ReDet: A Rotation-equivariant Detector for Aerial Object Detection

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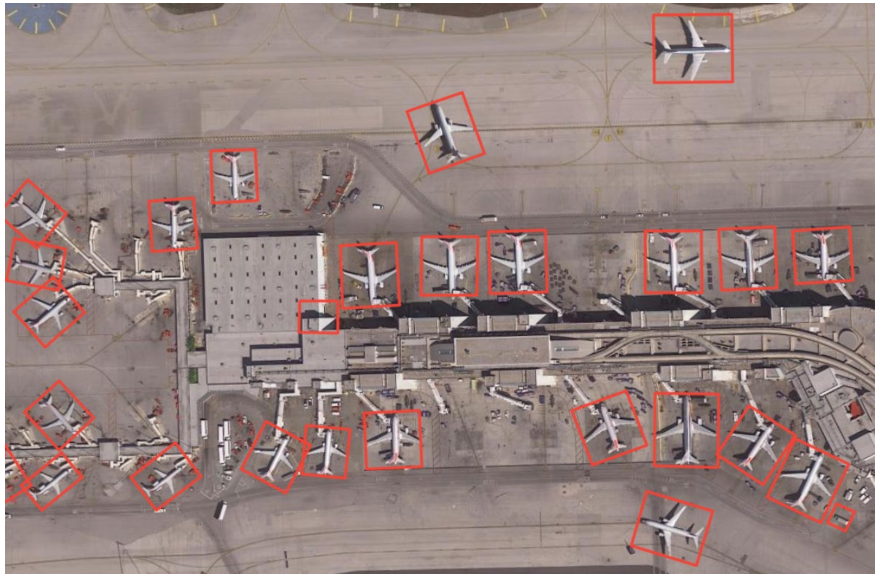
Introduction

