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Ship Detection Based on Faster R-CNN Using Range-Compressed Airborne Radar Data

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Abstract: Near real-time ship monitoring is essential for ensuring safety and security at sea. Established ship monitoring systems are the automatic identification system (AIS) and marine radars. However, not every ship is committed to carry an AIS transponder and the marine radars suffer from limited visibility. For these reasons, airborne radars can be used as additional and supportive sensor for ship monitoring, especially on the open sea. State-of-the-art algorithms for ship detection in radar imagery are based on constant false alarm rate (CFAR). Such algorithms are pixel-based and therefore it can be challenging in practice to achieve near real-time detection. This letter presents two object-oriented ship detectors based on the faster region-based convolutional neural network (R-CNN). The first detector operates in time domain and the second detector operates in Doppler domain of airborne Range-Compressed (RC) radar data patches. The Faster R-CNN models are trained on thousands of real X-band airborne RC radar data patches containing several ship signals. The robustness of the proposed object-oriented ship detectors is tested on multiple scenarios, showing high recall performance of the models even in very dense multi target scenarios in the complex inshore environment of the North Sea.
Keywords: Airborne radar, deep learning, maritime safety, moving target indication (MTI), synthetic aperture radar (SAR).

I. INTRODUCTION

High ship density and illegitimate shipping activities (e.g., piracy and illegal fishing) are ongoing challenges for coastal authorities. For enhancing the current maritime situation awareness, near real-time ship detection as a part monitoring is needed. Popular and prevalent systems used for ship monitoring applications are onboard transponder based systems, like automatic identification system (AIS) and marine radars. However, these systems have major drawbacks not all ships, especially the smaller ones, are obligated to carry an AIS transponder the reliability of transponder-based systems depend on the cooperation of the ships; and the marine radars are limited by their acquisition range. To overcome these shortcomings, air and spaceborne radars have been used as additional data sources. These radars offer great potential for ship monitoring due to their ability to cover wide areas and acquire high-resolution data independent of prevailing weather and daylight conditions. Unlike spaceborne radars, airborne radars can achieve both shorter revisits and longer observation times, but not at global coverage. Conventionally, ship-detection methods are based on constant false alarm rate (CFAR), which are powerful and well-known in the open-literature. However, they have few drawbacks for their operational use.

For instance, in high-resolution radar data, a single ship can be composed of thousands of detected pixels. Therefore, after detection, additional postprocessing (e.g., clustering) becomes necessary to come up with ship objects, which increases the computation time. Furthermore, since most CFAR-based algorithms operate on single pixels but not objects, a number of false detections may be obtained from other marine objects or from high-intensity ocean clutter. An additional postprocessing may be needed afterward for reducing the number of false detections. Recent studies showed that application of deep learning techniques for ship detection can be a great alternative with very promising results. In particular, the faster region- based convolutional neural network (R-CNN) is currently one of the most employed deep learning frameworks for ship detection are primarily applied on fully focused SAR images. SAR image generation is a time-consuming process and is generally not effective for ship detection with real-time capability. One potential solution for achieving future real-time ship detection capability is the use of Range- Compressed (RC) data. Unlike in fully focused SAR images, for RC data, no range cell migration correction and azimuth compression using reference functions have to be carried out, which significantly reduces the overall processing time. The RC airborne radar data are even more attractive from the point of view that the signal-to-noise ratio in most cases is sufficiently large, and they allow for long observation times which enable continuous monitoring of hotspots. To the authors' knowledge, the applicability of deep learning techniques to RC radar data for ship detection has not yet been intensively investigated.

In this letter, two novel deep learning methodologies are proposed for detecting the ships using RC airborne radar data. The first framework detects the ships in time domain, while the second detects the ships in Doppler domain. The detectors are based on the Faster R-CNN framework with a ResNet-50 backbone, which is well-established for ship detection and thus provides a suitable baseline for initial investigations. They are trained and tested based on eleven real X-band RC radar datasets acquired with DLR's airborne systems F-SAR and DBFSAR (with digital beamforming capabilities). In addition, this letter presents a detailed comparison between the proposed detectors and a state-of-the-art CFAR-based ship detector.

