

Literature Review on Ship Detection Methods using Satellite-borne Synthetic Aperture Radar for Maritime Surveillance

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Abstract—This paper, intends to survey major ship detection models and techniques based on conventional methods of modelling statistical data and also models based on deep Convolutional Neural Networks (CNNs) using satellite-borne Synthetic Aperture Radar (SAR) data. We aim to extract current research directions and limitations of existing models to gain insight understanding and suggestions from vast amount of research in ship detection using SAR. The literature review addresses key methods demonstrated by researchers for ship detections in SAR. Despite of rigorous research in this domain the application of organized knowledge is still being explored to demonstrate ship detection in SAR imagery field. Research papers and articles were gathered from standard publishers from last decade. The proceedings from significant publications in conference and transactions were included in this review.

Index Terms— Ship detection in SAR, Maritime Surveillance, Target detection, Satellite Imaging, Deep Learning, CNN.

I. INTRODUCTION

Human civilization is using the world's oceans from thousands of years for commercial transport, passenger ships, ferries-small and large, fishing vessels etc. The International Maritime Organization (IMO) mandated that all ships on international voyages above 300 gross tonnages must use Automatic identification system (AIS). Many countries have specified stricter rules, such as the United States (vessels above 65 feet) or the European Union (fishing vessels above 15 m) [1]. The IMO designed the AIS during 1990s, providing a complementary system to high-frequency radar. The aim is to provide safety and security to diverse maritime traffic necessary for functioning of increasingly globalized market economy and well-being of passengers and marine ecosystems. Hence, reliable communication has become an indispensable part of maritime transport. As per the report of The United Nations Conference on Trade and Development (UNCTAD) for the period 2023–2027, predicts sea trade to expand at an annual average of 2.1%. Also, the global maritime satellite communication market by 2025 is expected to grow at a compound annual growth rate (CAGR) of 8.9%. Hence, safety of navigation makes maritime surveillance a key research topic for military and civil institutions. Advances in Synthetic Aperture Radar over past decades have played a prominent role in maritime surveillance as per literature. Moreover, new generation of SAR sensors are playing a pivotal role by exploring high-resolution imaging at microwave

frequencies (L, C and X-bands) for maritime applications.

In context of review for ship detection, SAR data is characterized by parameter like frequency, viewing angle, radiometric resolution, geometric resolution, polarization, noise-equivalent sigma zero (NESZ). From the reviewed literature following points are evident for above characteristics: (a) for sea water, microwave penetration depth is negligible at most of SAR frequencies and hence sea reflection is due to surface spectral components. (b) Frequency and viewing angle determines surface wavelength of sea that contribute to backscattering of signal. (c) Uncertainty in measurement of target RCS due to speckle noise leads to data degradation. (d) Geometric resolution varies from less than few meters to few kilometers depending on acquisition geometry and pulse bandwidth. (e) SAR data has single, dual or quad polarization channels. (f) the thermal noise being expressed as NESZ (RCS per sq.m that would produce a received backscattered power equal to thermal noise power.).

TABLE I. MAIN SAR SATELLITE MISSIONS

SAR Satellites	Parameters					
	Launch Period	Frequency (GHz)	Polarization	Resolution (m)	Orbit Altitude (km)	Swath (km)
SEASAT	1978	1.27	HH	25	800	100
ERS 1 and 2	1991,95	5.30	VV	30	790	100
ENVISAT	2002	5.30	HH, VV	30	800	150-1000
TERRASAR-X	2005	9.65	Quad	1-20	514	5-100
ALOS/PalSAR	2006	1.27	Quad	10-150	691	70-350
TanDEM-X	2010	9.65	Single, dual, quad.	12	514	10-100
RISAT-1	2012	5.35	HH, HV, VH, VV, RH, RV	1	536	10-220
Sentinel-1	2014	5.405	Phase-preserving dual polarization	5	693	410
Gaofen-3	2016	5.4	Single, dual, quad	1	755	10-650
PAZ	2018	9.65	VV, HH, HV, VH	1	514	10-100
ASNARO-2	2018	9-9.3	HH / VV (selectable)	1-16	505	10-50
RISAT-2BR1	2019	9.59-10	-	1-8	576	5-10
EOS-04	2022	5.4	Single, dual, quad	1-50	529	10-240

The available literature has proposed various numerical and analytical solutions for detection, classification and tracking considering variety of datasets and customized software tools aiming to satisfy the requirements of accuracy, efficiency, computational complexity, speed, simplicity and generality. But broadly, the problem can be classified into two broad categories, viz; modelling of sea surface so as to properly describe it and development of electromagnetic methods to model interaction of scattered data from ship. The major techniques to describe scattering from a region of ship surface are reviewed in this paper and not those scattering model to describe sea surface. The problem thus is reduced to analytical description of scattering of electromagnetic fields from sea surface to detect ships in open seas or littoral areas. This leads us to an opportunity of retrieving remote information on electrical and geometrical properties at the sea and modeling their interaction with electromagnetic field.

