

R²CNN++: Multi-Dimensional Attention Based Rotation Invariant Detector with Robust Anchor Strategy

Xue Yang¹,³, Kun Fu¹,²,³, Hao Sun¹, Jirui Yang¹,³, Zhi Guo¹
Menglong Yan¹, Tengfei Zhang¹,³, Sun Xian¹
¹,²Institute of Electronics, Chinese Academy of Sciences, Beijing (Suzhou), China.
³University of Chinese Academy of Sciences, Beijing, China.
yangxue16@mails.ucas.ac.cn

Abstract

Object detection plays a vital role in natural scene and aerial scene and is full of challenges. Although many advanced algorithms have succeeded in the natural scene, the progress in the aerial scene has been slow due to the complexity of the aerial image and the large degree of freedom of remote sensing objects in scale, orientation, and density. In this paper, a novel multi-category rotation detector is proposed, which can efficiently detect small objects, arbitrary direction objects, and dense objects in complex remote sensing images. Specifically, the proposed model adopts a targeted feature fusion strategy called inception fusion network, which fully considers factors such as feature fusion, anchor sampling, and receptive field to improve the ability to handle small objects. Then we combine the pixel attention network and the channel attention network to weaken the noise information and highlight the objects feature. Finally, the rotational object detection algorithm is realized by redefining the rotating bounding box. Experiments on public datasets including DOTA, NWPU VHR-10 demonstrate that the proposed algorithm significantly outperforms state-of-the-art methods. The code and models will be available at [https://github.com/DetectionTeamUCAS/R²CNN-Plus-Plus_Tensorflow](https://github.com/DetectionTeamUCAS/R²CNN-Plus-Plus_Tensorflow).

1. Introduction

Object detection of aerial images has always been an important and challenging research direction. It is not only used in high-tech military confrontation to obtain precise battlefield information, capture strategic targets, provide accurate positioning information, but also plays a vital role in civil applications such as resource detection, environmental monitoring, and urban planning. The classic deep learning-based object detection algorithm [10] has achieved great success in the natural scene, prompting these object detection algorithms to be applied to the aerial scene by remote sensing researchers. However, these methods have not made breakthroughs in the field of aerial images. The main reasons are as follows:

1. Aerial images are very complex, not only because of the different image resolutions, but also due to the large number of interference objects.
2. Aerial images contain a large number of small objects whose feature information is often overwhelmed by complex surrounding scenes.
3. Some categories of objects are often densely arranged, such as vehicles, ships and so on, which pose challenges to detection algorithms.
4. Due to the high altitude imaging, the object is appeared in arbitrary orientations. In addition, large aspect ratio object detection is a technical difficulty.

Detection algorithms based on horizontal regions such as Faster-RCNN [26] are widely used for aeronautical object detection. After the prediction of the object position, post-processing methods such as non-maximum suppression (NMS) are used to obtain more accurate bounding boxes. However, the horizontal region detection method is not suitable for aerial images, because dense objects may cause excessive suppression by NMS. A better solution is to detect the arbitrary-oriented bounding box, the minimum bounding rectangle. Another advantage of using this approach is that it retains the orientation information, which is a significant feature of the remote sensing object.

In this paper, we propose a novel multi-category rotation detector, called R²CNN++. First of all, we construct an inception fusion network (IF-Net) that considers factors such as receptive field gaps, feature fusion, anchor sampling to effectively detect small objects. Following IF-Net, we design a multi-dimensional attention network (MDA-Net), consist of pixel attention network and channel attention network, which can weaken the noise information and...
highlight the objects feature. Finally, the rotational region detection is implemented by adding an angle parameter to overcome the difficulty of detecting dense objects while providing the object direction. In the oriented bounding boxes (OBB) and horizontal bounding boxes (HBB) tasks of the DOTA [34] dataset, our model achieves 71.16% and 75.35% mAP, respectively. For NWPU VHR-10 [4] dataset, we also achieve 91.75% mAP. In the published related papers using these two datasets, our methods ranked first. The main contributions of this paper are as follows:

1. We design a novel arbitrary-oriented object detection framework suitable for aerial images, which can detect the multi-category object in large-scale complex scenes.

2. We construct a targeted feature fusion structure, considering the receptive fields gap, feature fusion, and the anchor sampling, which can effectively detect small objects.

