URSI GASS 2020, Rome, Italy, 29 August - 5 September 2020

A Residual Pyramid Network Considering Scattering Information for Aircraft Detection in SAR Imagery

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Abstract

Target detection and recognition play an important role in SAR field. However, target in SAR image has special features, such as diversity and variability, which always degrades the performance of algorithm. In this paper, a novel algorithm is proposed for aircraft detection based on Scattering Information Enhancement (SIE) and Feature Pyramid Network (FPN). Strong Scattering Point (SSP) is selected as the scattering information enhancement basis for its scale invariance and affine invariance properties. The SIE is composed of SSP and its corresponding scattering region distribution model, which is extracted by Harris-Laplace detector and Gaussian Mixture Model (GMM). Specially, Density-Based Spatial Clustering of Applications with Noise (DBSCAN) is introduced to cope with sensitivity of GMM for the initial clusters. Then, the FPN which combines the high-resolution information of the shallow features with the high-semantic information of the deep features is applied to improve detection performance for small targets. In addition, residual blocks are introduced into the network to avoid the gradient disappearance in the process of deep network training. Experiments conducted on the GF-3 and TerraSAR-X datasets demonstrate the superiority and robustness of the proposed method.

Keywords—Synthetic Aperture Radar, Aircraft Detection, Scattering Information, Gaussian Mixture Model, Feature Pyramid Network

1 Introduction

Synthetic Aperture Radar (SAR) is an active microwave sensor which can operate in all-weather, day-and-night. Therefore, SAR is particularly suitable for target interpretation [1,2]. Aircraft as an important target, it is of great significance to detect this kind of targets precisely in high-resolution SAR images.

Plenty of researches have been done with quantities of achievements. The existing aircraft interpretation methods in SAR images can be mainly divided into two categories: based on traditional scattering feature extraction and based on deep learning. Traditional methods are mainly including three aspects [3,4]: saliency information-based, shape and texture information-based and statistical information-based.

This work was partially supported by National Key R&D Program of China (No.2017YFB0502703) and by the NSFC project (61822107).

The application of deep learning to SAR image target interpretation has become a research hotspot, and some domestic scholars have also made some representative achievements. Fu et al. [5] introduced a method based on shape prior knowledge for aircraft reconstruction. He et al. [6] proposed a multi-layer parallel network based on aircraft components. An et al. [7] improved the detection effect by using rotating adjacency rectangle box. However, the imaging results of the same target under different imaging conditions tend to be quite different, which is very unfavorable to the neural network. Therefore, aircraft detection in SAR images using typical deep convolutional neural network alone cannot obtain a robust result.

In a comprehensive view of the development of aircraft detection technology in SAR imagery, it has evolved from significant region and texture information based to the deep learning based. Essentially, both of them are through understanding the target features to realize high-precision target interpretation. In fact, SAR imagery contains not only the complex scattering characteristics of the target, but also the spatial clues such as the structure distribution of the background and the target, which have not been fully mined and organically combined in the two mainstream interpretation technologies. In response to the challenge mentioned, a novel algorithm based on scattering information extraction and deep learning is proposed in this paper.

2 Methodology

The flowchart of the proposed method for the aircraft detection in high resolution SAR images is shown in Fig.1, which are mainly divided into two parts: scattering information enhancement for robust prior information modeling and deep characteristic extraction for precise aircraft location.

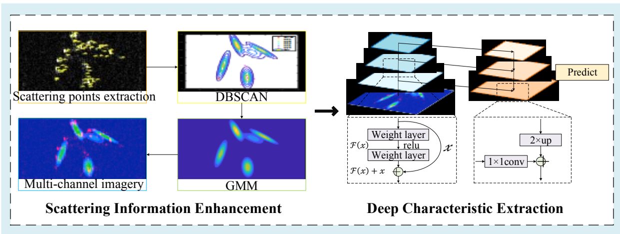


Figure 1. Flowchart of the algorithm.