- Aerial object detection

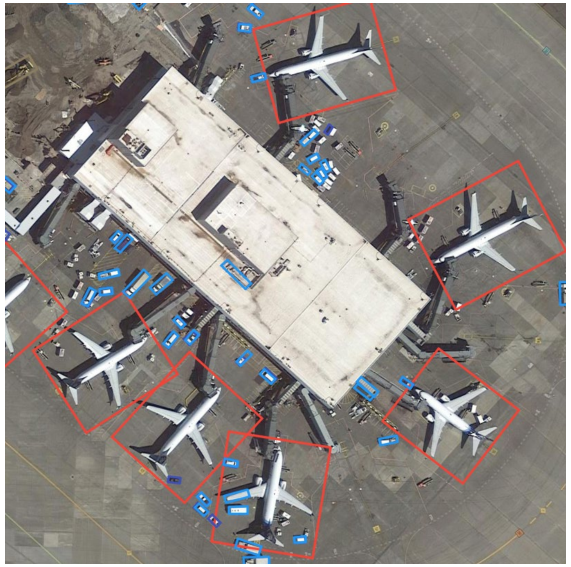
natural image: horizontal bounding box



aerial image: oriented bounding box

Introduction

- Challenges in aerial object detection



arbitrary orientations

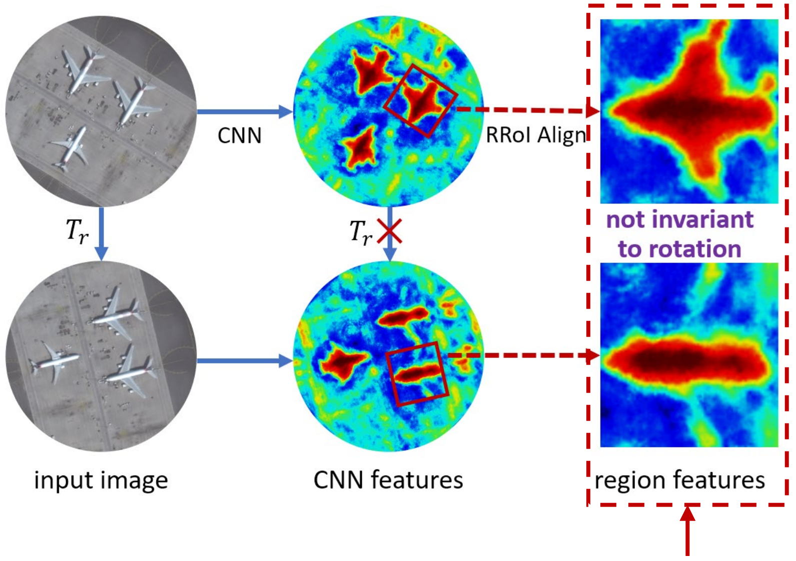
large scale variations

dense distribution

Introduction

■ Motivations

CNNs are not equivariant to rotation



unstable and delicate
as the orientation changes

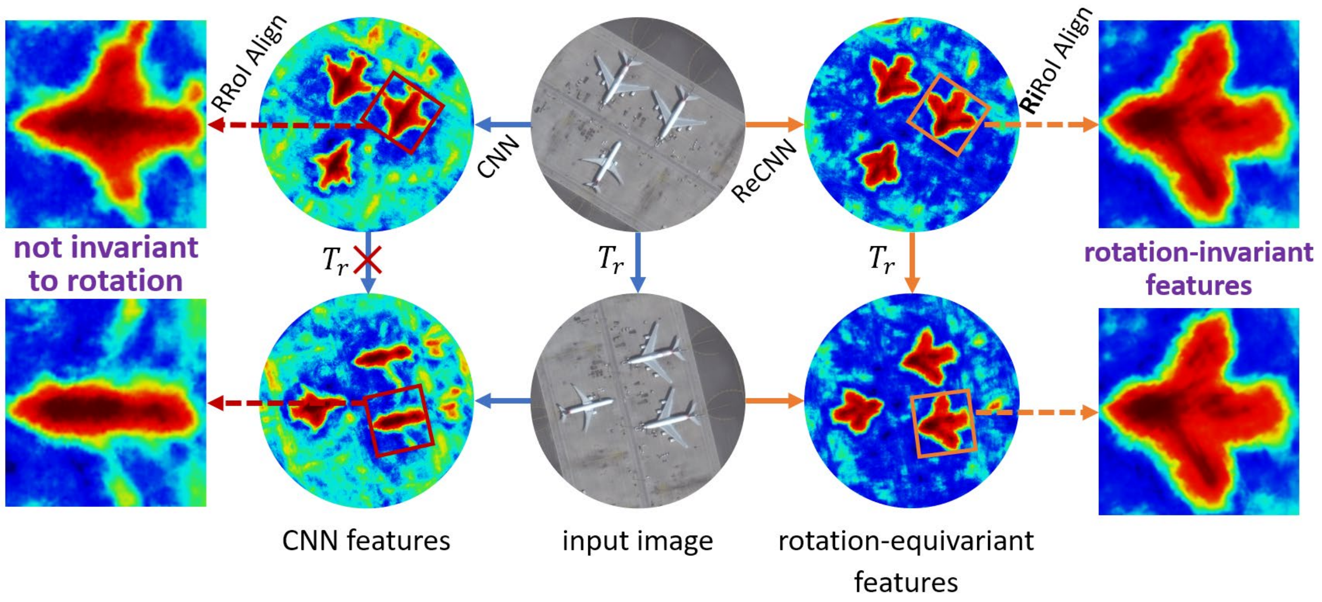
To train an accurate detector?
- ➢ more training data
- ➢ large capacity model

Problems:
- ➢ longer training time
- ➢ more computation
- ➢ more parameters
- ➢ slow inference speed

Introduction

- Motivations

- feature encoding: rotation equivariance, model orientation information
- object detection: rotation invariance, extract rotation-invariant feature for arbitrary oriented objects.