II. LITERATURE SURVEY

Ship detection can be achieved using broadly two means viz; cooperative systems where ships themselves report about their position and identity and non-cooperative system where ships are not equipped with any communication device. For cooperative systems, commonly used techniques are Automatic Identification System (AIS), Long Range Identification and Tracking (LRIT) and Vessel Monitoring System (VMS) out of which only AIS is available continuously and globally. For non-cooperative systems some detection mechanism is used like cameras and radars. Synthetic Aperture Radar (SAR) is not reliant on solar illumination and is rather independent of weather conditions, therefore enabling frequent monitoring. In this paper, we intend to review

major contributions of researchers who published their work in cited and referred publications for Ship detection in non-cooperative category of SAR system that enables detection of ship/vessels not equipped with tracking systems on board.

The paper et al. [2] analyses polarization scattering differences between ship and sea with two parameter CFAR for ship detection. The detector proposed here also amplifies the ship depolarization effect by sliding window processing along with SCR enhancement. The authors in this paper have explored polarization characteristics of target using Sinclair matrix, second-order statistical characteristics coherency matrix and kennaugh matrix. The data used here is a quad-polarization RADARSAT-2 images with different beam modes. The Ships in image had complex distribution with lengths varying from 35 to 230 meters. Samples were selected from the image for SCR enhancement with sea state level-1 as per Beaufort scale.

Based on various window sizes used in the study from 3×3 to 21×21 , the authors observed that size of test window is more sensitive to small targets and hence small test window is more suitable for small target detection. This observation is based on variation of SCR parameter of varying size vessel targets. Further, it is observed that larger is the detector value and computation time for longer ship lengths.

The authors explored the relation between T matrix and kennaugh matrix to compare polarization features, SPAN, polarimetric whitening filter (PWF), B_0 (total scattered power from target's irregular, rough and nonconvex depolarizing components), HV with the proposed detector Λ_M for various ship lengths for SCR enhancement to detect target(s). They studied reflectivity for small ships (3 wooden) in four polarization channels. It is claimed that the proposed detector followed by window test enhanced small ship detection.

The authors compared this algorithm with classical CFAR algorithm based on K-distribution model, SPAN, PWF and polarimetric notch filter (GNF) methods with metric as quality factor. This metric is used as it considers both detection rate and false alarm rate. The paper demonstrates better detection ability for small ships on the basis of less no. of targets missed by way of enhancing the target SCR.

The work in paper et al. [3] extracts three features from radar echo to classify clutter and target with intention to achieve small target on sea surface. The distribution of radar sea clutter depends on variety of factors and parameters and hence quite difficult to make model of sea clutter that could match the actual real-time environment. Here the authors focused on small target classification using convex hull method by means of extracting radar echo features namely; Relative Average Amplitude, Relative Peak High of Doppler and Relative Vector Entropy of Doppler Amplitude. Following the differentiation, as the echo may also contain multiple targets, time doppler curve was used to classify these multi-targets as different targets produce different time-doppler curve.

The authors here claim to have demonstrated classification of clutter and multi-targets in radar echo considering signal clutter/noise ratio as a metric. However, the work does not specify the trial data set used to further validate the proposed algorithm.

The authors et al. [4] advocated the need of automated detection systems as human observation of SAR data is cumbersome and impractical. Here, it is pointed out that for a system to function as automated for detection of ship(s) the required resolution is of the order of 25m to 100m. The dataset used were PALSAR and RADARSAT-1. The authors proposed a system with 3 independently running modules with their outputs combining in successive fusion steps.

The first module uses Haar Wavelet for initial Ship detection due to suitability of edge detection, spatial locality and multi-resolution, as a prescreening method. Due to the orthogonality property of wavelet, the noise effect decorrelate and hence suppressed. Ship signals were observed in all the sub-bands as spot-like objects with respect to Horizontal, Vertical and Diagonal directions. However, sea-ice structures also caused Ship like features that increased false alarm.

In the second module, authors used two parameter detector. Assuming Gaussian distribution for the background the first two moments are measured alongside target intensity. Then significance value was compared with a threshold for valid target.

The third module performs image segmentation of land and water bodies by extracting distinctive features viz; Brightness, Gray value variance and Gray value structure and applying the supervised classification using maximum-a-posteriori classifier.

The authors here further argued on three issues, first the use of Haar Wavelet as its use may not be much fruitful for edge detection with more than 50m resolution as target itself might appear diluted. Second, the use of 3 concentric window adaptive-threshold detector to reduce constant false alarm rate. The window size isn't variable due to computational efficiency reasons and uncertainty of characterization of background distribution due to limited non-random selection of samples from the original data. As a result fluctuations were observed due to factors like sea-clutter and other non-stationary effects. Finally, after applying image segmentation leads

to over-segmentation of coastal regions and land surfaces. However, they observed the proposed method performs well in open water.

