



Novel Approach for Ship Detection in Medium - Resolution SAR Images via VGGnet

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Abstract: Due to its noticeable advantages of working, Synthetic aperture radar (SAR), has become a significant device for many remote sensing applications. The Existing methods for SAR images perform well under some constraints. In this work, ship detection method based on CNN (Convolutional Neural Network) called VGGnet (Visual Geometry Group) is proposed. To improve the performance of ship detection by adopting multi-level features constructed by the convolution layers, which fits ships the different sizes of ships. The Simulation result of the proposed method is comparable with the existing method.

Keywords : Synthetic aperture radar (SAR), Convolutional Neural Network(CNN), Visual Geometry Group(VGGnet), SAR ship detection dataset (SSDD), etc.,

I INTRODUCTION

The fundamental component in the scientific field of global observation, Object detection, and ship detection, has made exceptional progress in recent years by means of adopting deep learning algorithms. Ship detection in high-resolution optical satellite imagery is a modern field at KSAT. Convolutional neural networks (CNNs) are the quintessential deep learning models, the main cause of the tremendous progress, and can be adapted to fit various problems. When a CNN is trained on appropriate training data, it has proved to perform better than traditional algorithms in a variety of computer vision and image analysis problems. Knowledge about the machine learning architecture and how it respond to different data is a necessity, and allows the opportunity of analyzing possible sources of errors.. One possible challenge is detecting the cause for false alarms. This risk can be mitigated by using a large amount of precise training data for optimization. The CNN can then learn to ignore these false alarms. In this work, ship detection method based on CNN (Convolutional Neural Network) called VGGnet (Visual Geometry Group) is proposed. The results of the proposed method is comparable with the existing method.

II RELATED WORK

Yinghua Wang presented high-resolution synthetic aperture radar (SAR) images for detecting ships. The scheme consists of two stages: detection and discrimination. Almost all the ship targets can be detected from the test image under an appropriate false alarm rate. Meanwhile, a great number of false detections occur.

G.Margarit presented a ship monitoring system conceived to reach the previous objective, SIMONS (Ship Monitoring with SAR). It is expected that data with improved resolution and polarimetric capabilities would permit to increase classification confidence, to detect a wide range of ships.

Zou et al (2020) developed an improved SSD algorithm based on MobilenetV2 convolutional neural network for ship image target detection and identification. ZHANG et al (2019) experimented a high-speed SAR ship detection approach by improved you only look once version 3 (YOLOv3). They experimented on a public SAR ship detection dataset (SSDD) which has been used by many other scholars. Tao et al (2018) implemented a new paradigm for synthetic aperture radar (SAR) observation of ship targets at sea.

ZHANG et al (2019) experimented a high-speed SAR ship detection approach by improved you only look once version 3 (YOLOv3). They experimented on a public SAR ship detection dataset (SSDD) which has been used by many other scholars.

III PROPOSED WORK

This project adopts the idea of deep networks and presents a fast VGG-based convolutional neural network (VGG-CNN) method to detect ships from high-resolution remote sensing imagery. This section is divided into three stages. Firstly, the deep learning is described with its applications. Second stage is the CNN which is the best example of deep learning and the third stage is the VGGnet of CNN which is the proposed model of ship detection.

A. VGG Model

In order to perform the Imagenet Large Scale Visual Recognition Challenge (ILSVRC) is demonstrated by VGGNet in 2014. It scored foremost place on the image localization task and next place on the image classification task. Localization specifies the position of certain objects in the image, described by a bounding box. Classification distinguishes what the object in the image is. This predicts a category label, such as “cat” or “bookcase”. ImageNet is a huge database of images for academic researchers.

While giving a test image the neural network produces an output which provides probability distributions for that image. This evaluates the probability value rise in the middle of 0 and 1 for each of the listed 1000 categories, finally it chooses the category which has the top most probability rate. If the certainty of the neural network regards prediction, then its top choice has a high probability, such as 77.78% for the book case.

In the ImageNet classification challenge you are to predict the right category, within the 5 chances that is why the demo app shows the 5 highest probabilities for computing. As the network also thinks the image could have been a library, bookshop, or comic book — but the probabilities indicate that it isn't as confident about those choices. Among the top performing CNN models, VGG is remarkable for its simplicity. Let's take a look at its architecture.