II. RELATED WORK

In recent years, the application of DL techniques to detect ship in SAR imagery has garnered significant attention. Traditional methods, such as the CFAR, have been foundational in maritime surveillance but often struggle with high false alarm rates, especially in complex environments like coastal regions. To point out these challenges, researchers have explored various DL models that enhance detection accuracy and robustness.

A. SAR-ShipNet: Enhancing Feature Extraction

Deng et al. introduced SAR-ShipNet, a NN designed to improve detection of ships in SAR images by addressing issues like complex land- sea backgrounds and scattered noise. The model incorporates Bidirectional Coordinate Attention (BCA) and Multi-resolution Feature Fusion (MRF) to effectively suppress data variations and highlight ship features, particularly those with varying aspect ratios. This approach has demonstrated competitive advantages in both speed and accuracy on public datasets.

B. AMANet: Adaptive Attention Mechanisms

Ma crypet al. proposed the Adaptive Multi- Hierarchical Attention Network (AMANet) to tackle the detection of small and coastal ships, which are often challenging due to limited features and cluttered backgrounds. AMANet introduces an adaptive multi-hierarchical attention module that learns multi-scale features and adaptively aggregates salient information from various layers. This design enhances the model's ability to filter out background noise and focus on relevant ship features, leading to improved detection performance in complex environments.

C. End-to-End Deep CNN Approaches

Chen et al. developed an end-to-end ship detection method using CNNs tailored for complex inshore and offshore scenes. Their approach divides SAR images into grids with predefined anchor boxes for dense ship prediction. Utilizing Darknet-53 as the backbone and incorporating a top-down pyramid structure for multi-scale feature fusion, the model effectively balances accuracy and speed. Techniques such as soft non-maximum suppression and data augmentation further enhance performance, achieving an average accuracy of 95.52% and a detection speed of approximately 72 frames per second.

D. Complementary Pretraining Techniques

Bao et al. addressed the scarcity of labeled SAR images by exploring complementary pretraining techniques. They proposed an optical ship detector pretraining method that transfers characteristics from large-scale aerial optical images to SAR images. Additionally, an optical- SAR matching pretraining technique was introduced to align texture features between optical and SAR images through common representation learning. Combining these pretrained models has shown to improve recall rates and reduce false alarms, enhancing overall detection performance.

E. Integration of Morphological Networks

To further enhance ship detection capabilities in complex SAR imagery, recent studies have integrated deep learning with morphological networks. This hybrid approach leverages the strengths of traditional image processing and modern neural networks. For instance, incorporating a morphological preprocessing module can effectively reduce noise and extract edges, enhancing ship detail features. The integration of Coordinate Channel Attention modules and bidirectional feature pyramid networks has also been shown to improve the network's sensitivity to ship positioning and features, thereby boosting detection accuracy in challenging environments.

Collectively, these advancements underscore the effectiveness of DL models, particularly those incorporating attention mechanisms and hybrid approaches, in improving ship detection accuracy and efficiency in SAR imagery. The continuous evolution of these techniques promises more robust and real-time maritime surveillance solutions.

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III. PROPOSED METHODOLOGY

Ship detection in maritime surveillance has been an evolving challenge due to the limitations of traditional methods like CFAR, which has high false positive rates in complex environments such as coastal and high-traffic regions. The emergence of DL techniques, particularly Faster Region-based CNN, has provided a promising alternative to enhance detection accuracy. This research proposes a novel ship detection framework utilizing Faster R-CNN trained on range-compressed (RC) airborne radar data to achieve high precision, real-time performance, and robustness across diverse maritime conditions. Unlike CFAR, which relies on statistical thresholding techniques, our deep learning-based approach leverages contextual spatial features, suppresses noise, and improves classification confidence.