3. A multi-dimensional attention mechanism is adapted to reduce the adverse impact of noise and improve the detection accuracy.

4. Our algorithm achieves state-of-the-art performance in both DOTA and NWPU VHR-10 datasets.

2. Related Work

Horizontal region object detection. Many advanced object detection algorithms are based on deep convolutional neural networks (CNNs) [18, 31, 14, 16]. Girshick et al. [10] proposed a multi-stage R-CNN detection network structure and achieved amazing results. Subsequently, region-based models such as Fast R-CNN [9], Faster R-CNN [26], and R-FCN [5] were proposed, which improved the detection speed while reducing computational storage. SSD [21] and YOLO [25] are regression-based object detection methods, and the single-stage structure allows them to have faster detection speeds. Many scholars have applied these methods to the field of remote sensing. Han et al. [12] proposed the R-P-Faster R-CNN framework and achieved satisfactory performance in small datasets. Xu et al. [35] combined both deformable convolution layers [6] and region-based fully convolutional networks (R-FCN) to improve detection accuracy further. Ren et al. [27] adopted top-down and skipped connections to produce a single high-level feature map of a fine resolution, improving the performance of the deformable Faster R-CNN model. However, the large degree of freedom scale, orientation, and density of the object make these horizontal region detection methods unable to achieve better results in large-scale complex scene datasets.

Arbitrary-oriented object detection. A series of arbitrary-oriented text detection models [17, 24] are proposed in the field of scene text detection. In contrast, aerial object detection is more challenging: first, many text detection models are only limited to single-object detection [39, 30, 7], which is not applicable to multi-category object detection of aerial images. Second, there is often a large gap between texts, while the objects in the aerial image are very close, so the segmentation based detection algorithm [7, 39] may not achieve good results. Third, aerial image object detection requires higher performance of the algorithm because of a large number of small objects. In the field of remote sensing, most of the rotational detection methods are designed for specific objects, such as vehicle detection [32], ship detection [36, 37, 23, 38, 22], aircraft detection [20] and so on. Multi-categories rotational region detection algorithms [2] are still rare in the field of remote sensing, mainly due to interference from factors such as scale, angle, density, and scene complexity. This paper considers these factors comprehensively, and proposes a general algorithm for multi-categories arbitrary-oriented object detection in aerial images.

3. Methodology

3.1. Pipeline

A high-level overview of our pipeline is illustrated in Figure 1. Our network is a two-stage method based on Faster-RCNN. In the first stage, the feature map contains more feature information and less noise information by
Figure 2: Anchor sampling in different $S_A$. The orange-yellow bounding box represents the anchor, the green represents ground-truth, and the red box represents the anchor with the largest IoU of ground-truth.

| $S_A$ (1w iters) | 4   | 6   | 8   | 10  | 12  | 14  | 16  |
|------------------|-----|-----|-----|-----|-----|-----|-----|
| OHR mAP (%)      | -   | 67.06 | 66.88 | 65.32 | 63.75 | 63.32 | 63.64 |
| HHR mAP (%)      | -   | 70.71 | 70.19 | 68.96 | 69.09 | 68.54 | 69.33 |
| Speed (s)        | 2.58 | 1.18 | 0.99 | 0.76 | 0.46 | 0.39 | 0.33 |

Table 1: Detection accuracy and training speed of DOTA datasets under different $S_A$.

adding IF-Net and MDA-Net. Taking into account the positional sensitivity of the angle parameters, this stage still regresses the horizontal box. After the five-parameter regression and the rotation nonmaximum-suppression (R-NMS) operation for each proposal in the second stage, we get the final detection results.

3.2. Network Design

3.2.1 IF-Net

Aerial images often contain a large number of small objects, such as the vehicle, ship, bridge, etc. How to effectively detect small objects is the key to applying the object detection algorithm to aerial images. There are two main reasons for the difficulty in detecting small objects: insufficient feature information and inadequate training samples.

**Feature information:** The low-level feature map preserves the location information of the small object, while the high-level feature map has higher-level semantic information. Feature pyramid networks (FPN) and U-Net are common feature fusion methods, but the former network has greater redundancy in terms of the amount of anchor and feature map, while the latter does not take into account the adverse impact of receptive field gaps.

