the existing bases. The development of such a method is the main contribution of this paper,

[6] Javed, S.; Mahmood, A.; Al-Maadeed, S.; Bouwmans, T.; Ki Jung, S. Moving Object Detection in Complex Scene Using Spatiotemporal Structured-Sparse RPCA. IEEE Trans. Image Process. 2018, 28, 1007–1022.

To address this issue, we propose a spatiotemporal structured sparse RPCA algorithm for moving objects detection, where we impose spatial and temporal regularization on the sparse component in the form of graph Laplacians. Each Laplacian corresponds to a multi-feature graph constructed over super pixels in the input matrix

[7] Biondi, F. Low-Rank Plus Sparse Decomposition and Localized Radon Transform for Ship-Wake Detection in Synthetic Aperture Radar Images. IEEE Geosci. Remote Sens. Lett. 2018, 15, 117–121.

The problem in obtaining stable motion estimation of maritime targets is that sea clutter makes wake, Structure detection and reconnaissance are difficult. This research presents a complete procedure for automatic estimation of maritime target motion parameters by evaluating the generated Kelvin waves detected in synthetic aperture radar (SAR) images.

[8] Li, C.; Yu, Z.; Chen, J. Overview of Techniques for Improving High-resolution Spaceborne SAR Imaging and Image Quality. J. Radars 2019, 8, 717–731.
The start-stop hypothesis considers that the radar does not move in the time between sending and receiving the signal of spaceborne SAR, but this assumption is not accurate. For this purpose, the literature established a two-way slant range model and proposed a strict single-base configuration with an equivalent center time, but it still did not have an explicit expression, which was not conducive to the research of specific imaging methods.

[9] Liu, T.; Yang, Z.; Yang, J.; Gao, G. CFAR Ship Detection Methods Using Compact Polarimetric SAR in a K-Wishart Distribution. IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens. 2019, 12, 3737–3745.
Synthetic aperture radar (SAR) is a microwave imaging sensor capable of all-day, all-weather observations of the ground. Therefore, SAR is widely used in disaster investigation, environmental monitoring, target detection and other fields. At present, SAR ship detection has important research value in both the military field

[10] Li, J.; Tian, J.; Gao, P.; Li, L. Ship Detection and Fine-Grained Recognition in Large-Format Remote Sensing Images Based on Convolutional Neural Network. In Proceedings of the IEEE International Symposium on Geoscience and Remote Sensing (IGARSS), Waikoloa, HI, USA, 26 September–2 October 2020; pp. 2859–2862.
Ship detection and fine-grained recognition in large-format remote sensing image are an important research direction in the field of remote sensing image detection. But less research has been done in this area. Aiming at this problem, this paper constructs a large-format remote sensing image ship target dataset with ship category information, and proposes a background filtering network and a ship fine-grained classification network.

[11] Ai, J.; Cao, Z.; Xing, M. An Adaptive-trimming-depth Based CFAR Detector of Heterogeneous Environment in SAR Imagery. Remote Sens. Lett. 2020, 11, 730–738.
Traditional CFAR detectors generally use all samples in the background window for parameter estimation. However, in the heterogeneous regions, these detectors will overestimate the parameters used for statistical modelling due to the interference of high-intensity interference pixels such as adjacent ships, ghosts, breakwaters and azimuth ambiguity

[12] Ai, J.; Cao, Z.; Mao, Y.; Wang, H.; Wang, F.; Jin, J. An Improved Bilateral CFAR Ship Detection Algorithm for SAR Image in Complex Environment. J. Radars 2021, 10, 499–515.
The intensity level division based on the nonuniform quantization method can improve the similarity and contrast information of weak targets, leading to improved ship detection rate. The information fusion of strength spatial domain is to fuse the spatial similarity, distance direction and strength information, which can further improve the detection rate and describe the ship structure information.

[13] Liu, T.; Yang, Z.; Jiang, Y.; Gao, G. Review of Ship Detection in Polarimetric Synthetic Aperture Imagery. J. Radars 2021, 10, 1–19.
Various sensing and imaging techniques are developed to record different information from four primary physical quantities related to the optical field: intensity, wavelength, phase, and polarization.

[14] Zou, B.; Qiu, Y.; Zhang, L. Ship Detection Using PolSAR Images Based on Simulated Annealing by Fuzzy Matching. IEEE Geosci. Remote Sens. Lett. 2022, 19, 1–5.
The detection statistics are binarized according to the local threshold set by the detection statistic value of the key point to complete the ship detection. Experiments on three data sets obtained from the RADARSAT-2 and AIRSAR quad-polarization data demonstrate that the proposed detector is effective for ship detection.