2.1 Scattering Information Enhancement

Compared with optical images, SAR images are not clear enough and lack important contour information. However, due to the excellent detection performance of synthetic aperture radar for metal materials, aircrafts in SAR images contain abundant scattering characteristics. In high-resolution SAR images, the aircraft size is much larger than the resolution unit, consequently, the scattering information is mainly contributed by the target dominant sub-components. Aircraft is basically composed of the nose, the fuselage, the tail, the wings and the engines. The primary scattering mechanism of each component is shown in Fig.2.

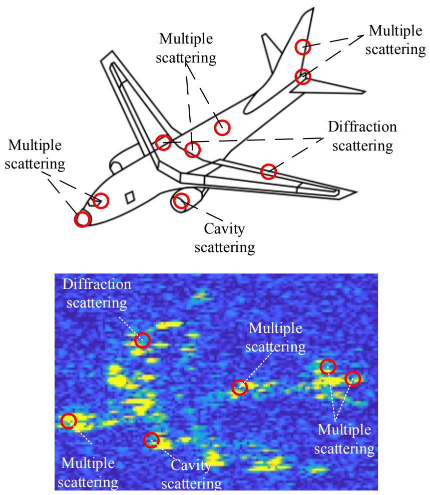


Figure 2. Scattering mechanism of each component.

Although the different components of the aircraft have different scattering mechanisms in SAR images, most of them can be described as a combination of strong scattering points. Strong scattering points in the SAR images is the peak of local scattering region of the aircraft which has strong gradient information. Therefore, it can be extracted by the corner detector. In order to obtain more robust scattering point information, Harris-Laplace detector with scale invariance and affine invariance properties is selected. Based on the extracted SSP information, the Gaussian Mixture Model is introduced to generate more stable and effective prior information for aircraft detection. Assuming that the GMM consists of $\mathcal{K}$ Gaussian models, the probability density function of the GMM is as follows:

$$p(x) = \sum_{k=1}^{\mathcal{K}} \pi_k \mathcal{N}(x|\mu_k, \Sigma_k) \quad (1)$$

Where $\mathcal{N}(x|\mu_k, \Sigma_k)$ represents the probability density function of the k Gaussian model. π_k is the weight of the k Gaussian model, called the prior probability of selecting the k model, and it satisfies $\sum_{k=1}^{\mathcal{K}} \pi_k = 1$.

2.2 Deep Characteristics Extraction

Deep Convolution Neural Network can extract deep features and learn the high-level semantic information of the target, which has achieved superior results in the field of computer vision. Most target detection algorithms only use top-level features for prediction. However, although the shallow features contain less semantic information, the target position is much more accurate. As for deep features, semantic information extracted is more abundant, but the target position information is coarser. Therefore, feature pyramid network which combines high-resolution information of shallow features and high-semantic information of deep features for object detection is applied in this experiments. The structure of FPN is shown in Fig.3.

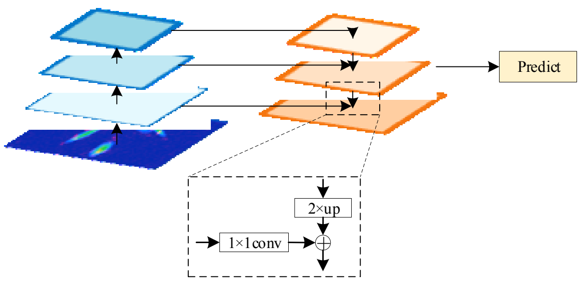


Figure 3. Structure of Deep Feature Pyramid Network.

Predictions are performed separately on each fused feature layer in FPN. Compared with other typical target detection algorithms, it adds top-down and horizontal connection structures to fuse the network features. Consequently, it can improve detection performance. ResNet-101 is utilized as the reference network, which has a stronger deep features extraction ability, at the same time, residual blocks can avoid the gradient disappearance in deep network training iterations.

3 Experiments and Analysis

3.1 Experimental Data

Experiments are conducted on GF-3 SAR images and TerraSAR-X images to illustrate the efficiency and robustness of the proposed method. The ground truth of the experimental data is manually labeled by comparing with the optical image which is considered reliable in this paper. The detailed information of the two datasets is described in the following. In our experiment, we use Constant False Alarm Rate (CFAR), faster-RCNN and the proposed method to illustrate the superiority of our method.

