HAL-Retina-Net: Hybrid attention based low-resolution retina-net

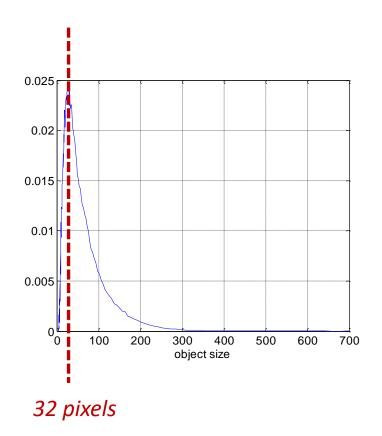
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Dataset Description



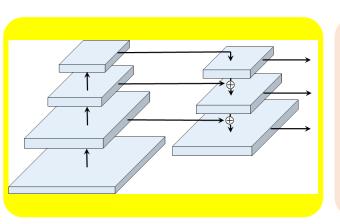
Dataset Description

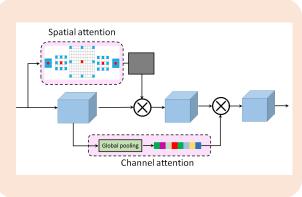
Drones, or general UAVs, equipped with cameras have been fast deployed to a wide range of applications, including agricultural, aerial photography, fast delivery, and surveillance. Consequently, automatic understanding of visual data collected from these platforms become highly demanding, which brings computer vision to drones more and more closely. We are excited to present a largescale benchmark with carefully annotated ground-truth for various important computer vision tasks, named VisDrone, to make vision meet drones. The VisDrone2018 dataset is collected by the AISKYEYE team at Lab of Machine Learning and Data Mining, Tianjin University, China. The benchmark dataset consists of 263 video clips formed by 179,264 frames and 10,209 static images, captured by various drone-mounted cameras, covering a wide range of aspects including location (taken from 14 different cities separated by thousands of kilometers in China), environment (urban and country), objects (pedestrian, vehicles, bicycles, etc.), and density (sparse and crowded scenes). Note that, the dataset was collected using various drone platforms (i.e., drones with different models), in different scenarios, and under various weather and lighting conditions. These frames are manually annotated with more than 2.5 million bounding boxes of targets of frequent interests, such as *pedestrians, cars, bicycles, and tricycles*. Some important attributes including scene visibility, object class and occlusion, are also provided for better data utilization.

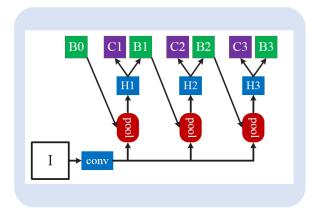


Network Architecture

- We choose Retina-Net as the baseline for this challenge.
- To detect low-resolution objects, we remove P6 and P7 from the feature pyramid structure and use the first three pathways, named as P3, P3, P5, for detection.