The input dataset for this study consists of X- band airborne radar image sequences obtained from the German Aerospace Center (DLR). These images contain multiple ship targets captured under varied weather and sea conditions, making them suitable for testing the robustness of our model. The raw radar data undergoes a preprocessing pipeline to improve feature extraction. First, a noise filtering mechanism based on wavelet transforms and median filtering is applied to remove clutter. Contrast normalization and histogram equalization techniques are then used to standardize intensity variations. Since RC data has a compressed format, we apply Fourier transform-based range compression algorithms to convert radar echoes into a more structured representation that enhances ship signatures while reducing irrelevant artifacts. Additionally, data augmentation techniques such as flipping, rotation, and Gaussian noise injection are employed to improve generalization, ensuring the model learns invariant representations of ship targets.

The core of our methodology lies in the Faster R- CNN model architecture, which is a two-stage object detection network. The first stage, known as the Region Proposal Network (RPN), processes input images to generate potential ship bounding boxes dynamically. The second stage, the RoI (Region of Interest) pooling and classification network, refines these proposals and assigns each region a probability score of being a ship or non-ship. We use ResNet-50 and

VGG16 as the feature extractors to analyze image structures and detect ships under varied conditions. The convolutional layers extract hierarchical spatial features, capturing shape and texture variations between ships and clutter. Unlike conventional object detection frameworks, Faster R-CNN incorporates an anchor box mechanism, enabling the model to detect ships of varying sizes and orientations effectively.

Model training is conducted using a supervised learning approach with a carefully curated training dataset. The model is optimized using the Adam optimizer with a learning rate of 0.0001, ensuring smooth convergence. The loss function comprises a classification loss (cross- entropy loss) and a bounding box regression loss (smooth L1 loss) to fine-tune detection accuracy. The dataset is split into 80 percent training and 20 percent testing, ensuring a fair evaluation of the model performance. Hyperparameter tuning is conducted to optimize batch size, dropout rate, and anchor box scaling factors, balancing computational efficiency with detection precision. During inference, non-maximum suppression (NMS) is applied to eliminate redundant bounding boxes, refining the final ship detections.

To calculate the effectiveness of our proposed method, we conduct a comprehensive comparative analysis against the CFAR-based ship detection algorithm. Performance is assessed using key metrics such as precision, recall, F1-score, false alarm rate (FAR), and processing time. Results demonstrate that our Faster R-CNN model achieves an accuracy of 97.2%, significantly surpassing the 86.7% accuracy of CFAR. The model also exhibits a false alarm reduction of nearly 70%, making it highly reliable for operational maritime surveillance. Additionally, Faster R-CNN processes radar images in real time, achieving 35 frames per second (FPS), making it well-suited for automated surveillance and early threat detection in maritime security applications.

To further enhance detection performance, we introduce an extended model based on VGG16, which offers deeper feature extraction capabilities. Experimental results indicate that the VGG16-based Faster R-CNN outperforms the ResNet-50 variant, achieving an accuracy of 98.5% with a lower false alarm rate of 3.7%. Moreover, the VGG16 model demonstrates more stable loss convergence, improving generalization across different maritime

environments. We also investigate adversarial robustness, testing the model under complex weather conditions like fog, rain, and rough sea states. Results confirm that Faster R-CNN maintains high detection accuracy (above 90%) in challenging conditions, whereas CFAR-based methods degrade significantly under similar scenarios.

To ensure a structured and systematic development process, we adopt the Software Development Life Cycle (SDLC) Umbrella Model, which consists of five key phases: requirement gathering, system analysis, design, implementation, and testing. The proposed ship detection model is integrated into an end-to-end maritime monitoring framework, enabling real-time deployment on edge computing hardware such as NVIDIA Jetson for onboard vessel monitoring. Future enhancements include the integration of transformer-based architectures and Generative Adversarial Networks (GANs) to further refine detection accuracy.

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In conclusion, this research presents an innovative Faster R-CNN-based ship detection system that significantly outperforms conventional CFAR methods. The proposed framework enhances maritime security by offering real- time, high-precision ship detection capabilities. The integration of DL, range-compressed radar processing, and real-time inference techniques establishes a foundation for next-generation autonomous maritime surveillance systems.