The authors et al. [5] proposed a system for surveillance of maritime activities using visible satellite image sequencing in day time for object detection, tracking and abnormal activity classification. The three step module is proposed here in which detection of object(s) is performed using morphological operations followed by application of machine learning method to filter out the false detections. The second step uses cam-shift method to track object movement. The third step analyzes the object trajectory by categorizing angles into four major behaviors viz; Stop, Wandering, Swapping and Gathering. The coordinates of the trajectory were used as a reference for designing these four detectors for behavior classification considering different time periods for motion of object. Further to enhance performance of abnormal detection decision tree classifier was applied as a machine training method.

The authors used Raspberry Pi3 platform to implement the proposed method limiting the accuracy due to limited processing power on embedded device giving recall object detection rate and recall detection anomaly to be 78% and recall tracking rate at 91%. The source of dataset used is not revealed in the paper.

The authors et al. [6] explore open-source tool SUMO (Search for Unidentified Maritime Objects) for Ship detection using SENTINEL-1 SAR data. Further, the algorithmic approach of marine object detection and elimination of negative false alarms is studied for SUMO. Certain attributes like length, width, heading direction etc. were measured for description and characterization of ship.

The SUMO algorithm may be divided into 3 steps for ease of understanding. First the landmask is used to remove land area from the loaded data by using global coastline vector files and seaward buffering. This step achieves differentiation between surface and sea level. Second, the K-distribution model is used for estimating background clutter characteristics. By computing and comparing the adaptive threshold, the target is considered detected if it was measured above the threshold in atleast one of polarization channels. Finally, the focus is on removing azimuth ambiguity which might not have been eliminated by landmask process and have bright pixels giving rise to false alarms. Further it computes the reliability value for each ship detected on basis of attributes and significance of ship(s).

The data has taken was in natural coordinates (range-azimuth) and georeferenced. The result section discusses about the attributes of detected target viz; location in terms of latitude and longitude, number of pixels which formed the ship, size in terms of length and width, heading direction and range. The SUMO algorithm gives user the flexibility of using semi-automatic mode to manually decide ship detection. In a nutshell, SUMO is basically a point detection approach based on pixel intensities and amplitude values of SAR that are higher in a given region hence eliminating range ambiguities without consideration of phase or polarization for improving detection.

Two datasets were selected for SUMO implementation: Hope Island and Jawaharlal Nehru Port of Bay of Bengal and Arabian Sea respectively.

Authors et al. [7], explore research approaches for ship detection based on both optical and SAR data. For optical data, authors discuss detection methods based on three categories viz; prior-based method (based on geographical information of port), edge-matching methods and methods based on local salient features. For SAR data, the paper discusses about detection methods that use segmentation algorithms to separate water and land. They observed that these methods to some extent solve ship detection issue but these approaches are strongly influenced by speckle noise. They used sea-land segmentation method to obtain sea and land region first. This was followed by extracting buffer region depending on coastline. This divided the problem into inshore and offshore ship detection. For offshore ship detection, Truncated Statistic Constant False Alarm Rate (TS-CFAR) method is used for multiple target situation. For inshore, a region-based saliency detection approach is used. Authors also explored many varieties of CFAR detector and advocated use of TS-CFAR due to its background clutter modelling capability and detection performance for high-target-density conditions. The proposed method was further compared with two classical CFAR methods: the two-parameter CFAR and the Automatic Censored-CFAR to demonstrate effective detection of different kinds of ship in the harbor. The experimental data set was a TerraSAR-X data, with a resolution of $1\text{ m} \times 1\text{ m}$ and a size of 277×403 pixels.

The authors et al. [8] proposed use of a texture feature named Image Uniformity Description Factor (IUDF), that extract uniformity information by analyzing gray value fluctuation in SAR data. This IUDF is used for ship detection by considering accuracy and processing time to test its usefulness. The authors explored information of uniformity with details like ocean background and man-made structures that were used to detect targets in SAR data. The algorithm proposed for using IUDF had two processing steps viz; fluctuation suppression and uniformity extraction.

For uniformity extraction the authors observed that when input data was constant, IUDF output is zero and area considered uniform and when irregularity raises, the IUDF also increases and hence patches of area considered non-uniform. Further, the gray values are higher in non-uniform patches for IUDF feature data and maintain a high value as compared to uniform patches. For processing time, mean and variance operators are used to satisfy faster time conditions, instead of complex operators. The authors pointed out that IUDF is not noise sensitive and do not advocate use of speckle filtering due to suppressing of fluctuations. The algorithm using IUDF first employs feature extraction to get image features. This is followed by gray level segmentation and water region extraction. The authors compare this algorithm with two algorithms viz; gray level segmentation without feature extraction and Gray level co-occurrence matrix (GLCM). The four statistics used for ship detection were; ships inside the port, ships outside the port, ships at the port and processing time. Further, authors found that IUDF and GLCM had similar performance for accuracy but IUDF based detection gave no undetected targets and less processing time but with higher false alarm ratio against GLCM. Gray level based segmentation method was outperformed by IUDF and GLCM for ship detection due to low contrast between target and background, however it had fastest processing time. The experimental data was an UAVSAR image of Half-moon Bay in California acquired by JPL with azimuth and range resolutions are 0.6m and 1.7m respectively. The image size was 3377×5501.