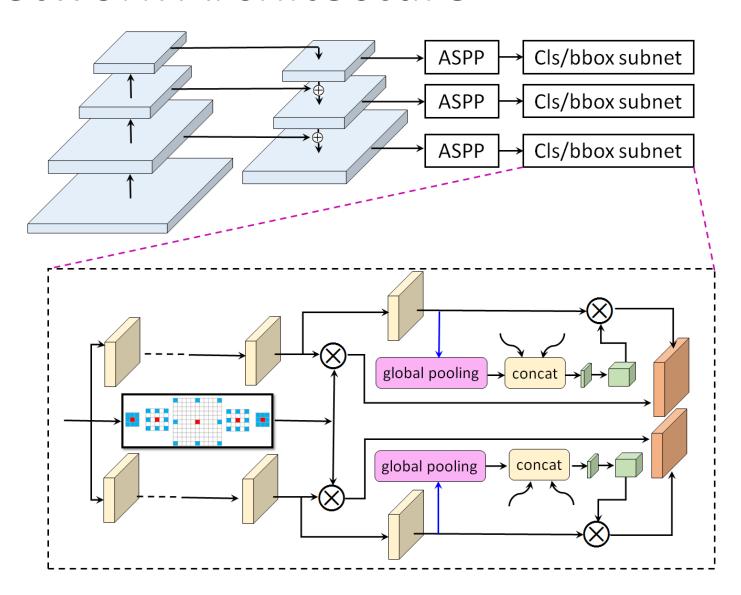


Feature pyramid network

Hybrid attention module

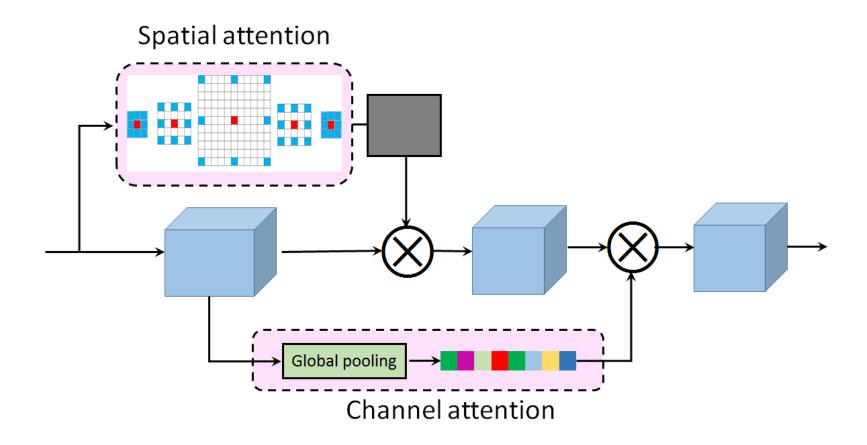
Refinement module with cascade

Network Architecture



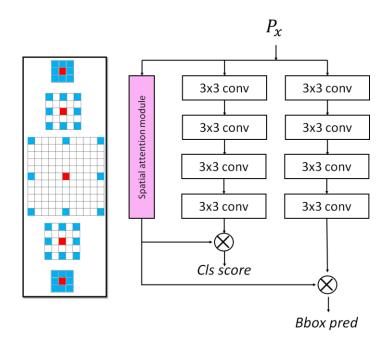
Hybrid Attention

- Network attention: Spatial attention + channel attention
- Learning attention: Multi-scale training



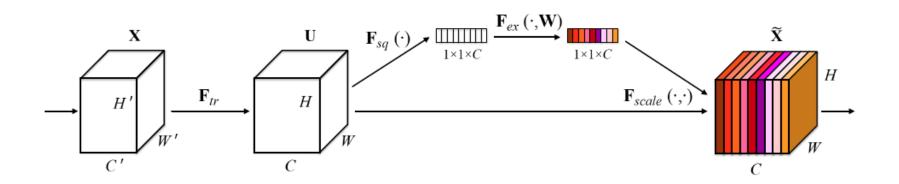
Spatial Attention

- Use stacked dilated convolution layers to learn the heat maps of interested objects.
- Dilation rate needs to be progressively decreased to decrease the gridding mosaic artifacts.



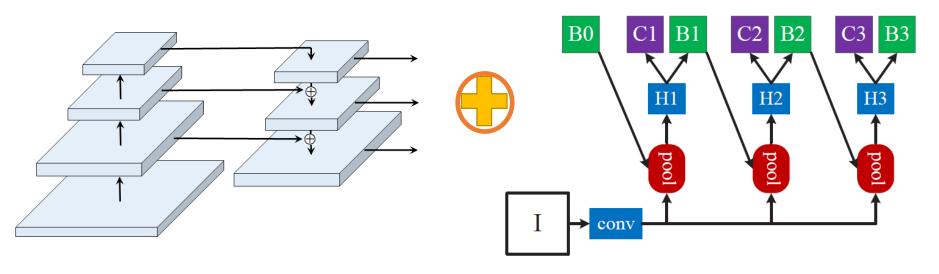
Channel Attention

- Squeeze-and-excitation (SE) modules are used to extract the channel relationship and learn the weights of different channels with the global information.
- The global information from different stream to learn the shared channel attention.