**Anchor sampling:** The detection network improves its ability by training positive and negative samples. Insufficient sample size and imbalance can significantly affect the detection and recognition results. Zhu et al. calculates the expected max intersection over union (IoU) between the anchor and the object by introducing the expected max overlapping (EMO) score. Finally, they find the smaller stride of the anchor ($S_A$) is, the higher EMO score achieves. Hence the average max IoU of all objects can be statistically increased. Figure 2 shows the results of small object sampling in the case of steps 16 and 8, respectively.

Based on the above analysis, we design IF-Net, as shown in Figure 3. Compared to the fusion strategy of FPN and U-Net, IF-Net is more generalized. It can set the value of $S_A$ and not limited to the exponent of 2. For the purpose of reducing network parameters, IF-Net only uses C3 and C4 as inputs because their semantic information and location information are balanced and the contributions of other feature maps are not visible. The first channel of IF-Net upsamples the C4 so that its $S_A = S$, where $S$ is the expected anchor stride. The second channel also upsamples the C3 to the same size. Then, we pass C3 through an inception structure to expand its receptive field and increase semantic information. The inception structure contains a variety of different ratio convolution kernels to accommodate the diversity of object shapes. Finally, a new feature map F3 is obtained by element-wise addition of the two channels. Table 1 shows the detection accuracy and training speed of DOTA datasets under different $S_A$. We find that the optimal $S_A$ of different data is different, depending on the size distribution of small objects. In this paper, the value of $S$ is set to 6, at which the model is fast and accurate.

In addition to the step size setting, we set the base anchor size to 256, and the anchor scales setting from $2^{-4}$ to $2^4$. Considering that the multi-categories objects in DOTA and NWPU VHR-10 dataset have different shapes, we set anchor ratios to $[1/1, 1/2, 1/3, 1/4, 1/5, 1/6, 1/7, 1/8]$. These settings ensure that most ground truths can sample positive samples. Specifically, when IoU > 0.7, the anchor is assigned as a positive sample, and the anchor is considered to be a negative sample if IoU < 0.3. Besides, due to the sensitive relationship between angle and IoU in the large aspect ratio rectangle, the two thresholds in the second stage are 0.4 and 0, respectively. During the training, the minibatch size in two stages is 512.

3.2.2 MDA-Net

Due to the complexity of aerial images, the proposals provided by RPN may introduce a large amount of noise information, as shown in Figure 4. Excessive noise will overwhelm the object information, and the boundaries between the objects will be blurred, refer to Figure 4a, resulting in missed detection and increasing false alarms. Therefore, it is necessary to enhance the object information and weaken the non-object information. Wang et al. solved the face occlusion problem by designing a single-channel attention...
Figure 3: IF-Net. F3 has a small $S_A$, while fully considering the feature fusion and adaptability to different scales.

Figure 4: Visualize multi-dimensional attention network. (a) Blurred boundaries. (b) Input feature map of attention network. (c) Output feature map of attention network. (d) Saliency map. (e) Binary map. (f) Ground-truth.

Figure 5: MDA-Net consists of channel attention network and pixel attention network.

Inspired by the above two structures, we design a multi-dimensional attention network (MDA-Net), as shown in Figure 5. Specifically, we use SENet as the channel attention network, and the value of reduction ratio is 16. In the pixel attention network, the feature map F3 passes through an inception structure with different ratio convolution kernel, and then learn a two-channel saliency map (as shown in Figure 4d) through a convolution operation. The saliency map represents the scores of the foreground and background, respectively. Then, following a softmax operation on the saliency map and select one of the channels to multiply with F3. Finally, a new information feature map A3 is obtained, as shown in Figure 4c. It should be noted that the value of the saliency map after the softmax function is at $[0, 1]$. In other words, it can weaken the noise and relatively enhance the object information. Besides, since the saliency map is a continuous feature map, non-object information will not be eliminated entirely, which is beneficial to retain certain context information and improve the robustness of the network. In order to guide the network to learning this process, we adopt a supervised learning method. Firstly, we can easily get a binary map as a label (as shown in Figure 4e) according to ground truth, and then use the cross-entropy loss of the binary map and the saliency map as the attention loss.