The authors et al. [9] propose a robust method of ship detection for complex background applied on ALOS-2 SAR data. This method comprises of three consecutive modules viz; land-sea segmentation, target ship detection and target discrimination. It uses a 250m water mask database to coarsely obtain land-sea segmentation. To further refine this segmentation, a multi-scale CFAR detector is proposed in this work based on generalized Gamma distribution (GrD). The use of multi-scale CFAR integrates both global and local information and hence has better computational performance as against pixel-based CFAR. Further, in order to get better clutter probability distribution parameter estimation the authors proposes to iteratively apply global-scale CFAR thresholding followed by large and small scale CFARs. The method of logarithmic cumulants (MoLC) is used for parameter estimation of GrD. The work comparatively studied SAR clutter models for fitment of PDFs for amplitude histogram viz; K-root distribution, Gamma distribution, Log-normal distribution and Weibull distribution to select GrD due to best fit. Finally, discrimination of non-ship targets is done using geometric shape and length-width ratio. To approximate a ship, the region for an ellipse with same variance as connected region is used since shape of ship is close to ellipse, called as Eigen-ellipse.

The authors et al. [10] argued that target(s) cannot be extracted by direct segmentation due to similarity of gray level for harbor and ship and that in the near shore areas. CFAR being a pixel-based detection method reduces detection rate and raised false positive alarm. Hence, they proposed a ship detection method based on the combination of feature-based and pixel-based method using SAR data in harbor. The authors utilized and combined advantages of both the methods viz; Faster R-CNN for target feature extraction and MSER (Maximally Stable External Region) for pixel-amplitude detection. The authors applied deep learning method to reduce contradiction between detection rate and false alarm rate by adopting MSER. In SAR data, ships are seen as stable external regions and hence used to remove false alarm. The proposed method can be divided into four steps viz; Firstly, R-CNN is used for feature extraction. Second, these extracted features are given to a region proposal network to produce set of rectangular object proposals. Third step is to form classification score by regression and further refine the bounding boxes. Finally, after having the final bounding boxes and classification score, bounding boxes with higher scores are marked as targets. With this approach and to avoid wrong detection, the threshold was increased to reduce false alarm rate. The results were compared with Faster R-CNN and it was found to be advantageous in both detection rate and false alarm rate. Dataset used were taken from RadarSat-2, TerraSAR-X and Sentinel-1 to consider diversified resolution and polarization.

Based on context information of SAR data, the paper et.al [11], proposes a multi-fusion neural network for ship detection. This method adopts high-resolution Region Proposal Network (RPN) and uses a target detection network with context information. In order to predict the bounding box for region proposal, the up-sampled deep layer and scale-down shallow layer is combined with middle layer to obtain feature map. This results in enhanced resolution of RPN spatially. Firstly, a pretrained ResNet101 was used with different scales for SAR images, anchors and other objects of different shapes. This model evaluation was based on precision rate, recall rate and F1 score. Secondly, for the target detection network, region proposal were mapped to multiple layers and method of ROIAlign is used to extract features. This was done to generate more precise ROIs. Finally, the context information is used at detection stage to enhance detection accuracy. As claimed in the work, this approach has improved both accuracy and speed. The authors have further analyzed the effect of scale-transfer module, ROIAlign attached to layers and context features. They observed that, by mapping candidate regions to high-precision feature maps improves detection. Also, by connecting transfer-scale module to different layers

had varying detection effects and connecting high-precision feature graph performed better as compared to low-precision feature graph for small target detection. In case of variation in context feature, small surrounding box improved the detection as compared to the method that did not use context feature. Hence, inclusion of context feature provides more information to model in terms of precision rate, recall rate and F1 score. However, with increase in surrounding box of context information decreases detection result. Finally, a comparison of proposed method with one-stage, two-stage detector of faster RCNN revealed improvement in recall rate and detection accuracy. As large context feature vectors are generated, speed is compromised as evident from results. The dataset used for the experiment were taken from Sentinel-1, RadarSat-2 and TerraSAR-X.

The authors et al. [12] argue that the use of CFAR based methods suffers from detection accuracy as they are based on effectiveness of feature extraction. They study YOLO model to propose YOLOv2 by means of batch normalization, multi-scale training and hierarchical classification for predicting target based on global information of SAR image. They used 19 convolutional layers and 5 maxpooling layers with a leaky rectified activation function. While training the network, final bounding box was accompanied by a confidence score that determined the probability of objects in the box. Three Sentinel-1 SAR satellite image database were used from three different high ship density regions which are; the strait of Gibraltar, the Bosphorus strait, and the coastal area around Guangzhou city. These datasets had low and high resolutions, with and without being de-speckled by Lee-Sigma filter but with thermal noise removal applied to all datasets. Method of transfer learning is used here to reduce network training time. The network was first trained on all 3 individual datasets after which the datasets were combined and re-trained to have new weights. The transfer learning added another layer to weights by still training the combined datasets. Finally, they had 5 sets of weight for testing at the end of network training. The results discussed in the paper reflected that network trained on combined three datasets had best accuracy although with large number of missed detections in unfiltered data as against filtered data that was further reduced by using a suitable threshold limit.