Rotation-equivariant Detector

■ Preliminaries

For a transformation group G and a function $\Phi: X \rightarrow Y$, equivariance is a property:

$$\Phi\left[T_g^X(x)\right] = T_g^Y[\Phi(x)], \forall(x,g) \in (X,G)$$

CNNs are known to be translation equivariant:

$$\left[[T_t f] * \psi\right](x) = \left[T_t[f * \psi]\right](x), \mathrm{x} \in (\mathbb{R}^2, +)$$

Rotation-equivariant network extends CNNs to rotation equivariance:

$$\left[\left[T_g f\right] * \psi\right](g) = \left[T_g[f * \psi]\right](g), x \in (\mathbb{R}^2, +) \rtimes C_N$$

Rotation-equivariant Detector

■ Preliminaries

For layer L_i, the rotation T_r can be preserved by the layer:

$$L_i[T_r(g)] = T_r[L_i(g)]\,, g \in G$$

For $\Phi = \{L_i \mid i \in \{1,2,\cdots,M\}\}$, the rotation T_r will be preserved by the whole network:

$$\left[\prod_{i=1}^{M} L_i\right](T_r I) = T_r\left[\prod_{i=1}^{M} L_i\right](I)$$

For an image region $I_R \in I$ and its rotated version $T_r I_R$, we have:

$$\Phi(T_r I_R) = T_r \Phi(I_R).$$

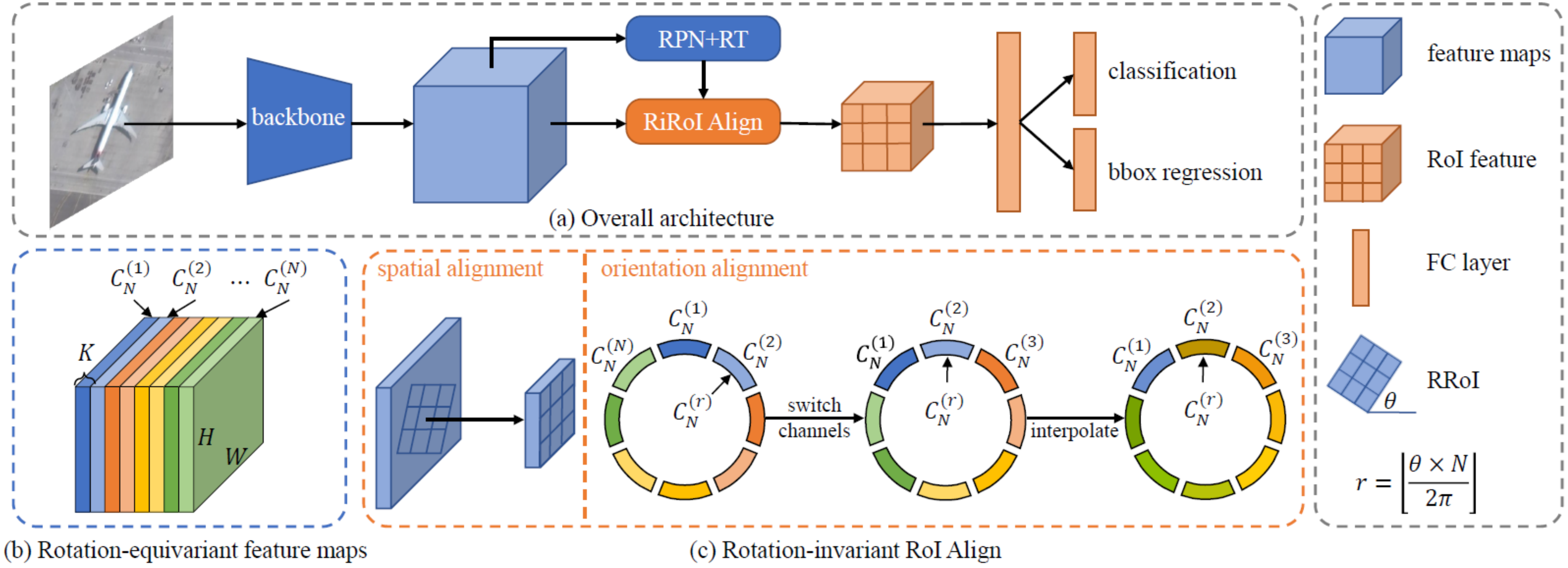
By applying an inverse rotation T_r', we get the rotation-invariant representation:

