

# Supplementary Material for Adaptive Rotated Convolution for Rotated Object Detection

## 1. Detailed Configurations

We use MMRotate toolbox [9] to produce all the experimental results in the paper, except that Oriented R-CNN [7] is implemented with OBBDetection codebase. The detailed model configurations of each detector are also obtained from these two codebases, and are illustrated in Tab. 1 (for DOTA) and Tab. 2 (for HRSC2016), respectively.

Method	Angle	Batch	LR
Rotated RetinaNet [3]	le90	2	$2.5 \times 10^{-3}$
R3Det [8]	oc	2	$2.5 \times 10^{-3}$
S <sup>2</sup> ANet [2]	le135	2	$2.5 \times 10^{-3}$
Rotated Faster R-CNN [5]	le90	2	$5.0 \times 10^{-3}$
CFA [1]	le135	2	$8.0 \times 10^{-3}$
Oriented R-CNN [7]	le90	2	$5.0 \times 10^{-3}$

Table 1. Configuration of each detector on **DOTA** [6] dataset. The column *Angle* refers to angle definition, where oc, le90 and le135 denotes opencv definition, long edge 90° definition, and long edge 135° definition, respectively. Besides, the column *Batch* means the batch size, while the column *LR* means and the learning rate.

Method	Angle	Aug	Batch	LR
Rotated RetinaNet [3]	le90	RR	2	$2.5 \times 10^{-3}$
S <sup>2</sup> ANet [2]	le135	-	2	$2.5 \times 10^{-3}$
Oriented R-CNN [7]	le90	-	2	$5.0 \times 10^{-3}$

Table 2. Configuration of each detector on **HRSC2016** [4] dataset. The meaning of column *Angle*, column *Batch* and column *LR* are the same as Tab. 1, while the column *Aug* means data augmentation. In this column, RR means random rotate.

While the detailed training configuration varies among different detectors and different datasets, we restate that the

experiment setting using our proposed backbone networks and that using the baseline backbone networks are kept the same in the experiments for fair comparisons.

## References

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