In this paper [13], the authors propose use of RasNet50 and Transfer Learning for better accuracy and improved speed by model training with less dataset. They proposed residual learning framework for ResNet instead of direct mapping since identity mapping learning is difficult. First 40 layers were used to extract features of SAR ship image to generate feature maps. Region proposal network was used to generate region of interest (ROI) that might contain targets. In order to fix the size, ROI pooling was done. Remaining layers of CNN are used for purpose of classification and bounding box regression. By this approach, authors intend to train a very deep network.

In the training stage, RasNet model was trained on open dataset PASCAL VOC 2007, by transfer learning. As the SAR ship dataset was divided for training and testing set, the training SAR ship dataset along with trained dataset by transfer learning achieved model training. Finally, the testing SAR ship dataset and model training are used to obtain SAR ship detection models that gave ship detection results. The authors compared the proposed approach with YOLOV2 and faster RCNN using average precision as a measure of evaluation on same dataset to achieve improvement in accuracy and training time. SAR ship dataset used here was obtained from sensors like Sentinel-1, RADARSAT-2 and Gaofen-3 with different polarization and resolutions. The tensorflow was used to train the model.

The authors et al. [14], proposed a new solution approach for maritime surveillance for case of Aegean Sea. The problem of maritime surveillance was explored in context to MTTSP-TW by motion of targets over a time period. Here the problem under consideration has a dynamic structure with the number and positions of targets changing continuously and coordinates for the pursuer and targets need to be redefined in each time frame. The methodology adopted as a solution is a simulated annealing algorithm developed by Kirkpatrick in 1983. Number of targets entering the system is generated randomly by Poisson distribution and time lapse between target arrival is also generated randomly by Exponential distribution. For Poisson distribution and Exponential distribution, Knuth's algorithm and Inverse transformation function were used for random number generation respectively. In addition, authors analyzed 5 parameters to proposed simulated annealing viz; no. of breaking solutions, cooling rate, no. of iterations at each temperature, initial and final temperature. Experimental tests were done to achieve parameter tuning in their work. With number of targets ranging from 20 to 100 the algorithm was tested in 50 different scenario. The authors produced two results based on two values of λ for Poisson distribution giving different processing time of 10% variation with increase in solution time as number of targets increased. The purpose of this approach is to find fastest route for the pursuer to visit all targets, neutralizing them and return to origin in given time frame. The pursuer used in the study was S-70-B2 Seahawk helicopter with velocity of 200 to 270 km/hr with payload. The targets velocity (20 to 60 km/hr) and angles were time independent.

Representative method of CNNs for single-stage method, the YOLOv3 framework is explored to improve the detection speed [15]. This framework consists of input, feature extraction network and multi-scale output. YOLO generates sub-blocks from an image and whenever center of object lay within certain sub-block, that sub-block detects the object. DarkNet53 was used as a feature extraction network. Here, batch normalization and leaky rectified linear activation were added to all convolutional layers of DarkNet53. After this, dimension clustering is used to predict the bounding box coordinates. Finally, this step was followed by predicting bounding boxes at 3 different scales utilizing the scales of feature map. To achieve this, the feature map was up-sampled by 2 from 2 pervious layers, i.e., Up-sampled feature map and feature map from low-level layer were merged to obtain a combined feature map.

The evaluation metric used here are precision-recall curve (PRC) and average precision (AP). The quantitative values of recall, precision and AP were calculated and compared with four other methods viz; YOLOv2, Faster R-CNN, Cascade R-CNN and RetinaNet by using the public SSDD dataset having 1160 images and 2456 ships in different environments. This dataset was split into three parts, training set, validation set and testing set with the ratio of 7:2:1. The quantitative comparison revealed good balance between accuracy and speed. The experiment was performed on TensorFlow framework and a pretrained ResNet-50 to initialize the feature extraction network.

The authors et.al [16], have an opinion that the pixel based detection method is difficult to extract effective features for SAR and hence detection accuracy falls in various situations and scales. They pointed out the use of CNN for ship detection and ship classification as this approach is more promising at various scales in SAR. This work involves classification of ship type after detecting ships by deep learning method. For machine learning based on CNN, training AIS dataset was prepared. The ship on SAR data was labelled using AIS signal. The SAR data was divided into pieces of 90×90 pixels. These pieces were labelled as Tanker, Cargo etc,. Here, they used two types of data products; original SAR images and Pseudo color images (obtained from the original SAR images with red and green channels and used to compare conventional method with machine learning).