$$\Phi(I_R) = T_r' \Phi(T_r I_R).$$

Rotation-equivariant Detector

- Architecture

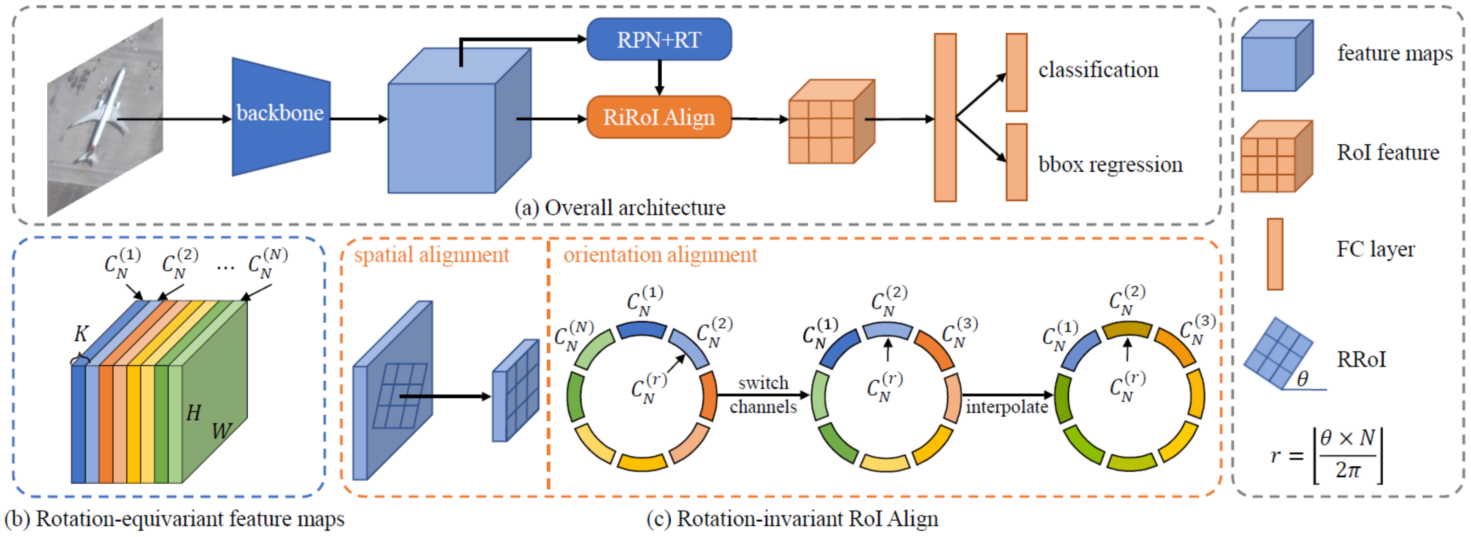
- two-stage framework: based on RoI Transformer
- rotation-equivariant backbone: encodes orientation information explicitly
- rotation-invariant RoI Align: get rotation-invariant feature representation of objects.



Rotation-equivariant Detector

- Rotation-equivariant backbone

- a rotation-equivariant backbone: ReResNet + ReFPN
- equivariant to discrete rotation group $(\mathbb{R}^2, +) \rtimes C_N$.
- feature maps f have N orientation channels: $f = \{f^{(i)} \mid i \in \{1,2,\dots,\mathrm{N}\}\}$
- feature maps from each orientation is corresponding to an element in C_N.