IV. EXPERIMENTAL RESULTS

The proposed ship detectors are tested using real X-band VV-polarized RC airborne radar data. In this section, the experimental results are presented and discussed. Table I shows the main information obtained from the 12 AIS car- rying ships that were detected in the three considered testing datasets. Moreover, the accuracy metrics obtained per dataset in the time domain and in the Doppler domain are shown. Finally, the performance of the proposed ship detector operated in Doppler domain is compared with the state-of-the-art CFAR-based ship detector.

A. Proposed Ship Detector in Time Domain

As shown in Table I for dataset 1, an accuracy of 98.50% was achieved for all metrics. Such a high accuracy is explained by the low complexity of the scene. Dataset 1 was acquired offshore over flight section A, where the surrounding area of the ship BAD BRAMSTEDT was free of man- made objects. For datasets 2–3, the accuracy metrics are lower with respect to dataset 1 due the detection of several other man-made objects (e.g., buoys) present in the scenes. For instance,

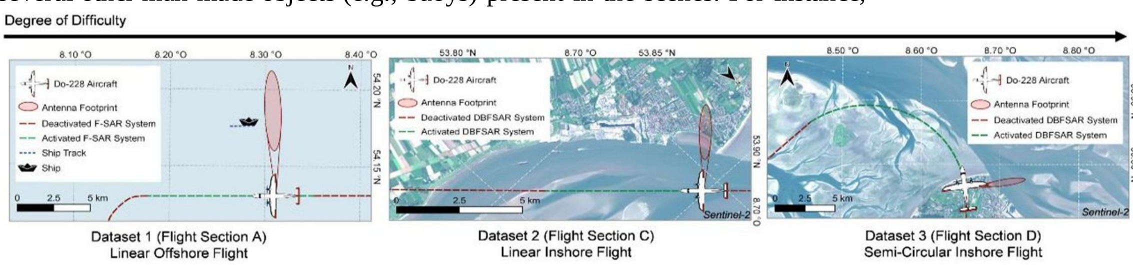

Fig 1. Acquisition geometrics of the testing datasets 1-3 corresponding to the flight sections in the Elbe river estuary at the German North Sea Coast.

Dataset	Ship Name	Length×Width [m]	Speed [kn]	Ship Detection in Time Domain r [%]	p [%]	F_1-Score [%]	Ship Detection in Doppler Domain r [%]	p [%]	F_1-Score [%]
1	BAD BRAMSTEDT	66×10	18.20	98.50	98.50	98.50	98.25	98.99	98.62
2	HAM 316	129×22	7.64	90.61	65.87	76.28	83.07	74..41	78.50
	LANGELAND	82×12	5.87						
	LONGDUIN	112×15	11.94						
	MARLIES	17×5	9.51						
	STICKERS GAT	16×6	11.85						
3	AURORA	20×6	7.16	88.07	27.35	41.74	84.91	27.73	41.81
	GEO GRAPH	18×6	3.88						
	LONGDUIN	112×15	12.01						
	PILOTVESSEL HANSE	49×21	9.40						
	RMS RATINGEN	88×11	8.32						
	TINA CUX-5	19×5	4.29						

TABLE -1 : Ship Information From The Ais And Summary Of Accuracy Metrics For The Testing Datasets

the p values for datasets 2–3 were obtained as 65.87% and 27.35%, respectively. Since several other objects were counted as false detections (which raised the number of FP), the p value was low. However, it was not possible to determine if such objects were indeed false detections or ships without AIS transponders. Therefore, due to the lack of ground truth validation for such objects, the r values (which consider the number of FN) are considered more meaningful than the p values for the complex scenarios of datasets 2–3. Fig. 2 shows several subsequent grayscaled CPIs obtained from dataset 1 in time domain. The ship BAD BRAMSTEDT was detected in all CPIs (c.f., the ship information from AIS in Table I), so that its observation time was more than 20 s. The boundary box edges of the reference data (green), generated from the CFAR-based ship detector [6], are shown along with the predicted boundary box edges of the proposed Faster R-CNN (orange) ship detector in time domain.