This work can be divided into two experiments. First, identification of ship. The category of ships were Tanker, Cargo etc. Other category has speckle noise, drifting objects and blank. It also included pseudo color images. Second, is the classification in four categories viz; Cargo, Tanker, Tugboat and others. For both the experiments, accuracy and validation accuracy was calculated for number of Epochs. For ship detection these values were 100% and 95% for first experiment and 100% and 75% respectively for second experiment for ship classification.

The datasets were divided for training and testing in ratio of 8 : 2. For learning model, sequential CNN is used here, with convolutional filters of 3×3 size. The framework used is TensorFlow. The dataset used were SAR images in HV polarization of PALSAR2/ALOS2 having target length of upto 300m and having resolution of 100m/pixel in ScanSAR mode and 10m/pixel in StripSAR mode for identification and classification of ships respectively.

The paper et.al [17] analyzed both CFAR and CNN based detectors and pointed out that CFAR based detection methods in SAR data ignore local characteristics hence giving low detection in performance for complex background. Also they are slow with low precisions. Further, for CNN variants, it was pointed out that SSD detectors have low accuracy, faster R-CNN ignores multi-scale characteristics of SAR data, missing the lower-level features and RetinaNet does not perform well for small target detection. Hence, they proposed a Multi-scale Faster R-CNN where multi-scale features of ships are extracted to accumulate them into Region Proposal network (RPN). This in turn is used to generate candidate regions.

Multi-scale Faster R-CNN has three components, the backbone with the multi-scale network, RPN, classification and regression. A multi-scale sub-network architecture is proposed with bottom-up line, top-down line and horizontal connection. The bottom-up line uses ResNet and has many convolutional modules. The output of every module is used in top-down line. This reduces spatial dimension by $\frac{1}{2}$. For top-down line, spatial dimension is upsampled by 2 using close neighbors. This is then followed by merger of feature map using element-wise addition from bottom-up line and top-down line. Final feature map is generated from each layer by using 3×3 convolutional filter. This feature map is given as input to RPN. The feature maps of various scales are generated by multi-scale network are input of RPN head. RPN head generate the Anchors which are input to two full-connection layers, classification and regression layers. The probability of every anchor being an object or not is the output of classification layer. For the purpose of classification and regression RoIAlign is used here. The proposals generated after RoIAlign are inputs to full connection layers to achieve classification and regression.

The performance evaluation of the proposed method was compared with SSD, RetinaNet and Faster R-CNN, with improvement in the mean average precision as evaluation index. The Chinese Gaofen-3 images and 108

Sentinel-1 images are used for the analysis having 43,819 ship slices (each slice 256×256) containing 59,535 ship targets. The ship slices were selected randomly for training and validation set in 8 : 2 ratio.

The detection method based on eigensubspace projection (ESSP) is proposed in this paper [18]. A new observation matrix is generated from original SAR in the direction of azimuth with purpose to enhance its low rank. The phase space matrix of this new observation matrix replaces that of the original SAR. The autocorrelation matrix of this new observation matrix is further decomposed using Eigen Value Decomposition. Based on these eigen values eigen vectors form two parts that makes up the ship subspace and clutter subspace. As the size of phase space matrix is small as compared to SAR data, time complexity of the method is low. Lastly the original SAR is projected into ship subspace and ship data in this ship subspace are arranged to get detection results. The results reflect higher detection accuracy and fewer false alarms when compared with Superpixel-Level CFAR method and Robust Principal Component Analysis method.

Quality Factor, missed detection rate, false alarm rate, and time complexity were the evaluation metric used for comparison with other two methods. A public sample dataset was used named AIR-SARShip-1.0 with 31 images with different levels of sea-state taken from Gaofen-3 SAR satellite in single polarization. The experiment used SAR data both for nearshore and offshore, two each. The result reflected missed detections for offshore case due to strong sea clutter for complex sea state.

The incompatibility for SAR data and ImageNet was explored here, instead to designing deep learning networks for SAR ship detection [19]. It proposes a pretraining technique called optical ship detector (OSD) that aims to improve feature learning ability of ships for SAR which is based on large-scale aerial image dataset. This detector aims to transfer ship characteristics to SAR data by using large-scale aerial image dataset. With different imaging geometry for SAR and Optical image a pretraining technique called optical-SAR matching (OSM) is proposed here aiming to embed texture feature from optical to SAR data using Bridge Neural Network (BNN). These two pre-training methods were used to get OSD pre-training based SSD (OSD-SSD) and OSM pre-training based SSD (OSM-SSD). Further, they proposed to combine the detectors for using more data features by employing weighted boxes fusion technique (WBF). The experiment was carried out on three CNN modules to verify the performance of OSD-SSD, OSM-SSD and combination of two detectors. DOTA dataset was used for OSD pretraining, QXS-SAROPT used for OSM pre-training, and four SAR ship detection datasets used for OSD-SSD and OSM-SSD.

To evaluate the performance of proposed methods on one-stage and two-stage CNNs, three metrics were used viz; precision, call and F1 score. Comparison with different CNN-based ship detectors on the SSDD dataset revealed betterment in all three metrics. PyTorch 1.7 framework was used for this experiment.