Existing System Issue

- ARC map is crashing
- Many defined functions not working in visual studio code.
- Problem in mapping 2D tif image information.
- Tensor flow2.1 and keras 2.4 are not working simultaneously
- A lot of ship detection models are already there that use deep learning to detect the ships but none of them use raw satellite data for training and testing the model.
- This is the differentiating factor of our project that it uses raw Sentinel-1 data to detect the ships.
- In order, to convert the raw data into a visual format we incorporated various data pre-processing techniques.

Proposed System Design

There are many ship detection techniques in computer science but all of them have the same shortcoming that they use raw satellite images. Our proposed model uses raw satellite data after pre-processing and uses UNIT to detect the ships in the images.

Hardware Requirements

- At least 8GB RAM
- 32-bits or 64 bit architecture
- 2GHz or more CPU
- Good amount of Storage

Software Requirements

- ArcMap
- Numpy
- Matplotlib
- OS
- SnapPy
- PyroSAR
- Tensorflow
- Keras
- Sklearn

Algorithm Discussed

U-Net:
The U-Net is a deep convolutional neural network architecture that is widely used for image segmentation tasks, including ship detection in satellite images. To detect ships in satellite images using U-Net, the network is trained on a large dataset of annotated satellite images, where the ships are labeled as the foreground and the background is labeled as the sea or sky. During training, the network learns to identify the unique features of ships, such as their shapes, colors, and textures, and to distinguish them from the surrounding background.
Once the U-Net is trained, it can be used to detect ships in new satellite images by segmenting the image into foreground (ship) and background (sea/sky) regions. This segmentation process involves passing the input image through the U-Net and obtaining a segmentation map, which indicates the probability of each pixel belonging to the foreground or background. The segmentation map is then thresholded to obtain a binary mask, where the foreground pixels correspond to the ship and the background pixels correspond to the sea/sky.
Overall, U-Net provides an efficient and accurate way to detect ships in satellite images, which can have many applications in fields such as maritime surveillance, environmental monitoring, and navigation. The U-Net model is a popular neural network architecture for semantic segmentation tasks, including ship detection. Here's a general overview of how the U-Net algorithm works for ship detection:

- **Input:** The U-Net model takes as input an image that contains one or more ships.
- **Encoding Path:** The image is first passed through a series of convolutional layers that extract features from the image. The size of the feature maps is reduced at each layer, while the number of feature maps is increased.
- **Decoding Path:** The feature maps obtained from the encoding path are then passed through a series of transposed convolutional layers that upsample the feature maps back to the size of the input image. At each layer, the feature maps are concatenated with the corresponding feature maps from the encoding path, allowing the decoder to combine information from different scales.
- **Output:** The final layer of the U-Net model produces a segmentation mask that indicates which pixels in the input image belong to a ship and which do not. The output mask has the same size as the input image.
- **Training:** The U-Net model is trained using a loss function that measures the difference between the predicted segmentation mask and the ground truth mask. The most common loss function used for semantic segmentation is the cross-entropy loss.

By training the U-Net model on a large dataset of ship images with their corresponding ground truth masks, the model can learn to accurately detect ships in new images.