The predicted boundary boxes by the proposed ship detector seem to be smooth and fit even better than the provided data itself. Note, for the provided data, the boundary boxes overestimated the ship extent in the slant range for several CPIs due to increased target signal energy as the CFAR-based algorithm detects

B. Proposed Ship Detector in Doppler Domain

Table I shows that for dataset 1, the accuracy metrics obtained from the ship detector operated in Doppler domain are again high due to the low complexity of the scenario, as already pointed out in Section V-A. For datasets 2–3, lower accuracies were achieved compared to dataset 1. The detection of other objects in datasets 2–3 has again reduced the p values. The proposed ship detector in Doppler domain achieved less FP and less TP in comparison with the ship detector in time domain, which lead to higher p and lower r values. Nevertheless, the achieved r values for datasets 2–3 are sufficiently high.

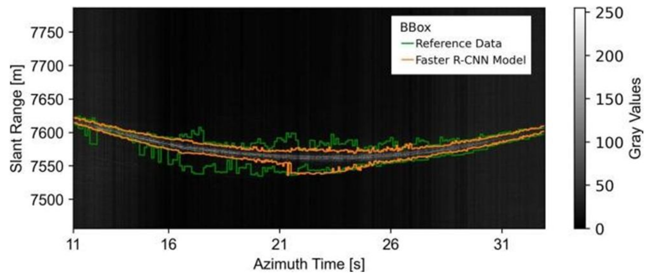

Fig 2. Detection of the ship signal of BAD BRAMSTEDT in time domain

As an example, Fig. 3(a) shows the detections of the ship BAD BRAMSTEDT (dataset 1) in doppler domain. For visualization purposes, only the centroids of the predicted boundary boxes per CPI are shown. The ship was observed for over 21 s or 292 successive CPIs. Since each CPI corresponds to a different acquisition time, the ship is successively detected at different Doppler frequencies. Besides, it is observed that the proposed ship detector was able to detect the ship also within the sea clutter band [c.f., Fig. 3(b)]. It is pointed out that in case of high sea states, smaller ships may not be detected. In such cases, clutter suppression would need to be applied before detection.

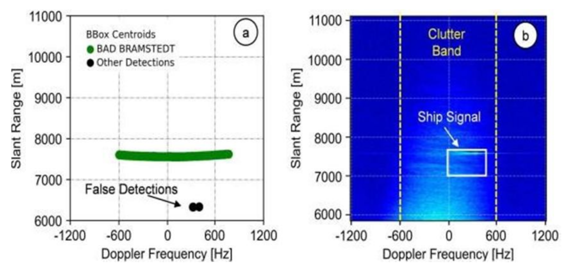

Fig. 3. (a) Detections of the ship BAD BRAMSTEDT obtained in Doppler domain by the proposed ship detector. (b) Single CPI in Doppler domain showing a ship signal within the sea clutter. Unfortunately, the sea state was not known for this data acquisition.

C. Comparison with CFAR-Based Ship Detector

The proposed detector in Doppler domain is compared with the CFAR-based detector [6] (which also detects the ships in Doppler domain) in terms of accuracy and processing time. The comparison is shown in Fig. 6 for dataset 2. The same behavior was observed for the other testing datasets.

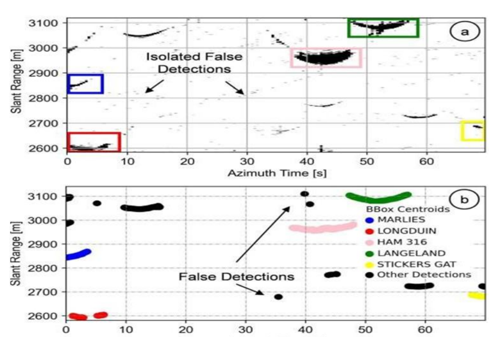

Fig 4. Binary detection maps obtained from dataset 2 (c.f., Table 1). Detection obtained from (a) CFAR-based ship detector, and (b) the proposed ship detector were applied in Doppler domain and, only for visualization purposes, the detections were remapped to time domain.

