## **Specific Object Detection And Recognition in Optical Remote Sensing Images**

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### ABSTRACT

This article uses ten typical man-made targets such as airplane, ship, storage tank, harbor, bridge, and vehicle as objects of detection. Specific object detection algorithms for optical remote sensing image are studied to meet the application needs of more recognition accuracy and higher speed. Applying Faster R-CNN algorithm and YOLO v2 algorithm to the object detection task, adaption changes are applied at the application level targeted at specific requirements of optical remote sensing images. Faster R-CNN realized the detection and recognition of remote sensing multi-category man-made objects with an average accuracy of 71.2%. The recognition speed of YOLO v2 detector can reach 67FPS with a detection time of about 15ms/image, and meet the real-time detection requirements.

#### INTRODUCTION

#### RESULTS



The degree of discrimination of different targets at different resolutions (unit: meter)					
OBJECT	Detection	Identification	Classification	Description	
BRIDGE	6	4.5	1.5	0.9	
ROAD	9	6	1.8	0.6	
VEHICLE	1.5	0.6	0.3	0.05	
AIRPLANE	4.5	1.5	0.9	0.15	
HARBOR	30	15	6	3	







- The scale variations of object instances in aerial images are huge.
- Many small object instances are crowded in aerial images. Moreover, the frequencies of instances in aerial images are unbalanced.
- Objects in aerial images often appear in arbitrary orientations.

### **METHODS**







(a)



data/10.jpg: Predicted in 0.01539

airplane : airplane : 86 airplane : 90

airplane : 88

irplane : 90 airplane : 84% airplane : 86% airplane : 889







		Test parameter			
	Iteration	IOU	Recall	Proposals	Precision
3 seconds.	times				
	50,000	50.57%	64.38%	431	80.10%
	100,000	66.89%	80.22%	5176	88.90%
	150,000	67.38%	80.94%	5087	91.33%





(a) The original input image; (b) Convolution layer 1\_2 feature map; (c) Convolution layer 2\_2 feature map; (d) Convolutional layer 3\_3 feature map; (e) Convolutional layer 4\_3 feature map; (f) Convolutional layer 5\_3 feature map







#### **Clustering analysis of remote sensing dataset NWPU VHR-10**

Four kinds of anchor boxes of different sizes calculated under the optimal clustering result, one of which is a square and the other three are thin and high rectangles, and the four kinds of frames are basically small for the overall image size, which can reflect the remote sensing image object detection dataset is more of a small-scale target.



panning, rotation, and color jitter, etc.



(b)

The first two layers mainly extract the edge structure feature information, after reaching the upper level gradually becomes more comprehensive semantic information, which is not easy to understand.



ᆯ正确检测 ∎正确检测 4∐ 30% 100 160 240 目标尺寸/像素 目标尺寸/像素

(a) size distribution of aircraft recalls and missed inspections; (b) size distribution of ship recalls and missed inspections; (c) size distribution of aircraft correct detection and misjudgment; (d) size distribution of ship correct detection and misjudgment

The bounding box that is not properly recalled mainly exists on the **smaller target**. This phenomenon is more obvious on the aircraft target. The lowest recall rate is the target with the size between 50-60 pixels. The detection accuracy of small targets are also lower.





The expanded sample size significantly improves the model training results, and the average accuracy is achieved by using model migration learning.

 $39.3\% \rightarrow 47.2\% \rightarrow 71.2\%$ 

data augmentation 1	.5 times
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Object Category	AP (ImageNet pre-training)	AP (data augmentation)	AP (original dataset)
Airplane	80.3	45.5	36.1
Ship	68.1	45.4	44.3
Storage tank	45.9	45.0	25.7
Baseball diamond	90.6	50.0	45.3
Tennis court	71.5	45.4	40.4
Basketball court	67.7	45.5	40.7
Ground track field	89.2	50.0	45.4
Harbor	76.9	50.0	40.8
Bridge	57.2	50.0	40.8
Vehicle	64.6	45.2	33.9
Mean AP	71.2	47.2	39.3

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