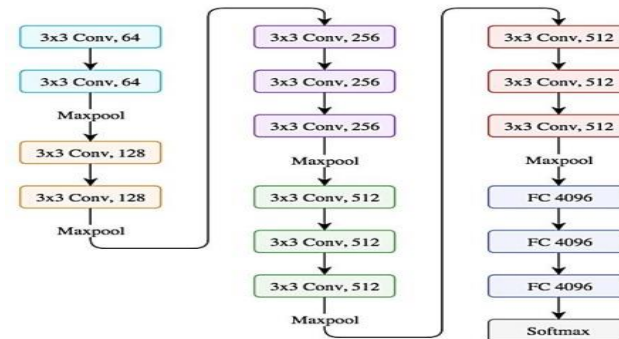


Fig.1 VGG architecture

VGG16 layer neural net, not enumerating the maxpool layers and the softmax at the end. In this architecture stacked convolution + pooling layers succeeded by fully connected ANN. A few observations about the architecture: It only uses 3x3 convolutions throughout the network. Note that three stacked 3x3 convolutions have the receptive field of a single 7x7 one. Hence 5x5 convolution results from two stacked 3x3 convolutions of visualization.

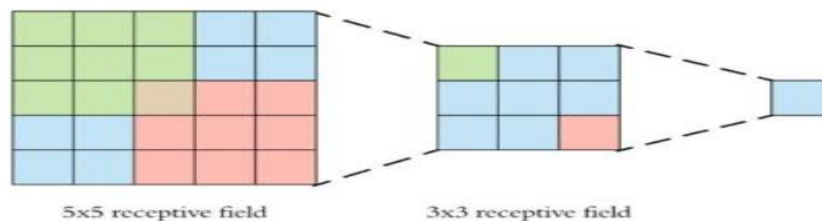


Fig.2 Two stacked 3x3 convolutions visualization

Another advantage of stacking two convolutions instead of one is given by two relu operations, and it produces higher non-linearity gives higher power to the model. The sum of filters enlarge as we go deeper into the network. Since we do pooling, the spatial size of the feature maps decreases, but the depth of the volumes rise as we use increased number of filters.

VGG is a very fundamental CNN model. It's the first one that comes to mind if you need to use an off-the-shelf model for a particular task. There are much more complicated models which perform better, for example The winner of 2015 ImageNet challenge was Microsoft's ResNet model with error rate of 3.6%, the model composed 152 layers!

IV IMPLEMENTATION RESULTS

In order to verify the effectiveness of the proposed method are carried out by the extensive experiments. First, images with pixels containing ships, seawater, islands and without ships are prepared to verify the performance of the proposed ship candidate-extraction method. We tested our method on taking the ship and no ship images at different times and locations and containing coastal landscapes. The public SAR Ship Detection Dataset (SSDD) is used in this work. The SSDD includes SAR images collected from Radarsat-2, TerraSar-x, and Sentinel-1 with resolutions ranging from 1 to 15 m and polarimetric modes of HH, HV, VV, and VH. The details about SAR images are listed in table 1.

TABLE I DATA DESCRIPTION

Sensors	Resolution	Size(pixel)
Sentinel-1	20m	1024x1024
RadarSat-2	1-100m	8192x8192
TerraSAR-X	10m	8891x8676

In this work, accuracy is widely used to quantitatively evaluate the ship detection performance.

$$\text{Accuracy} = \frac{TP+TN}{TP+FP+FN+TN}$$

Herein, TP, FN, and FP denote true positive, false negative, and false positive, respectively. The accuracy for the input images is presented in Table 4.2.

TABLE II: THE ACCURACY OF THE PROPOSED ALGORITHM FOR VARIOUS DATA SET

Name of the Image	Accuracy (in %)
Image1	93.5
Image2	94.2
Image3	93.6
Image4	94.1
Image5	92.3
Image6	90.5
Image7	93.7
Image8	94.4
Image9	95.1
Image10	93.5
Image11	91.8
Image12	92.7
Image13	90.2
Image14	92.1
Image15	92.4

