A novel Ship detection method from SAR image with reduced false alarm

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Abstract. Many research works using deep learning techniques for automatic ship detection from SAR images have good detection accuracy. But the main problem in these methods is false detection, mostly due to speckle presence. Therefore, we propose a new deep learning model with a novel preprocessing stage to address this problem. We are introducing a deep learning architecture to detect and localize ships in the SAR image. First, generate a three-channel image from gray-scale SAR image. Then, this image is used to train the model to predict the ship’s position in the SAR image. We experimented on the public SAR ship detection dataset (SSDD) and Dataset of Ship Detection for Deep Learning under Complex Backgrounds (SDCD) to validate the proposed method’s feasibility. We used python 3.5 for coding with the Keras framework in the NVIDIA Tesla K80 GPU hardware platform. The experimental results indicated that our proposed method’s ship detection accuracy has increased with reduced false detection percentage.

1. Introduction
Ship detection from aerial SAR image is more challenging than from normal images (nonaerial RGB images) because the objects in normal images are mostly up-down due to the gravitational force of Earth, but in SAR, objects are arbitrarily oriented and also the presence of speckle noise in SAR makes it more complex [1], [2]. Synthetic aperture radar (SAR) is the most commonly used active sensor imaging operation under the Earth observation area. Its self-illuminating ability overcomes the problem of extreme weather conditions. In the marine field, SAR comes up with many services like sea monitoring, marine pollution control, traffic control, fishery management, etc [3]. Here, automatic SAR ship detection is essential for maritime rescue and pollution control.

There are generally two types of object detection methods in deep learning (DL): (a) two stage region proposal based methods and (b) one stage regression based methods. In two stage methods, region proposals are estimated in the first stage and classification is done in the second stage. Region-convolution neural network [4] is the first two stage method in deep learning. Li at el [3] improved the standard R-CNN and used for SAR ship detection. One stage detectors process the image only once for the prediction of object location and class, the time required is less when compared to two stage detectors. YOLO (you only look once) [5] is the first one stage detector. YOLOv2 [6] and YOLOv3 [7] were introduced to improve the detection accuracy.
Real time ship detection methods with good detection accuracy based on Yolo was proposed by Chang et al. [8]. To eliminate the struggle of detecting small targets and densely clustered ships, Zhao et al. [9] introduced coupled convolution neural network (CCNN) for detection of ships. Zhang et al. [10] developed SAR ship detection based on depthwise Separable CNN. Image preprocessing techniques before training the deep learning model has improved the performance of SAR image classification [11]. ShipDeNet-20 [12] is a light weight SAR ship detector, which uses only 20 convolutional layers with less than 1 MB model size.

In most of all the methods using deep learning techniques, the images are directly given to model for the prediction. So, in this work we are presenting a novel algorithm to detect and localize ship from SAR image. The proposed system reduces the false prediction percentage and improves detection accuracy.

2. Sar Ship Dataset

In this work, we use two datasets. The first one is the SAR ship detection dataset (SSDD) [13]. SSDD is a public dataset and benchmark for researches to evaluate their approaches. In this dataset, 1160 images are coming from three different sensors, with 2456 ships with 2.03 ships in one image on average. These images are annotated by a popular open-source software called ‘labelImg’. SAR images in this dataset possess different satellite sensors, multiple resolutions, various polarization modes, abundant ship sizes, and different scenes to verify the robustness of techniques.

The second one is the SAR Dataset of Ship Detection for Deep Learning under Complex Backgrounds (SDCD) [14]. It consists of 43,819 images with 256 pixels in both azimuth and range. As the name indicates, this dataset is more challenging with complex background. They are collected from Gaofen-3 and Sentinel-1 sensor data.

| Table 1. Detailed information of SSDD and SDCD dataset |
| --- | --- | --- |
| Descriptions | SSDD | SDCD |
| Sensors | Sentinel-1, RadarSat-2, TerraSAR-X | Gaofen-3, Sentinel-1 |
| Resolution | 1m-10m | 3m-22m |
| No. of Images | 1,160 | 43,819 |
| No. of Ships | 2,456 | 59,665 |
| Average size (pixel × pixel) | 500×500 | 256×256 |

Table 1 shows the details descriptions of the two datasets. So, total there are 44,979 images with 62,121 ships.

3. Methodology

Figure 1. Approach overview, raw sar image is preprocessed to generate 3 channelled image, this is given to deep learning model and predicts the ship’s localization
In the deep learning techniques, how the data is fed into the deep learning model during training stage is important. Modification of raw data into meaningful is essential for accuracy improvements and reduction of false prediction. The overview of our work is shown in fig 1. The work-flow is illustrated by using the detection of ships in a SAR image.