3.2.3 Rotation Branch

The RPN network provides coarse proposals for the second stage. In order to improve the calculation speed of RPN, we take the highest score of 12,000 regression boxes for NMS operation in the training stage and get 2,000 as proposals. In the test stage, 300 proposals are taken from 10,000 regression boxes by NMS.

In the second stage, we use five parameters $(x, y, w, h, \theta)$ to represent arbitrary-oriented rectangle. The $\theta$ is defined in
4. Experiments

4.1. Dataset and Setting

DOTA [34] is a large-scale dataset for object detection in aerial images. It contains 2806 aerial images from different sensors and platforms. Each image is of the size in the range from about $800 \times 800$ to $4,000 \times 4,000$ pixels and contains objects exhibiting a wide variety of scales, orientations, and shapes. These DOTA images are then annotated by experts in aerial image interpretation using 15 common object categories. The fully annotated DOTA images contain 188,282 instances, each of which is labeled by an arbitrary quadrilateral. DOTA contains two detection tasks: HBB and OBB. Half of the original images were randomly selected as the training set, 1/6 as the validation set, and 1/3 as the testing set. We divide the images into $800 \times 800$ subimages with an overlap of 200.

NWPU VHR-10 [4] dataset is also a publicly available 10-class geospatial object detection dataset. This dataset contains 800 very-high-resolution (VHR) remote sensing images that are cropped from Google Earth and Vaihingen dataset and then manually annotated by experts.

All experiments are implemented on the deep learning framework, tensorflow [1]. We use the pretraining model ResNet-101 to initialize the network. For DOTA dataset, we trained 300k iterations totally, and the learning rate changed during the 100k and 200k iterations from 3e-4 to 3e-6. For NWPU VHR-10 dataset, the split ratios of the training dataset, validation dataset, and test dataset were 60%, 20%, and 20%, respectively. We trained totally 20k iterations with same learning rate as DOTA dataset. Besides, weight decay and momentum are 0.0001 and 0.9, respectively. The optimizer chosen was MomentumOptimizer. Furthermore, we had no data augmentation except random flip images during training.

4.2. Evaluation

4.2.1 Ablation Study

Baseline setup. In this paper, Faster-RCNN-based R$^2$CNN [17] is used as the baseline of the ablation experiments. To ensure the fairness and accuracy of the experiment, all experimental data and parameter settings are strictly consistent. We use mean average precision (mAP) as a measure of model performance. The results of DOTA dataset reported here were obtained by submitting our predictions to the official DOTA evaluation server.

The effect of MDA-Net. As discussed in 3.2.2, the attention structure is beneficial to weaken the influence of noise and highlight the object information. It also can be evidenced in Table 2 that the detection results of most objects have been improved to varying degrees after adding the pixel attention network, and the total mAP increase by...
Table 2: Ablative study of each components in our proposed method on DOTA dataset.