The simulation results of ship detection are given below

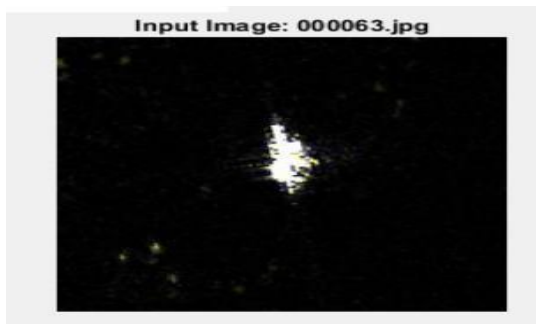


Fig.3 Input image

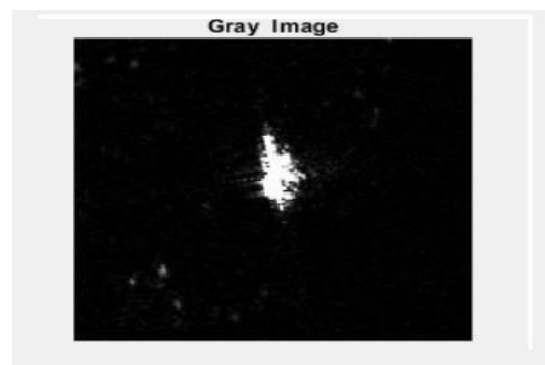


Fig.4 Gray image

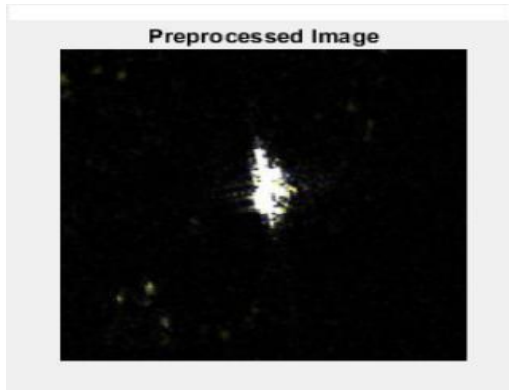


Fig.5 Preprocessed Image

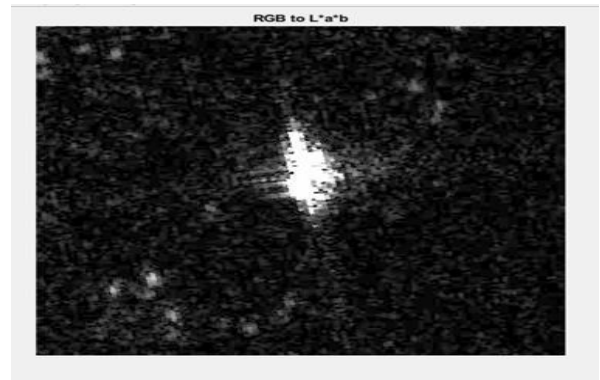


Fig.6 RGB to L*a*b

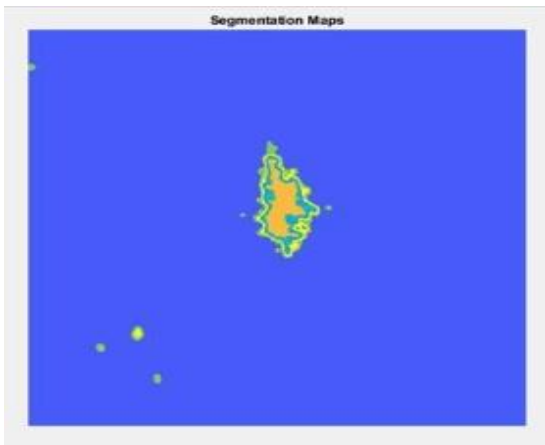


Fig.7 Segmentation maps

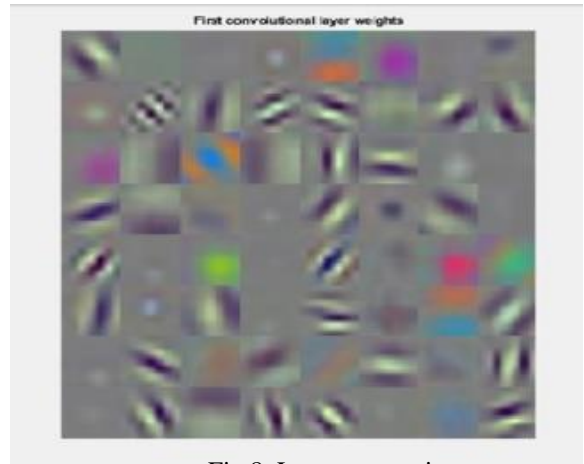


Fig.8 Layer processing



Fig.9 Classification result



Fig.10 Classification result

V ACCURACY COMPARISON

The accuracy of the proposed method is compared with the existing method and is illustrated in Table

TABLE III: PERFORMANCE COMPARISON OF THE PROPOSED METHOD WITH THE EXISTING METHOD

S.No	Method	Average Accuracy (in percentage)
1	CNN	89
2	RNet	92
3	Proposed VGGNet	92.94

From the table 4.2, it is observed that the proposed method provides better average accuracy than the existing methods.

VI CONCLUSION

This project proposed a multitask learning framework for ship detection in multi resolution SAR images. To explore more effective feature extractors, a task-specific designed backbone network is developed inspired by the VGG-Nets. The simulation results prove that the proposed network is powerful to extract discriminative representations for effective SAR ship classification. The recognition performance is improved by combining the triplet similarity constraint combined with the softmax classification error penalty forming the multitask learning prototype, which can achieve good classification performance by pulling the deep representations coming from the same class closer to each other and pushing those of different classes far apart in the learned embedding space. To improve the generalization performance of triplet CNNs in the DML, the Fisher regularization term is imposed on the deep embeddings to take full advantage of the triplets in a training batch. Hence, the global information of the pairwise distances of the deep embedding is fully mined and more robust models learned are obtained.

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