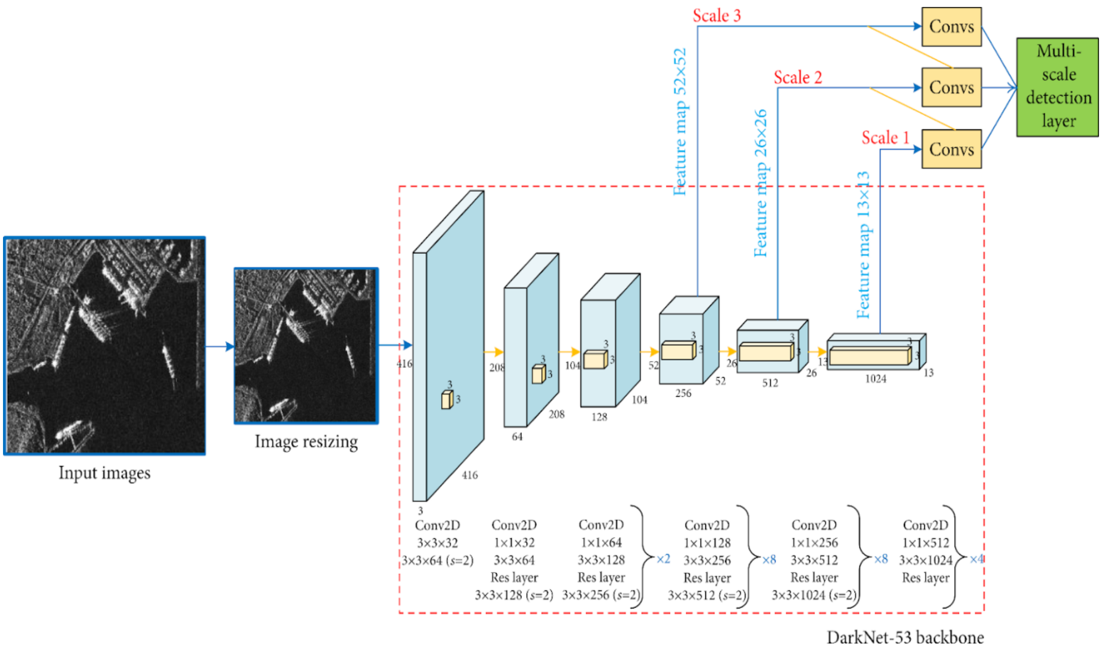

Fig No.1 U-net backbone structure for the model

Use Case Diagram

Use case diagrams are the most common type of system/software requirements for newly produced software programmes. Use cases describe the desired behavior (what), not the precise means of achieving it (how). Once defined, use cases can be used to indicate both textual and graphic representation (i.e., Use Case Diagram). Use case modeling ability to assist in system design from the standpoint of the end user is a fundamental idea. By describing all externally observable system behavior, it is a useful tool for explaining system behavior to users.