The authors et.al [20] explore upon the effectivity of feature fusion methods to solve multi-scale object detection whereby the feature information for small targets is lost in deep features. Hence their approach is by fusing the feature information effectively in each feature map to justify multi-scale detection of ships. This work aims to improve accuracy of ship detection using YOLO algorithm. They proposed a bi-directional feature pyramid network to counter the large scale differences in SAR data and low detection accuracy for small targets. A coordinate attention mechanism is used to enhance feature extraction.

The YOLOv5 scales the input data adaptively and uses a genetic algorithm for adjusting the anchor frame to predict target location. This work proposed improved YOLOv5 object detection method and can be broadly divided into three parts viz; feature extraction network, feature pyramid network and detection network. Since low-level features have more spatial information and high-level features have more semantic information, the aim is to add spatial and semantic information to improve detection accuracy at same speed as of YOLOv5. Attention mechanism is used to inform the model of content available and identification of regions that need attention. Hence a coordinate attention mechanism is designed in the study with negligible computational burden. The researchers claim that this attention mechanism improved efficiency of information flow in neural network by paying attention to valid coordinates and neglecting invalid coordinates. For feature extraction network Bi-directional FPN is used. With this a path from high to low resolution is added thus improving the efficiency of feature fusion process. It also removes the nodes that receive input from single node, making it efficient and lightweight. Further in order that network should learn to balance ratio of low and high level features during feature fusion, skip connections are added from input layer to output layer. This makes feature fusion becoming adequate as model becomes deep. The proposed network has loss function made up by addition of classification, regression and confidence loss.

The dataset used for the study are SSDD and HRSID. SSDD has 1160 images and 2456 targets, whereas HRSID has 5604 SAR slices and 16591 targets. A stochastic gradient descent optimizer is used here with learning rate of 0.01 initially and 0.9 momentum. The batch size for the experiment is 4 and training epoch is 300. To evaluate the detection performance, precision, recall and mean average precision were used as performance metric. Also

frame per second metric is used to evaluate detection speed of proposed network. Results were compared with YOLOv5 as benchmark using different backbone and different feature fusion network. First with DarkNet53 as backbone and FPN as feature fusion network, second with DarkNet53 as backbone with Attention module and FPN as feature fusion network, third DarkNet53 as backbone and modified BIFPN as feature fusion network. Finally, the proposed DarkNet53 as backbone with Attention module and modified BIFPN as feature fusion network. The result comparison revealed improvement in precision, frame per second and mean average precision.

III. CONCLUSIONS

In this paper, we attempt to survey ship detection from SAR data for maritime surveillance as it is helpful in identification of non-collaborative ships. The approach is broadly divided into two categories i.e., traditional methods and deep-learning-based methods. Further the traditional methods broadly fall under three approaches viz; first based on modelling mathematically the characteristics of statistical distribution of data, second matrix decomposition of original SAR data into low-rank and sparse matrix that reflects clutter and target respectively and third one is based on polarization properties in which the difference in scattering mechanism is explored to differentiate target and clutter. We observed that ship detection is broadly a two-step procedure; prescreening detection phase followed by discrimination phase for lowering false alarm rate due to ambiguities in range and azimuth. For traditional methods, CFAR as a metric is prominently used in the reviewed literature for detection phase and precise description of sea clutter amplitude pdf is critical for reliable CFAR performance. This makes traditional methods specific to local scenario hence may not be robust for generalization as is evident from high false alarms and missed detections for complex backgrounds. Moreover, applying pre-processing techniques also contributes to poor generality and low efficiency. Recently, CNNs have gained popularity in ship detection for single-stage and two-stage representative methods. The single-stage detection methods are based on regression to locate target position by predicting the category confidence. Whereas, the two-stage model has a region proposal network structure, generating boxes having potential targets. This is followed by correcting bounding boxes to determine target category. This ability of CNN of self-learning for automatic feature extraction have made them a natural choice for detection problems. This eliminates the need of predefined distributions and mathematical modelling. It seems that with the development in deep learning, target detection based on this has surpassed traditional methods. It is further observed in general that two-stage detectors are more accurate as compared to single-stage but affects the real-time performance.