| Method          | PL | BD   | BR   | GTF | SV | LV | SH | TC  | BC | ST  | SBF | RA | HA | SP | HC | mAP |
|-----------------|----|------|------|-----|----|----|----|-----|----|-----|-----|----|----|----|----|-----|
| baseline [17]   | 80.94 | 69.59 | 35.34 | 67.44 | 92.91 | 50.21 | 55.81 | 90.67 | 66.92 | 72.38 | 55.00 | 52.33 | 55.14 | 53.35 | 48.22 | 60.67 |
| +Pixel Attention | 81.17 | 75.23 | 36.71 | 68.14 | 62.33 | 48.22 | 55.75 | 89.57 | 78.40 | 76.61 | 54.08 | 58.32 | 63.76 | 61.94 | 54.89 | 64.34 |
| +MDA            | 84.89 | 77.07 | 38.55 | 67.88 | 61.78 | 51.87 | 56.23 | 89.82 | 75.77 | 76.30 | 53.68 | 63.25 | 63.85 | 65.05 | 53.99 | 65.33 |
| +MDA+AS        | 81.27 | 76.49 | 38.16 | 69.13 | 54.03 | 46.51 | 53.03 | 89.80 | 69.92 | 75.11 | 57.06 | 58.51 | 62.70 | 59.72 | 48.20 | 62.78 |
| +MDA+AJ        | 81.13 | 76.02 | 32.79 | 66.94 | 60.73 | 48.12 | 54.86 | 90.29 | 74.54 | 76.25 | 54.00 | 57.27 | 63.87 | 60.24 | 43.48 | 62.70 |
| +MDA+BU        | 84.63 | 75.34 | 42.84 | 68.47 | 63.11 | 53.69 | 57.13 | 90.70 | 76.93 | 75.28 | 55.63 | 58.28 | 64.57 | 67.10 | 49.19 | 65.53 |
| +MDA+BUS       | 87.50 | 76.50 | 42.41 | 69.48 | 62.45 | 50.89 | 56.10 | 90.87 | 78.41 | 75.68 | 58.94 | 58.68 | 63.87 | 67.38 | 52.78 | 66.07 |
| +MDA+DC        | 87.01 | 76.66 | 42.25 | 68.95 | 62.55 | 53.62 | 56.22 | 90.83 | 78.54 | 75.49 | 58.54 | 57.17 | 63.99 | 66.77 | 57.43 | 66.40 |
| +MDA+IF        | 89.65 | 79.51 | 43.86 | 67.69 | 67.41 | 55.93 | 64.86 | 90.71 | 77.77 | 84.42 | 57.67 | 61.38 | 64.29 | 66.12 | 62.04 | 68.89 |
| +MDA+IF+F      | 89.66 | 81.22 | 45.50 | 75.10 | 60.27 | 60.17 | 66.83 | 90.90 | 80.69 | 86.15 | 64.05 | 63.48 | 65.34 | 68.01 | 62.85 | 71.16 |

3.67%. MDA-Net further improves the detection accuracy of large aspect ratio targets such as bridge, large vehicle, ship, harbor and so on. Compared to attention, MDA-Net increases mAP by about 1% to 65.33%.

The effect of IF-Net. Reducing the step size of the anchor and the feature fusion is effective means to improve the detection of small objects. We conducted a comparative experiment on the various methods proposed in the paper [40]. Both SA and SJ use the idea of using a single feature point to regress the bounding boxes of multiple sub-areas, so their effect is close. It can be seen from the experimental results that these two strategies do not improve the final detection performance but decreased slightly. We believe that a single feature point contains limited information, and using the same information to regress to the bounding box of different sub-regions is inherently problematic. In the original paper, the performance improved by these two methods is also very small. Enlarged feature maps is a good strategy to reduce $S_A$, including bilinear upsampling (BU), bilinear upsampling with skip connection (BUS), dilated convolution (DC). BU avoids the case where the feature point and feature field tend to be one-to-many. Good performance can be seen in small object detection such as bridge, large vehicle, ship. BUS, feature fusion unit of FPN, combines feature fusion and small $S_A$ size, increasing by 0.54%. However, the high-low level feature maps in BUS have a large receptive field gap, which makes the detection efficiency of small objects not good. The DC expands the feature map while maintaining the receptive field through dilated convolution and modifying the step size. Although it does not consider feature fusion and, the final mAP still reaches 66.40%. In addition, the $S_A$ of the above methods is limited to the exponent of 2. IF-Net comprehensively considered the receptive field matching, feature fusion, $S_A$ size, we finally achieve the best performance of 68.89%.

The effect of image pyramid. Image pyramid training and test is an effective means to improve performance. ICN [2] uses the image cascade network structure, which has similar ideas to the image pyramid. In this paper, we randomly scale the original image to [600 × 600, 800 × 800, 1,000 × 1,000, 1, 200 × 2,000] and sent it to the network for training. At the time of testing, each test image is tested at four scales and combined by R-NMS. As shown in the Table 2 image pyramid can greatly improve the detection efficiency and achieve 71.16% mAP. The detection results for each class on the DOTA dataset are shown in Figure 6.

### 4.2.2 Comparison Study

**OBB Task.** Besides the official baseline given by DOTA, we also compare with RRPN [32], R2CNN [17], R-DFPN [56], and ICN [2], which are all applicable to multi-category rotation object detection. Table 3 shows the performance of these methods. The excellent detection performance of...
ICN and R²CNN++ in small object detection is attributed to feature fusion. R²CNN++ considers the expansion of the receptive field and the attenuation of noise in the fusion, so it is better than ICN in the detection of large objects. The survey found that our method rank first in the existing article, reaching 71.16% mAP.

