Introduction

- Rotation Object Detection
  - Task: design a novel multi-category rotation detector for small, cluttered and rotated objects.
  - Challenges
    - Small objects: Aerial images often contain small objects overwhelmed by complex surrounding scenes.
    - Cluttered arrangement: Objects for detection are often densely arranged, such as vehicles and ships.
    - Arbitrary orientations: Objects in aerial images can appear in various orientations. It is further challenged by the large aspect ratio issue which is common in remote sensing.

- Our main contributions
  - For small objects, a tailored feature fusion structure is devised by feature fusion and anchor sampling.
  - For cluttered, small object detection, a supervised multi-dimensional attention network is developed to reduce the adverse impact of background noise.
  - Towards more robust handling of arbitrarily-rotated objects, an improved smooth L1 loss is devised by adding the IoU constant factor, which is tailored to solve the boundary problem of the rotating box regression
  - Codes: https://github.com/DetectionTeamUCAS

Proposed Approach

- Pipeline
  In the first stage, the feature map is expected to contain more feature information and less noise by adding SF-Net and MDA-Net. For positional sensitivity of the angle parameters, this stage still regresses the horizontal box. By improving the five-parameter regression and the rotation nonmaximum-suppression (R-NMS) operation for each proposal in the second stage, we can obtain the final detection results under arbitrary rotations.

- Sampling and Fusion Network (SF-Net)
  - Feature fusion: SF-Net only uses C3 and C4 in ResNet for fusion to balance the semantic information and location information while ignoring other less relevant features.

- Multi-Dimensional Attention Network (MDA-Net)
  - The supervised pixel attention network and the channel attention network are jointly explored for small and cluttered object detection by suppressing the noise and highlighting the objects feature.

- IoU-Smooth L1 Loss
  - For more accurate rotation estimation, the IoU constant factor is added to the smooth L1 loss to address the boundary problem for the rotating bounding box. The IoU-Smooth L1 Loss is defined as follows:

\[
L_{\text{reg}} = \frac{1}{N} \sum_{n=1}^{N} \sum_{j \in \{x,y\}} \| \frac{\text{IoU}(v'_j, v_j)}{\log(IoU)} - \log(IoU) \|
\]

Experiments

- Ablative study of each components in our proposed method on the DOTA dataset.
- Performance evaluation of OBB and HBB task on DOTA datasets.
- Performance on NWPU VHR-10.
- Effectiveness of the proposed structure on generic datasets.
- Visualization on different datasets.

Recent Works

- We have designed a fast and accurate single-stage based refined rotation detector that solves the problem of feature misalignment. [arXiv:1808.03766]