REFERENCES

- [1] Wolsing, K.; Roepert, L.; Bauer, J.; Wehrle, K. "Anomaly Detection in Maritime AIS Tracks: A Review of Recent Approaches". *J. Mar. Sci. Eng.* 2022, 10, 112. <https://doi.org/10.3390/jmse10010112>.
- [2] Genwang Liu, Xi Zhang and Junmin Meng, "A Small Ship Target Detection Method Based on Polarimetric SAR", *J. Remote Sensing* 2019,11,2938, doi: 10.3390/rs11242938.
- [3] Lianqing Yu, Yun Li, Ning Wang, Jin Jiang, "Small Target Of Sea Surface Detection Algorithm Research Based on Feature Classification", *IEEE 2014 12th International Conference on Signal Processing (ICSP)*, DOI: 10.1109/ICOSP.2014.7015353.
- [4] Meyer, Franz J. and Stefan Hinz. "Automatic Ship Detection in Space-borne SAR Images." *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences* 38 (2009).
- [5] Chin-Shyurng Fahn, Jer Ling, Ming-Yuan Yeh, Po-Yen Huang, and Meng-Luen Wu, "Abnormal Maritime Activity Detection in Satellite Image Sequences Using Trajectory Features", *International Journal of Future Computer and Communication*, Vol. 8, No. 1, March 2019, doi: 10.18178/ijfcc.2019.8.1.535.
- [6] Aayush Grover, Shashi Kumar, Anil Kumar, "SHIP DETECTION USING SENTINEL-1 SAR DATA", *SPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, Volume IV-5, 2018, <https://doi.org/10.5194/isprs-annals-IV-5-317-2018>.
- [7] Liang Zhai, Yu Li, Yi Su, "Segmentation-based Ship Detection in Harbor for SAR Images", *IEEE 2016 CIE International Conference on Radar (RADAR)*, DOI: 10.1109/RADAR.2016.8059479.
- [8] WeiKe Li, Bin Zou and Lamei Zhang, "SHIP DETECTION IN A LARGE SCENE SAR IMAGE USING IMAGE UNIFORMITY DESCRIPTION FACTOR", *IEEE 2017 SAR in Big Data Era: Models, Methods and Applications*, DOI: 10.1109/BIGSAR.2017.8124933.
- [9] Wei Ao and Feng Xu, "Robust Ship Detection in SAR Images from Complex Background", *2018 IEEE International Conference on Computational Electromagnetics (ICCEM)*, DOI: 10.1109/COMP.2018.8496647.
- [10] Rufe Wang, Fanyun Xu, Jifang Pei, Chenwei Wang, Yulin Huang, Jianyu Yang, and Junjie Wu, "AN IMPROVED FASTER R-CNN BASED ON MSER DECISION CRITERION FOR SAR IMAGE SHIP DETECTION IN HARBOR", *2019 IEEE International Geoscience and Remote Sensing Symposium*, DOI: 10.1109/IGARSS.2019.8898078.

- [11] Yunchuan Gui, Xiuhe Li, Lei Xue, Jijie Lv, “A scale transfer convolution network for small ship detection in SAR Images”, 2019 IEEE 8th Joint International Information Technology and Artificial Intelligence Conference, DOI: 10.1109/ITAIC.2019.8785805.
- [12] Hamza Mehdi Khan and Cai Yunze, “Ship Detection In SAR Image using YOLOv2”, 2018 37th Chinese Control Conference (CCC), DOI: 10.23919/ChiCC.2018.8482863.
- [13] Yong Li, Zegang Ding, Chi Zhang, Yan Wang and Jing Chen, “SAR Ship Detection Based on Resnet and Transfer Learning”, IEEE 2019, IGARSS, DOI: 10.1109/IGARSS.2019.8900290.
- [14] Selçuk K. İşleyen, Ukbe Uçar and Figen Balo, “A New Solution Approach for Maritime Surveillance Operation: The Case of Aegean Sea”, Research Article, Hindawi, Article ID 8575219, <https://doi.org/10.1155/2019/8575219>
- [15] Mingming Zhu, Guoping Hu, Hao Zhou, Chunguang Lu, Yule Zhang, Shijie Yue and Yao Li, “Rapid Ship Detection in SAR Images Based on YOLOv3”, IEEE 2020 5th International Conference on Communication, Image and Signal Processing (CCISP), DOI: 10.1109/CCISP51026.2020.9273476.
- [16] Takashi Sonoke and Hirohide Demura, “Identification and Classification of Ships SAR Data Using Machine Learning”, 2020 The Japan Society for Aeronautical and Space Sciences, Vol. 18, No. 6, pp. 391-397, 2020, DOI: 10.2322/tastj.18.391.
- [17] Yiqing Zhou, “Automatic ship detection in SAR Image based on Multi-scale Faster R-CNN”, 2020 4th International Workshop on Advanced Algorithms and Control Engineering (IWAACE 2020), Journal of Physics: Conference Series-1550 042006.
- [18] Shu, G., Chang, J., Lu, J. Wang, Q., Li, N. “A Novel Method for SAR Ship Detection Based on Eigensubspace Projection”, Remote Sens. 2022, 14, 3441. <https://doi.org/10.3390/rs14143441>.
- [19] Wei Bao, Meiyu Huang, Yaqin Zhang, Yao Xu, Xuejiao Liu, Xueshuang Xiang, “Boosting Ship Detection in SAR Images with Complementary Pretraining Techniques”, IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing (Volume:14), 2021, doi: 10.1109/JSTARS.2021.3109002.
- [20] Chushi Yu and Yoan Shin, “SAR Ship detection based on improved YOLOv5 and BiFPN”, Elsevier, ICT Express 2023, <https://doi.org/10.1016/j.icte.2023.03.009>.