**HBB Task.** We use DOTA and NWPU VHR-10 to validate our proposed framework and shield the angle parameter in the code. Table 4 and Table 5 show the performance of the test model on the two datasets, respectively. We also get the first place in the existing article about DOTA, at 75.35% or so. For the NWPU VHR-10 dataset, we compare it with twelve methods and achieve the best detection performance, at 91.75%. We have the best detection accuracy in more...
Table 5: Comparative experiment of HBB task on NWPU VHR-10 datasets.

| Method                  | PL   | SH   | ST   | BD   | TC   | BC   | GTF  | HA   | BR   | VE   | mAP |
|-------------------------|------|------|------|------|------|------|------|------|------|------|-----|
| Transferred CNN [4]     | 66.10| 56.90| 84.30| 81.60| 35.00| 45.90| 80.00| 62.00| 42.30| 42.90| 59.70|
| RICNN [4]               | 88.35| 77.34| 85.27| 88.12| 40.83| 58.45| 86.73| 68.60| 61.51| 71.10| 72.63|
| R-P-Faster R-CNN [12]   | 90.40| 75.00| 44.40| 89.90| 79.00| 77.60| 87.70| 79.10| 68.20| 73.20| 76.50|
| SSD512 [21]             | 90.40| 60.90| 79.80| 89.90| 82.60| 80.60| 98.30| 73.40| 76.70| 52.10| 78.40|
| DSSD321 [8]             | 86.50| 65.40| 90.30| 89.60| 85.10| 80.40| 78.20| 70.50| 68.20| 74.20| 78.80|
| DSOD300 [29]            | 82.70| 62.80| 89.20| 90.10| 87.80| 80.90| 79.80| 82.10| 81.20| 61.30| 79.80|
| R-FCN [5]               | 81.70| 80.60| 66.20| 90.30| 80.20| 69.70| 89.80| 78.60| 47.80| 78.30| 76.30|
| Deformable R-FCN [5]    | 87.30| 81.40| 63.60| 90.40| 81.60| 74.10| 90.30| 75.30| 71.40| 75.50| 79.10|
| Faster R-CNN [5]        | 94.60| 82.30| 65.32| 95.50| 81.90| 89.70| 92.40| 72.40| 57.50| 77.80| 80.90|
| Deformable Faster R-CNN | 90.70| 87.10| 70.50| 89.50| 89.30| 87.30| 97.20| 73.50| 69.90| 88.80| 84.40|
| RDAS512 [3]             | 99.60| 92.00| 83.20| 97.20| 90.80| 92.60| 98.10| 82.10| 81.20| 61.30| 79.80|
| Multi-Scale CNN [11]    | 100  | 89.41| 97.22| 97.00| 83.15| 87.54| 99.17| 99.40| 74.51| 90.10| 91.75|
| Ours                    | 100  | 89.41| 97.22| 97.00| 83.15| 87.54| 99.17| 99.40| 74.51| 90.10| 91.75|

than half of the categories. The detection results for each class on the NWPU VHR-10 dataset are shown in Figure 7.

4.2.3 Future Study

From the test results, we can see that the detection performance of some categories is not ideal. Apart from false alarms and missed detections caused by complex scenes, a large part comes from false detections. Figure 8 is the confusion matrix obtained by our model on the DOTA verification set. We can find that there are misclassifications be-

Figure 7: Detection results for each class on the NWPU VHR-10 dataset.

Figure 8: Confusion matrix obtained by our model on the DOTA verification set.

between some classes, such as small vehicle and large vehicle, tennis court and basketball court, plane and helicopter, especially between object and background. We will improve the performance of the model from this aspect in the future.

5. Conclusion

In this paper, an end-to-end multi-category arbitrary rotation object detection algorithm is proposed for the complex aerial image. Considering the three factors of receptive field matching, feature fusion, and anchor sampling, a feature fusion network with smaller $S_A$ is added. At the same time, the algorithm weakens the influence of noise and highlights the object information through a multi-dimensional attention network with a sizeable receptive field. Moreover, we implement rotation detection to preserve orientation information and solve intensive problems. Finally, we have the state-of-the-art performance in the open source dataset DOTA and NWPU VHR-10.
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