1) GF-3 Aircraft dataset:

GF-3 is a C-band SAR satellite which can work in 12 different modes and provide images with different resolutions. In this experiments, 94 C-band HH-polarimetric images from GF-3 satellite involving 9 types of airports with 0.56m×0.34m resolution are chosen to illustrate the performance of the proposed algorithm. The original images are cut into slices with 3000×3000 pixels in aircraft detection stage. Furtherly, the training set and test set are divided with a ratio of 9:1. The images in GF-3 aircraft dataset covers more scenarios, and aircrafts which are adjacent to buildings are common, therefore this dataset is used to verify the performance of algorithm in complex scenarios.

2) TerraSAR-X Aircraft dataset:
TerraSAR is a X-band SAR satellite which can work in Spotlight, Stripmap and ScanSAR modes. TerraSAR-X data obtained from Davis-monson Air Force Base are adapted in this experiment. The SAR imagery which include 752 aircrafts has a resolution of 1m×1m and the image size is 8984×18284 pixels. The SAR imagery and the corresponding optical imagery are shown in Fig.4 for contrast. Likewise, TerraSAR-X aircraft dataset is composed of slices with 2000×2000 pixels. Furtherly, the training set and test set are divided with a ratio of 9:1. The aircrafts are densely arranged in images, therefore it is necessary to avoid objects interference with each other.

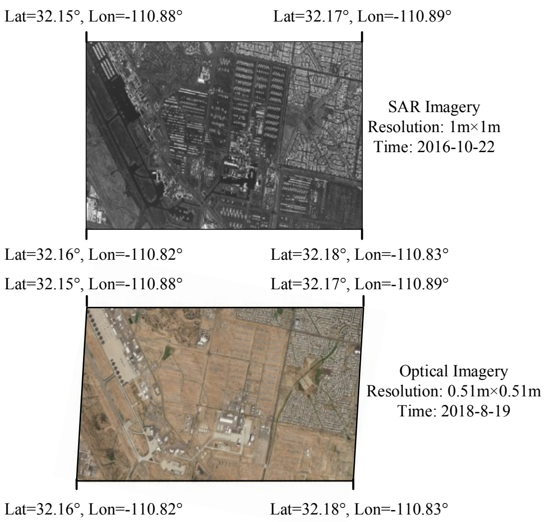
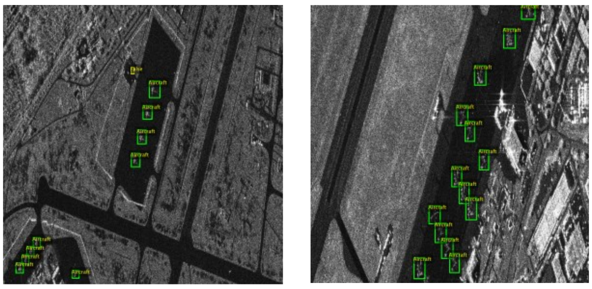


Figure 4. TerraSAR-X data adapted in the experiment

3.2 Comparison With State-of-the-Arts

Accurate airport detection algorithm [8] facilitates rapid location of the airport area in the large scene of SAR images, and it can reduce the amount of computation as well as avoids a multitude of false alarms. By extracting the scattering information of suspicious targets in the airport area, the SAR image initial information can be enhanced. Accordingly, prior information can be provided for the FPN which is conductive to the neural network to extract more significant features. The results of aircraft detection in several areas are given in Fig.5 and Fig.6. The yellow boxes, red boxes and green boxes represent false alarms, missed detection and correct detection respectively.



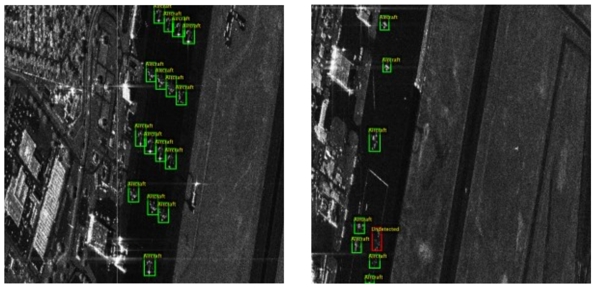


Figure 5. Aircraft detection results in GF-3 dataset.