Cascade CNN

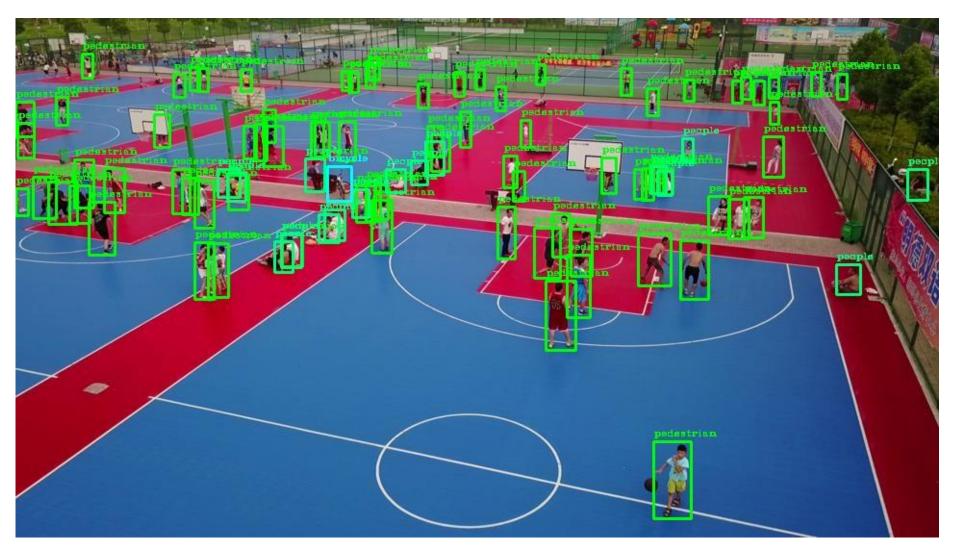
- Iterative box to improve the localization accuracy
- Integral loss to improve the detection accuracy.
- We add the cascade module for further refinement.