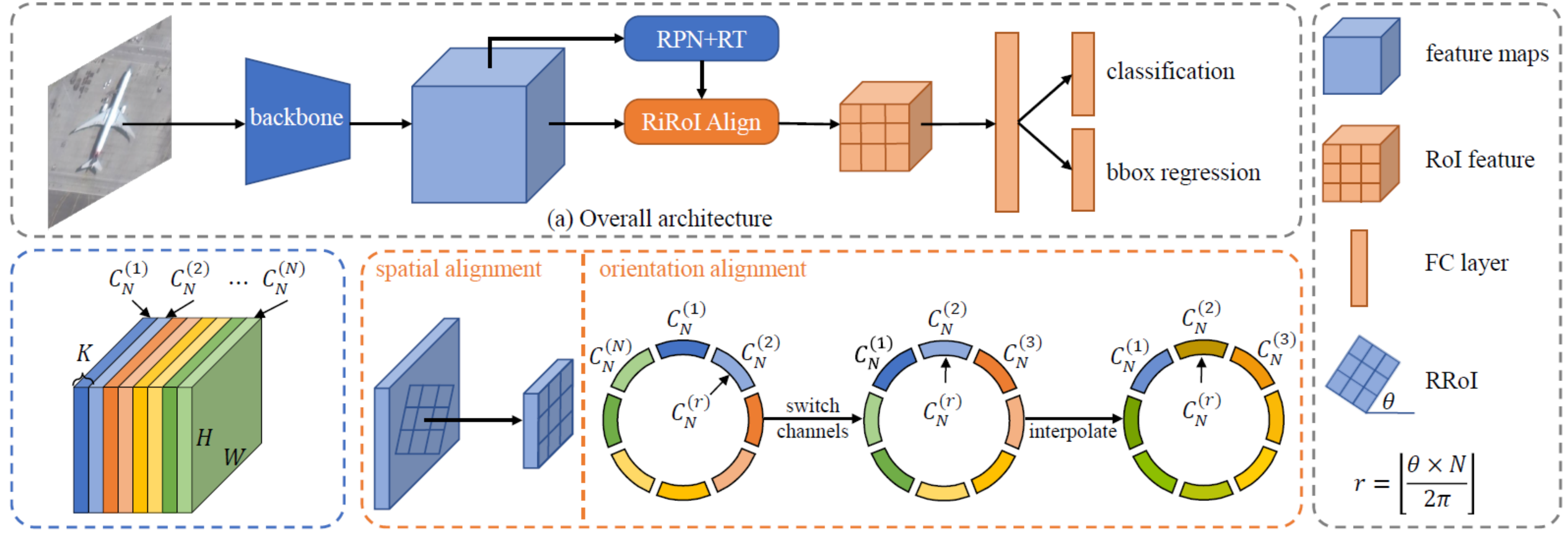


Rotation-equivariant Detector

- Rotation-invariant RoI Align
  - spatial alignment: same as RoI Align.
  - orientation alignment: align features from different orientation channels.

$$\hat{f}_R = \mathrm{Int}(SC(f_R, r), \theta), r = \lfloor \theta N / 2\pi \rceil$$

SC: switch channels Int: interpolation



(b) Rotation-equivariant feature maps

(c) Rotation-invariant RoI Align

Experiments

■ Datasets

➢ DOTA-v1.0: 188, 282 instances, 2806 images, 15 categories, size: 800~4000

➢ DOTA-v1.5: 402, 089 instances, 2806 images, 16 categories, size: 800~4000

➢ HRSC2016: ship detection, 1000 images, size: 300~1500

■ Implementation Details

➢ ImageNet pretrain: train ReResNet on ImageNet.

