R^2 -CNN FAST TINY OBJECT DETECTION IN LARGE-SCALE REMOTE SENSING IMAGES

ABSTRACT

Recently, the convolutional neural network has brought impressive improvements for object detection. However, detecting tiny objects in large-scale remote sensing images still remains challenging. First, the extreme large input size makes the existing object detection solutions too slow for practical use. Second, the massive and complex backgrounds cause serious false alarms. Moreover, the ultra-tiny objects increase the difficulty of accurate detection. To tackle these problems, we propose a unified and self-reinforced network called remote sensing region-based convolutional neural network (R2-CNN), composing of backbone Tiny-Net, intermediate global attention block, and final classifier and detector. Tiny-Net is a lightweight residual structure, which enables fast and powerful features extraction from inputs. Global attention block is built upon Tiny-Net to inhibit false positives. Classifier is then used to predict the existence of target in each patch, and detector is followed to locate them accurately if available. The classifier and detector are mutually reinforced with end-to-end training, which further speed up the process and avoid false alarms. Effectiveness of R2-CNN is validated on hundreds of GF-1 images and GF-2 images that are 18 000×18 192 pixels, 2.0-m resolution, and 27 620 × 29 200 pixels, 0.8-m resolution, respectively. Specifically, we can process a GF-1 image in 29.4 s on Titian X just with single thread. According to our knowledge, no previous solution can detect the tiny object on such huge remote sensing images gracefully. We believe that it is a significant step toward practical real-time remote sensing systems.

EXISTING SYSTEM

Despite significant progress in object detection tasks, remote sensing image target detection is still challenging owing to complex backgrounds, large differences in target sizes, and uneven distribution of rotating objects. In this study, we consider model accuracy, inference speed, and detection of objects at any angle. We also propose a RepVGG-YOLO network using an improved RepVGG model as the backbone feature extraction network, which performs the initial feature extraction from the input image and considers network training accuracy and inference speed. We use an improved feature pyramid network (FPN) and path aggregation network (PANet) to reprocess feature output by the backbone network. The FPN and PANet module integrates feature maps of different layers, combines context information on multiple scales, accumulates multiple features, and strengthens feature information extraction. Finally, to maximize the detection accuracy of objects of all sizes, we use four target detection scales at the network output to enhance feature extraction from small remote sensing target pixels. To solve the angle problem of any object, we improved the loss function for classification using circular smooth label technology, turning the angle regression problem into a classification problem, and increasing the detection accuracy of objects at any angle. We conducted experiments on two public datasets, DOTA and HRSC2016. Our results show the proposed method performs better than previous methods.

DISADVANTAGES

- Low detection Precision
- Locate objects with horizontal bounding box
- Poor results for small and dense objects

PROPOSED SYSTEM

We proposed R2-CNN, a unified and self-reinforced convolutional neural network under the end-to-end training framework, which joint the classifier and detector elegantly. The lightweight backbone Tiny-Net extracts the powerful features from inputs quickly, and the intermediate global attention block enlarges the receptive field to inhibit false positives. The classifier first predicts the existence of detection target in the current patch, and the specifically designed detector is followed to locate them accurately if available. The high recall and precision in GF-1 and GF-2 validate the effectiveness of our network. Specifically, we can process a GF-1 image in 29.4 s on Titian X just with single thread. All those experiments prove that our R2-CNN is efficient in computation and memory consumption, robust to false positives, and strong to detect tiny objects.

ADVANTAGES

- Little dependence on pre processing
- Decreasing the needs of human effort developing its functionalities.
- It is easy to understand and fast to implement.
- It has the highest accuracy among all algorithms that predicts images.

SYSTEM REQUIREMENT:

HARDWARE REQUIREMENTS:

Processor	:	Intel
Ram	:	2 GB (Minimum)
Monitor	:	15” COLOR
Hard Disk	:	500 GB
Keyboard	:	STANDARD 102 KEYS
Mouse	:	3 BUTTONS

SOFTWARE CONFIGURATION:

Operating System	:	Windows 7 / 10
Environment	:	MATLAB
Matlab	:	Version 18a

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