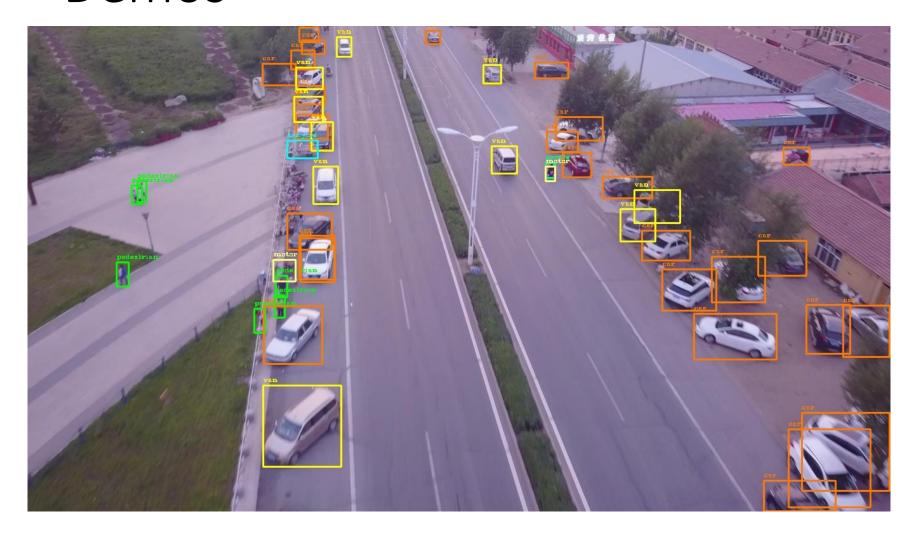


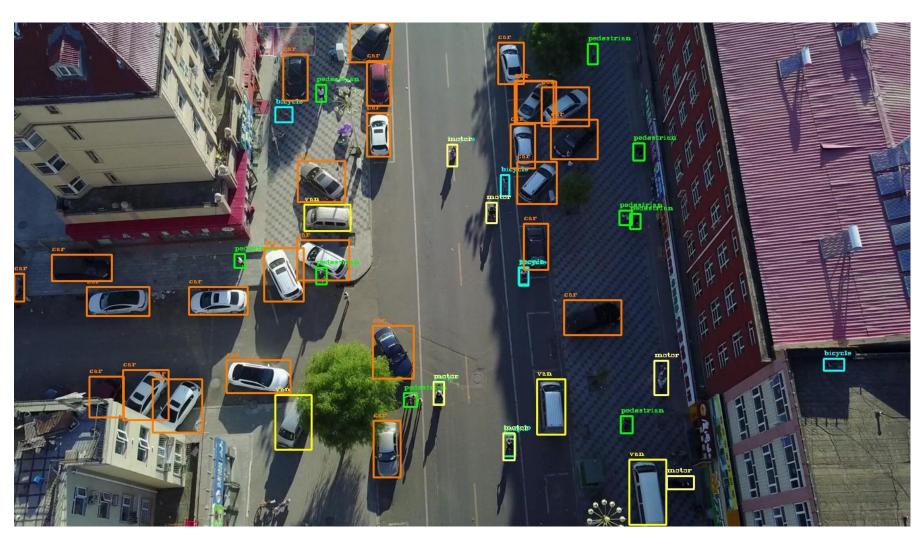
Implementation details

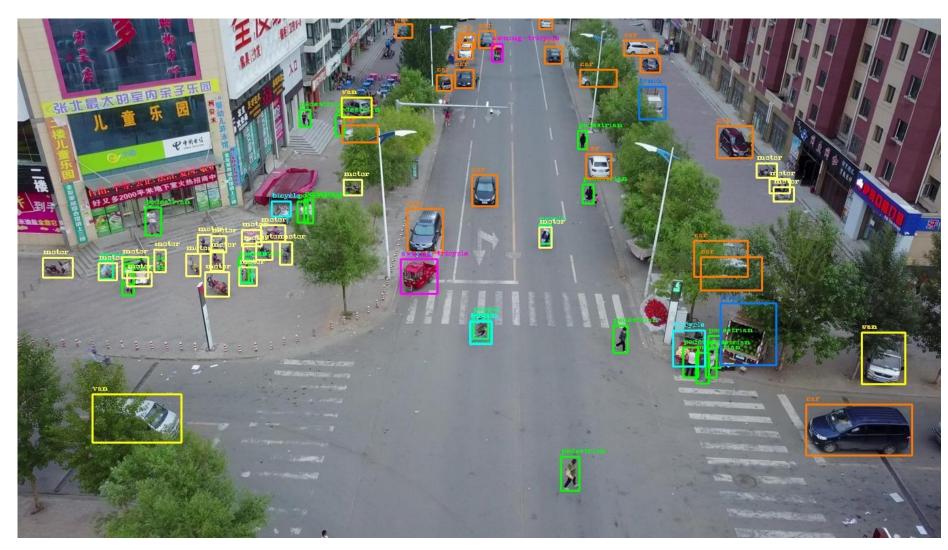
- Backbone network: SE-ResNeXt-50/SE-ResNeXt-101
- Training: firstly trained on COCO[1], with 45.7% mAP, then finetuned with VisDrone2018 train/val set.
- Single scale training: learning rate 0.005 of 24k iterations then decreased to 0.0005 with 27k iterations.
- Multi-scale training: split the original images into patches (size: 512, 640, 768, 896, 1024), with DOTA devkit [2], nearly 180k sub-images for training.
- Weight decay of 0.0001 and momentum of 0.9 are used.
 The training loss is the sum of focal loss and standard smooth L1 loss used for box regression.