➢ Fine-tuning on detection: 1x for DOTA, 3x for HRSC2016

Experiments

■ Ablations

- ➢ rotation-equivariant backbone

backbone	group	cls. (%)	det. (%)	size (Mb)
R50-FPN	-	**76.55**	65.03	103
ReR50-ReFPN	C_4	72.81	65.43	24
ReR50-ReFPN	C_8	71.20	**66.86**	12
ReR50-ReFPN	C_{16}	61.60	64.36	**6**

- ➢ extend to other detector

method	backbone	mAP (%)	size (Mb)
FR-O	R50-FPN	62.00	158
	ReR50-ReFPN	**62.36**	**68**
RetinaNet-O	R50-FPN	58.74	140
	ReR50-ReFPN	**59.64**	**34**

- ➢ RiRoI Align

method	#interpolate	mAP (%)
RRoI Align	-	65.99
RRoI Align+*MP.*	-	64.60 (-1.39)
RiRoI Align	1	66.44 (+0.45)
RiRoI Align	2	**66.86 (+0.87)**
RiRoI Align	4	66.32 (+0.33)

- ➢ vs. rotation augmentation

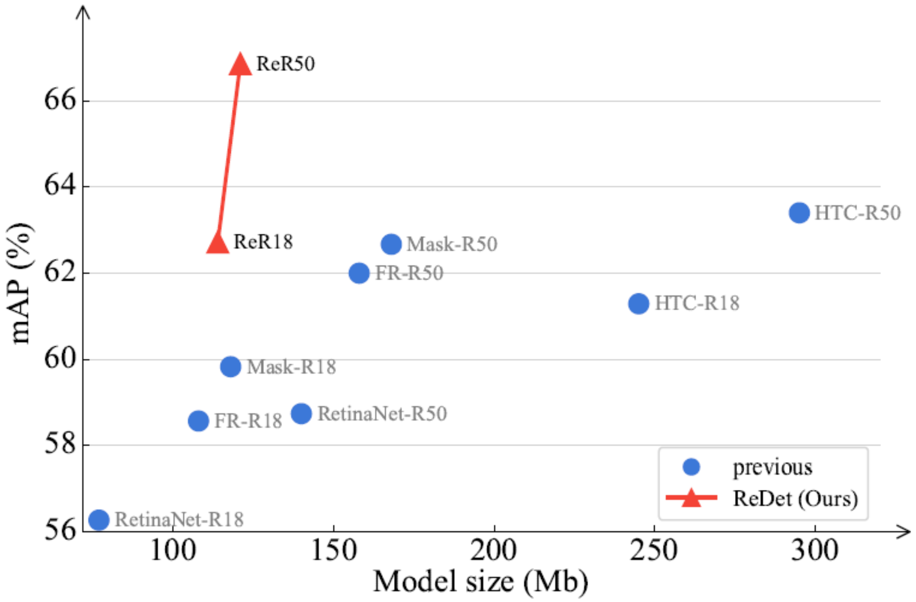
method	rot.	schd.	mAP (%)	training (h)
ReDet	×	1x	62.62	**8**
baseline	✓	1x	64.07	11
ReDet*	×	1x	66.66	13
baseline	✓	2x	**67.34**	22

Experiments

- Ablations
  - other datasets

method	DOTA-v1.0			HRSC2016		
	AP50	AP75	mAP	AP50	AP75	mAP
baseline	75.62	48.37	46.13	90.18	80.48	68.17
ReDet	76.25	50.86	**47.11(+0.98)**	90.46	89.46	**70.41(+2.24)**

  - accuracy vs. params



Experiments

- Ablations
  - SOTA on DOTA-v1.0.