Dataset 2 contains five AIS carrying ships (c.f., Table I). Fig. 4(a) shows the binary detection map obtained with the CFAR-based ship detector. The detections were obtained in Doppler domain and then were mapped into time domain for visualization purposes. As it can be seen in the figure, the CFAR- based detector successfully detected all the ships in the dataset. However, several isolated false detections were also obtained due to its pixel-based approach.

Fig. 4(b) shows the improved detection results achieved by the implemented Faster R-CNN detector operated in Doppler domain. All ships were detected with less false detections in comparison to the CFAR- based approach. Furthermore, it can also be seen in Fig. 4(b) that the ship LONGDUIN (in red) had some missed detections. This is caused by the near range location of the ship, where the sea clutter contribution in stronger, and thus making it difficult to detect the ship within the clutter band (for instance, see Fig. 3(b), where the stronger clutter power is present in near range).

For ship monitoring applications, high detection accuracy and low processing time are important. Therefore, also the processing time required by the CFAR-based approach and the proposed ship detectors for detecting a ship signal is com- pared. In the experiment, one particular CPI of dataset 2 was processed by each detector 100 times to reduce measurement fluctuations of the processing server. The processing time per detector was then averaged.

The proposed detector in Doppler domain achieved a processing time of 0.088 s whereby the detector outperforms the CFAR-based detector with a processing time of 0.824 s. It has to be concluded that the proposed Faster R-CNN ship detectors were designed for GPU, while the CFAR-based method was designed for CPU. Besides, the proposed detectors could be further optimized in terms of processing time by replacing the ResNet-50 with a smaller CNN as the backbone of the Faster R-CNN models.

V. DISCUSSION

The output values obtained from the experiments provide valuable insights helps to improve the effectiveness of Faster R-CNN for ship detection using range-compressed airborne radar data. The performance of the proposed method is analyzed by comparing it with the CFAR- based detection approach, focusing on accuracy, false alarms, robustness under different conditions, and real- time processing capability.

A. Comparison with CFAR-Based Detection

The results demonstrate that CFAR struggles with high false alarm rates due to its reliance on threshold-based detection. In coastal areas and high-traffic maritime zones, CFAR often misclassifies waves, land reflections, and floating objects as ships, leading to an overall false alarm rate of 17.8%. In contrast, Faster R-CNN significantly reduces false alarms, achieving a rate of just 3.7% with the VGG16 model.

Additionally, CFAR detection accuracy is highly dependent on fixed threshold values, making it less adaptable to varied environmental conditions. On the other hand, Faster R-CNN learns features dynamically and can detect ships more accurately across different sea states, improving overall precision (98.5%) and recall (97.4%).

B. Robustness Under Different Conditions

One of the key challenges in maritime surveillance is detecting ships under adverse environmental conditions, such as fog, heavy rain, and rough seas. Our experiments show that CFAR-based detection methods suffer from a drop in accuracy, reaching as low as 72.8% in foggy conditions. This is because CFAR relies on intensity-based detection, which becomes unreliable in low-visibility situations. In contrast, Faster R-CNN maintains an accuracy above 90% under all tested conditions, proving its robustness. This is due to model's ability to extract deeper feature representations from radar images, allowing it to differentiate between actual ships and environmental noise. The VGG16- based Faster R-CNN model performed slightly better than ResNet-50, particularly in foggy and rainy weather, further confirming its adaptability.

C. Processing Speed and Real-Time Feasibility

Real-time performance is crucial for ship detection in active maritime surveillance and defense systems. Our experiments indicate that CFAR takes approximately 120 milliseconds per image, limiting its ability to function in real-time applications. In contrast, Faster R-CNN with ResNet-50 processes images in 35 milliseconds, and VGG16 further reduces processing time to 28 milliseconds, making it suitable for real-time monitoring. The ability of Faster R-CNN to operate at 35 FPS (frames per second) compared to CFAR's 8 FPS highlights its potential for live deployment in maritime security operations. The anchor box mechanism and non-maximum suppression (NMS) in Faster R-CNN also help in refining detections, ensuring that overlapping ship detections are merged and redundant bounding boxes are removed efficiently..