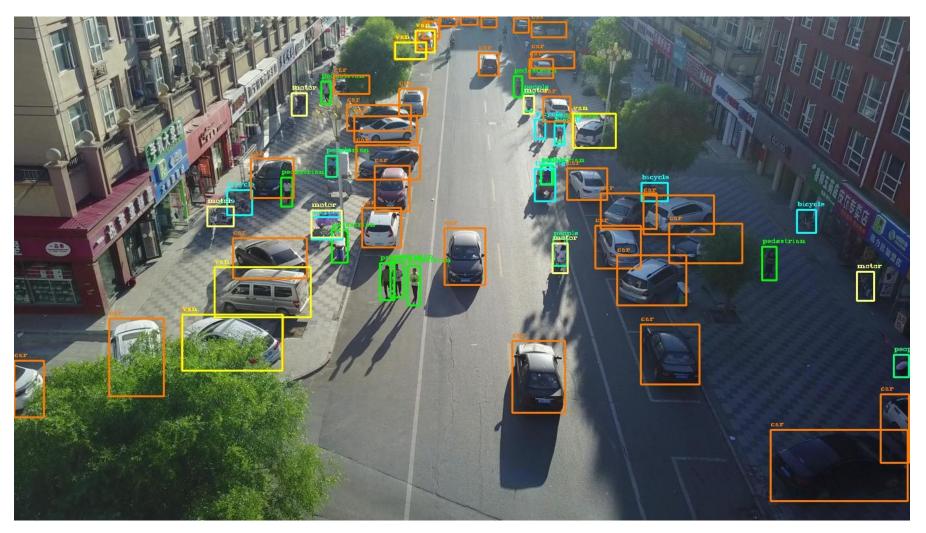


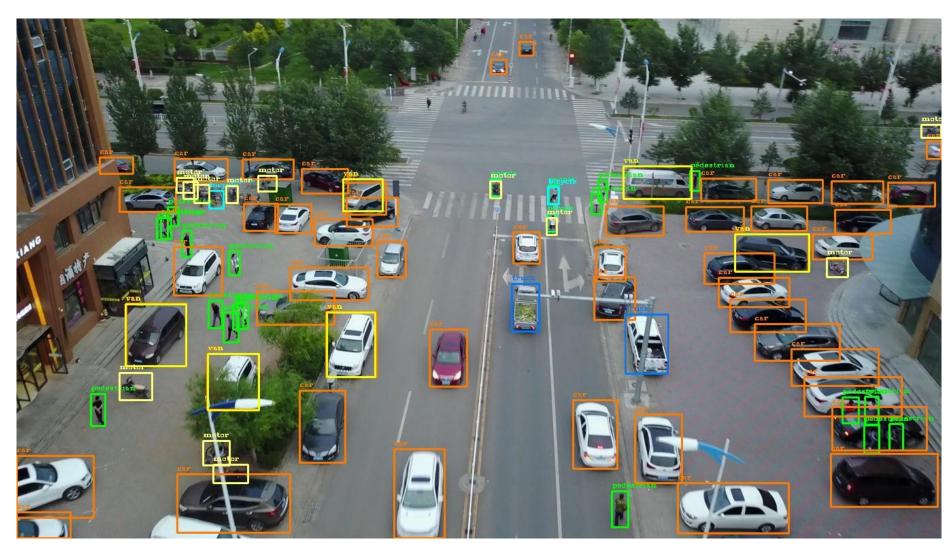




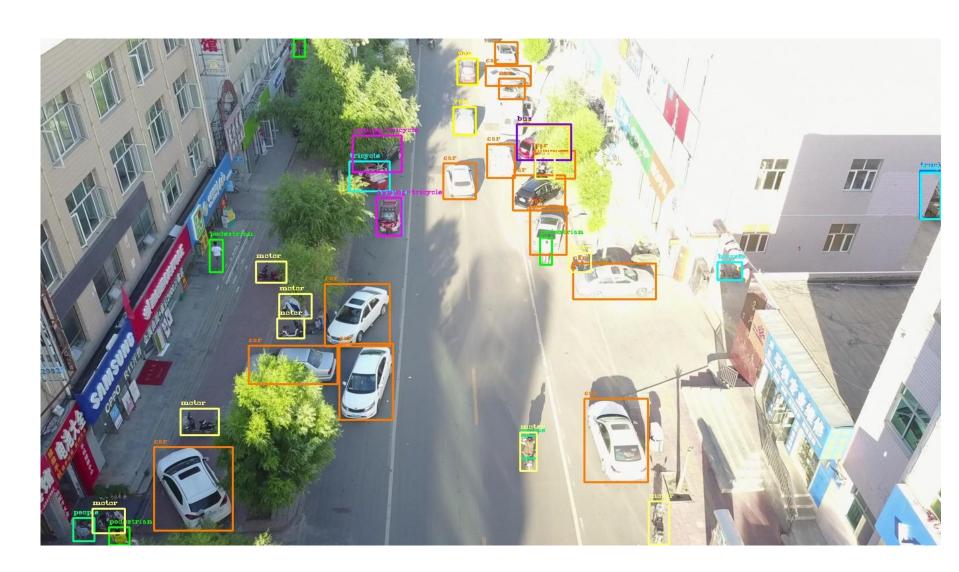












Thanks for your attention!