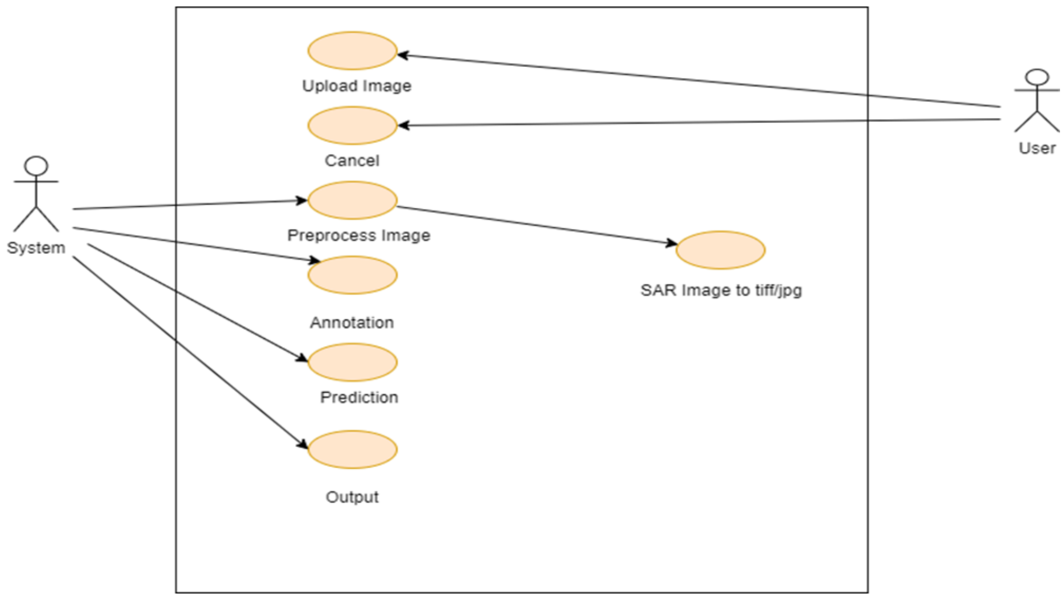

Fig No.2 use case diagram

Result And Discussion

Fig No.3 Landscape image generated finally after Arc-Map

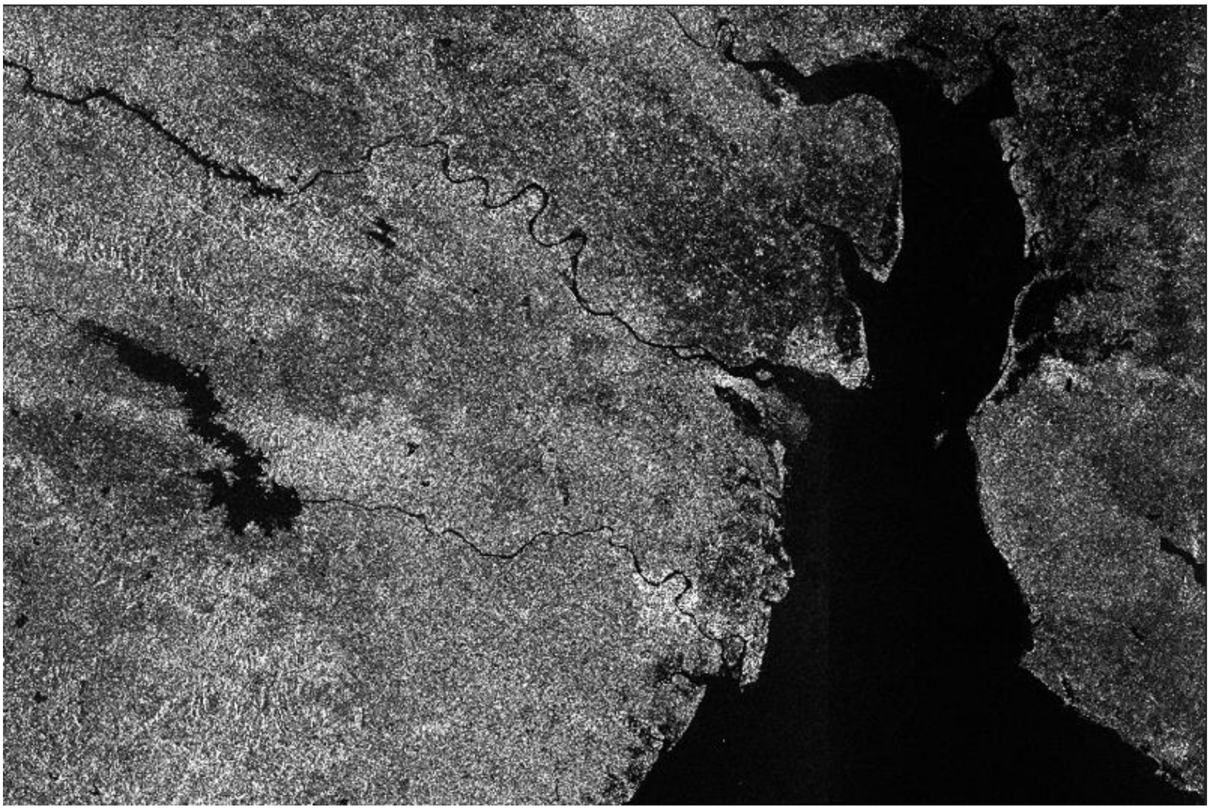

Fig No.4 Landscape image generated finally after Arc-Map(Raw-Data)

Future work

The use of deep learning techniques for ship detection and localization using satellite imagery is a rapidly evolving field, and there are several future scope and potential directions for further research and development.

- Multi-modal Data Fusion: One potential area of future research is to combine different data sources, such as radar and optical data, to improve ship detection and localization accuracy. Such a multi-modal data fusion approach can provide complementary information that could help reduce false positives and increase the overall accuracy of the system.

- Fine-grained Ship Classification: Another area of potential research is to extend the current approach to enable fine-grained ship classification. This could involve identifying specific ship types or even individual ships, which could be useful for maritime surveillance and monitoring applications.

- Real-time Detection: Real-time ship detection and localization is a challenging problem that could have many practical applications. Future research could focus on developing more efficient deep learning algorithms that can run in real-time, enabling the detection and tracking of ships in near real-time.

- More Generalized Approach: The current approach is designed specifically for ship detection and localization, but similar techniques could be applied to other object detection problems in satellite imagery, such as detecting airplanes, cars, or buildings. Future research could focus on developing more generalized deep learning models that can detect different types of objects.

- Improved Data Availability: The availability of high-quality satellite imagery is critical for developing and testing deep learning models. However, obtaining such data can be expensive and time-consuming. Future research could focus on developing more efficient and cost-effective ways of collecting and processing satellite imagery, making it more widely available for research and development purposes.

Overall, the future scope for ship detection and localization using deep learning is vast and exciting, with many potential directions for further research and development.

Reference

[1] Chong, J.; Zhu, M. Survey of the Study on Ship and Wake Detection in SAR Imagery. Acta Electron. Sin. 2003, 31, 1356–1360.

[2] Xi, Y.; Zhang, X.; Lai, Q.; Li, W.; Lang, H. A New PolSAR Ship Detection Metric Fused by Polarimetric Similarity and the Third Eigenvalue of the Coherency Matrix. In Proceedings of the IEEE International Geoscience and Remote Sensing Symposium, Beijing, China, 10–15 July 2016; pp. 112–115

[3] Yu, W.; Wang, Y.; Liu, H.; He, J. Superpixel-Based CFAR Target Detection for High-Resolution SAR Images. IEEE Geosci. Remote Sens. Lett. 2016, 13, 730–734.

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[7] Biondi, F. Low-Rank Plus Sparse Decomposition and Localized Radon Transform for Ship-Wake Detection in Synthetic Aperture Radar Images. IEEE Geosci. Remote Sens. Lett. 2018, 15, 117–121.

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[12] Ai, J.; Cao, Z.; Mao, Y.; Wang, H.; Wang, F.; Jin, J. An Improved Bilateral CFAR Ship Detection Algorithm for SAR Image in Complex Environment. J. Radars 2021, 10, 499–515.

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[14] Zou, B.; Qiu, Y.; Zhang, L. Ship Detection Using PolSAR Images Based on Simulated Annealing by Fuzzy Matching. IEEE Geosci. Remote Sens. Lett. 2022, 19, 1–5.