There are two stages; in the initial stage, the SAR image is pre-processed to generate a three-channel image with different data in each channel using image processing techniques and lee filter. By adding this preprocessing stage, we could reduce false prediction. Then the deep learning model, designed mostly using depthwise separable CNN is trained using this generated images. And, this trained model is used to predict the position of all ships in the SAR data.

3.1. Three channelled data generation

The SAR image is a grayscale 2D image. In this pre-processing stage, a modified three-channel image (channels: RA, RB and RC) is generated by using the SAR data as follows:

- first channel (RA): same original grayscale 2D SAR
- second channel (RB): Lee filtered 2D value of SAR
- third channel (RC): Image inversion of Lee filtered image (255 − RB)

![Figure 2. Pre-processing stage](image)

Fig 2 shows this image processing operation graphically. The presence of speckle-noise reduces the quality of the SAR image. In the ship detection applications, the contribution of speckle for false prediction is very high. J.S. Lee’s filter [15] is well-known for despeckling and enhancing SAR images. In this method, minimum mean square error (MMSE) technique is used for despeckling.

Here, RB is the filtered result image channel,

\[ R_B = \bar{I}_B + k(I_B - \bar{I}_B) \]  \hspace{1cm} (1)

where \( I_B \) is the noise free image and \( \bar{I}_B \) is the mean of \( I_B \), \( k \) is the weighting function and is expressed as:

\[ k = 1 - \frac{C_v}{C_i} \]  \hspace{1cm} (2)

\( C_i \) is the coefficient of variance of noise-free image and \( C_v \) is the coefficient of variance of speckled image.

The inversion of data is done using:

\[ R_C = 255 - R_B \]  \hspace{1cm} (3)

Fig 3 shows the visualization of the results of some of the images from various datasets after the pre-processing. Although this preprocessed image is showing not much different than raw SAR, the improvements we are getting in reducing false detection is excellent.
3.2. Architecture

Figure 4 shows the network architecture of the SAR ship detection system. The deep learning model is designed with Conventional CNNs at the initial and final stage for maximum feature extraction and good output result, also depth-wise separable CNNs are used in all other stages, this is to make the model light weight. The model is designed with depth-wise separable CNN in such a way without affecting the detection accuracy. Our system is based on single stage object detection system, here the image is divided into (20×20) grids. Each grid is responsible to predict ships inside it. For each grid, predicts 5 values: (x,y,w,h,score), score is the probability of detected ship or confidence of detection. (x,y) values are the midpoint value of the bounding box with respect to its grid and (w,d) are the width and height of the bounding box. So, the shape of the output is (20×20×5).

Figure 3. Visualization of pre-processed images in 3 channels separate, (a): image from SSDD dataset, (b) and (c): image from SDCD dataset
4. Experiments and Results

Our deep learning model is trained and evaluated on a 64 bits Windows computer, with Intel® Xeon® CPU @ 2.60GHz ×16 and NVIDIA Tesla K80 GPU with 11G memory. Programs are written using python based deep learning library - keras with tensorflow as backend. Input image size is fixed as 160×160. The model is trained for 150 epochs using 31,486 train images keeping 13,493 images as validation data. We used Adam optimizer with learning rate: 0.00005, beta_1: 0.9, beta_2: 0.999, and decay: 0.0005. The best model is saved by using the ‘callback’ feature of model.fit_generator of keras on monitoring validation loss (min) while training. On 60th epoch, got the best model with least validation loss (58). Figure 5 shows the loss curves of the training set and the validation set.

![Loss curves of the training set and the validation set](image)

Table 2. The mean average precision (AP) of different SAR ship methods

| methods                        | mAP  |
|--------------------------------|------|
| YOLO v2                        | 66.91% |
| YOLO v3 tiny                   | 54.15% |
| YOLO v3                        | 80.35% |
| Our model (without preprocessing stage) | 84.76% |
| Our model (with preprocessing stage) | 88.26% |

Figure 6 shows the ship detection results with and without preprocessing stage. From this figure, it is understood that preprocessing stage decreases the false prediction rate. Table 2 shows the mean Average Precision of different methods, here our system with preprocessing stage has the highest mAP of 88.26%. Figure 7 shows the Precision Recall curves of different object detectors. So, our proposed model with preprocessing stage has highest ship detection accuracy with least false prediction.

5. Conclusion

Ship detection from the SAR image with a preprocessing stage is implemented. From the analysis and comparison of the result, our proposed method has got the best performance. The pre-processing method improves the detection accuracy by reducing the false prediction rate. The information from the generated multi-channel image enhances performance without much
Figure 6. Ship detection results: (a),(c),(e) - output without preprocessed image (raw sar image as input) and (b),(d),(f) - output with preprocessing; green box-true detection and red box-false detection.

Figure 7. Precision Recall curves of different object detectors affecting the detection speed. By adding multi scale and anchor box based detection techniques, detection accuracy can be increased further. The proposed model is lightweight and can be transplanted on digital signal processors.
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