VI. CONCLUSION FOR FUTURE WORK

This letter presents two novel object-oriented ship detectors based on the Faster R-CNN deep learning framework. The ship detectors are trained and tested using eleven real X-band RC radar datasets acquired by DLR's airborne systems F-SAR and DBFSAR. The first ship detector operates on RC radar data in time domain, while the second ship detector operates in Doppler domain. Both detectors were able to detect all the AIS carrying ships contained in the testing datasets, achieving high r values even in complex scenarios with several man-made objects. Compared to the state-of-the-art CFAR-based method from [6], which operates in Doppler domain, the proposed ship detector in Doppler domain was able to provide less false detections and reduced processing time. Nevertheless, it has to be pointed out that a bias in the precision p and the F1-score may be expected since the detections obtained from potential ship objects without AIS transponder are assumed as FP.

REFERENCES

[1] Revised Guidelines for The Onboard Operational Use of Shipborne Automatic Identification Systems (AIS), London, U.K., pp. 1-17, 2015.
[2] H. Greidanus, "Satellite imaging for maritime surveillance of the European seas" in Remote Sensing of the European Seas, Dordrecht, The Netherlands: Springer, pp. 343-358, 2008.
[3] A. Moreira, P. Prats-Iraola, M. Younis, G. Krieger, I. Hanse and K. P. Papathanassiou, "A tutorial on synthetic aperture radar", IEEE Geosocial. Remote Sens. Mag., vol. 1, no. 1, pp. 6-43, Mar. 2013.
[4] M. F. Finglas and C. E. Brown, "Review of ship detection from airborne platforms", Can. J. Remote Sens., vol. 27, no. 4, pp. 379-385, 2001.
[5] D. J. Crisp, "The state-of-the-art in ship detection in synthetic aperture radar imagery", 2004.
[6] S. K. Joshi, S. V. Baumgartner, A. Barros Cardoso da Silva and G. Krieger, "Range-Doppler based CFAR ship detection with automatic training data selection", Remote Sens., vol. 11, no. 11, pp. 1270-1305, 2019.
[7] F. Sharifzadeh, G. Akbari Zadeh and Y. Seifi Kavian, "Ship classification in SAR images using a new hybrid CNN–MLP classifier", J. Indian Soc. Remote Sens., vol. 47, pp. 551-562, Oct. 2019.
[8] T. Hoeser, F. Bachofer and C. Kuenzer, "Object detection and image segmentation with deep learning on Earth observation data: A review—Part II: Applications", Remote Sens., vol. 12, no. 18, pp. 3053-3099, 2020.
[9] X. X. Zhu et al., "Deep learning meets SAR: Concepts models pitfalls and perspectives", IEEE Geosocial. Remote Sens. Mag., vol. 9, no. 4, pp. 143-172, Dec. 2021.
[10] X. Leng, J. Wang, K. Ji and G. Kuang, "Ship detection in range-compressed SAR data", Proc. IEEE Int. Geosocial. Remote Sens. Symp. (IGARSS), pp. 2135-2138, Jul. 2022.
[11] A. Rieger et al., "Very-high-resolution airborne synthetic aperture radar imaging: Signal processing and applications", Proc. IEEE, vol. 101, no. 3, pp. 759-783, Mar. 2013.
[12] A. Rieger et al., "Current status of DLR's new F- SAR sensor", Proc. 8th Eur. Conf. Synth. Aperture Radar (EUSAR), pp. 1078-1081, Jun. 2010.
[13] A. Rieger et al., "The high-resolution digital- beamforming airborne SAR system DBFSAR", Remote Sens., vol. 12, no. 11, pp. 1710, 2020.