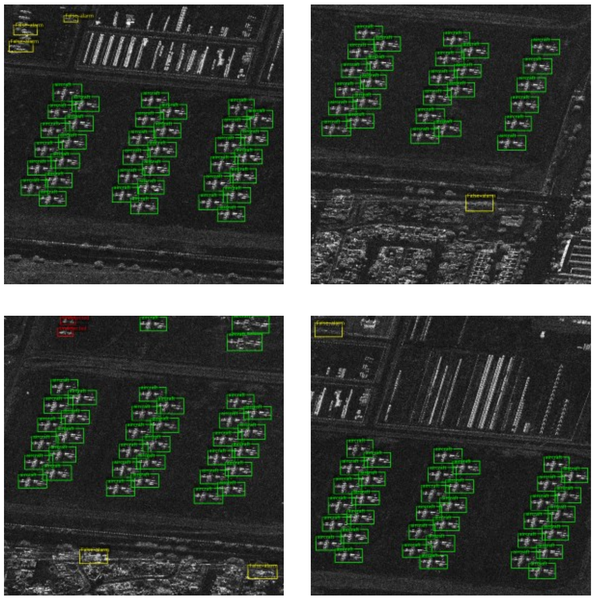


Figure 6. Aircraft detection results in TerraSAR dataset.

Table 1. Detection Results of the proposed method

Satellite	GF-3			TerraSAR-X		
Results		P	N		P	N
G-Truth	T	445	26	T	135	2
	F	43	N/A	F	7	N/A
False alarm Rate	8.8%			4.9%		
Recall Rate	94.5%			98.5%		
Precision Rate	91.2%			95.1%		
F1-Measure	92.8%			96.8%		

As shown in Table 1, the experimental results show that the proposed algorithm can achieve satisfied detection rate with low false alarm rate.
CFAR and faster R-CNN algorithms are applied to demonstrate the superiority of the proposed algorithm. CFAR is an algorithm based on clutter statistics and brightness threshold extraction, while faster R-CNN is a representative target detection algorithm based on deep learning. The test results are shown in Table 2.

Table 2. Comparison of different methods

Method	Recall Rate	False Alarm Rate

CFAR	92.6%	54.7%
Faster R-CNN	93.8%	12.1%
Proposed Method	**95.4%**	**7.9%**

Comparison between different methods shows that CFAR is not stable, and the detection results are prone to generate a large number of false alarms, besides, incomplete target detection results are common; Faster R-CNN loses the high resolution information of the shallow layers of the network in the process of network training iteration due to its own network structure, resulting in its poor detection effect on small targets; The algorithm proposed in this paper avoids above problems and improves the algorithm's ability dealing with the discreteness and variability of the aircraft target by combining the scattering information with the feature pyramid network, which has a high detection effect and good robustness.

4 Conclusion

Aircraft targets in SAR images have abundant scattering characteristics for SAR superior metallic materials detection ability. However, due to the diversity and variability of aircrafts in SAR images, as well as the influence of background strong scattering points, such as runway and oil storages, etc., the design of an effective and robust scattering feature extraction method plays a key role in the accurate detection of aircraft targets.

Aiming at aircraft detection in SAR images, this paper proposes an aircraft detection algorithm based on scattering information enhancement and feature pyramid network. By combining the powerful feature extraction capability of neural network and the context information of target and background, the aircraft can be detected precisely. Firstly, accurate airport detection algorithm is conducive to quickly extract the airport in the large SAR imagery, reducing the computation and eliminating a large quantity of false alarms. Secondly, the multi-channel image enhanced by the scattering feature information can provide effective prior information for the feature pyramid network. FPN further improves the detection performance of the network for small targets by fusing the shallow high-resolution information and deep high-semantic information. Experiments conducted on GF-3 and TerraSAR-X datasets demonstrate the feasibility and robustness of the proposed method.

5 Acknowledgements

The authors would like to acknowledge the CASC for providing the GF-3 satellite images and the EADS for providing the TerraSAR-X satellite images used in this study.

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