method	backbone	PL	BD	BR	GTF	SV	LV	SH	TC	BC	ST	SBF	RA	HA	SP	HC	mAP
single-scale:																	
FR-O [35]	R101	79.42	77.13	17.70	64.05	35.30	38.02	37.16	89.41	69.64	59.28	50.30	52.91	47.89	47.40	46.30	54.13
ICN [1]	R101-FPN	81.36	74.30	47.70	70.32	64.89	67.82	69.98	90.76	79.06	78.20	53.64	62.90	67.02	64.17	50.23	68.16
CADNet [42]	R101-FPN	87.80	82.40	49.40	**73.50**	71.10	63.50	76.60	**90.90**	79.20	73.30	48.40	60.90	62.00	67.00	62.20	69.90
DRN [24]	H-104	88.91	80.22	43.52	63.35	73.48	70.69	84.94	90.14	83.85	84.11	50.12	58.41	67.62	68.60	52.50	70.70
CenterMap [30]	R50-FPN	88.88	81.24	**53.15**	60.65	**78.62**	66.55	78.10	88.83	77.80	83.61	49.36	**66.19**	**72.10**	**72.36**	58.70	71.74
SCRDet [40]	R101-FPN	**89.98**	80.65	52.09	68.36	68.36	60.32	72.41	90.85	**87.94**	**86.86**	**65.02**	**66.68**	66.25	68.24	**65.21**	72.61
R^{3}Det [37]	R152-FPN	**89.49**	81.17	50.53	66.10	70.92	**78.66**	78.21	90.81	85.26	84.23	**61.81**	63.77	68.16	**69.83**	**67.17**	73.74
S^{2}A-Net [10]	R50-FPN	89.11	**82.84**	48.37	71.11	78.11	78.39	**87.25**	90.83	84.90	85.64	60.36	62.60	65.26	69.13	57.94	**74.12**
ReDet (Ours)	ReR50-ReFPN	88.79	**82.64**	**53.97**	**74.00**	**78.13**	**84.06**	**88.04**	**90.89**	**87.78**	**85.75**	61.76	60.39	**75.96**	68.07	63.59	**76.25**
multi-scale:																	
RoI Trans.* [7]	R101-FPN	88.64	78.52	43.44	75.92	68.81	73.68	83.59	90.74	77.27	81.46	58.39	53.54	62.83	58.93	47.67	69.56
O^2-DNet* [31]	H104	89.30	83.30	50.10	72.10	71.10	75.60	78.70	**90.90**	79.90	82.90	60.20	60.00	64.60	68.90	65.70	72.80
DRN* [24]	H104	89.71	82.34	47.22	64.10	76.22	74.43	85.84	90.57	86.18	84.89	57.65	61.93	69.30	69.63	58.48	73.23
Gliding Vertex* [36]	R101-FPN	89.64	85.00	52.26	77.34	73.01	73.14	86.82	90.74	79.02	86.81	59.55	**70.91**	72.94	70.86	57.32	75.02
BBAVectors* [41]	R101	88.63	84.06	52.13	69.56	78.26	80.40	88.06	90.87	**87.23**	86.39	56.11	65.62	67.10	72.08	63.96	75.36
CenterMap* [30]	R101-FPN	**89.83**	84.41	54.60	70.25	77.66	78.32	87.19	90.66	84.89	85.27	56.46	**69.23**	74.13	71.56	66.06	76.03
CSL* [38]	R152-FPN	**90.25**	**85.53**	54.64	75.31	70.44	73.51	77.62	90.84	86.15	86.69	69.60	68.04	73.83	71.10	68.93	76.17
SCRDet++* [39]	R152-FPN	88.68	**85.22**	54.70	73.71	71.92	**84.14**	79.39	90.82	87.04	86.02	67.90	60.86	74.52	70.76	**72.66**	76.56
S^{2}A-Net* [10]	R50-FPN	88.89	83.60	**57.74**	**81.95**	**79.94**	83.19	**89.11**	90.78	84.87	**87.81**	**70.30**	68.25	**78.30**	**77.01**	69.58	**79.42**
ReDet* (Ours)	ReR50-ReFPN	88.81	82.48	**60.83**	**80.82**	**78.34**	**86.06**	**88.31**	**90.87**	**88.77**	**87.03**	**68.65**	66.90	**79.26**	**79.71**	**74.67**	**80.10**

Experiments

- Ablations

- SOTA on DOTA-v1.5.

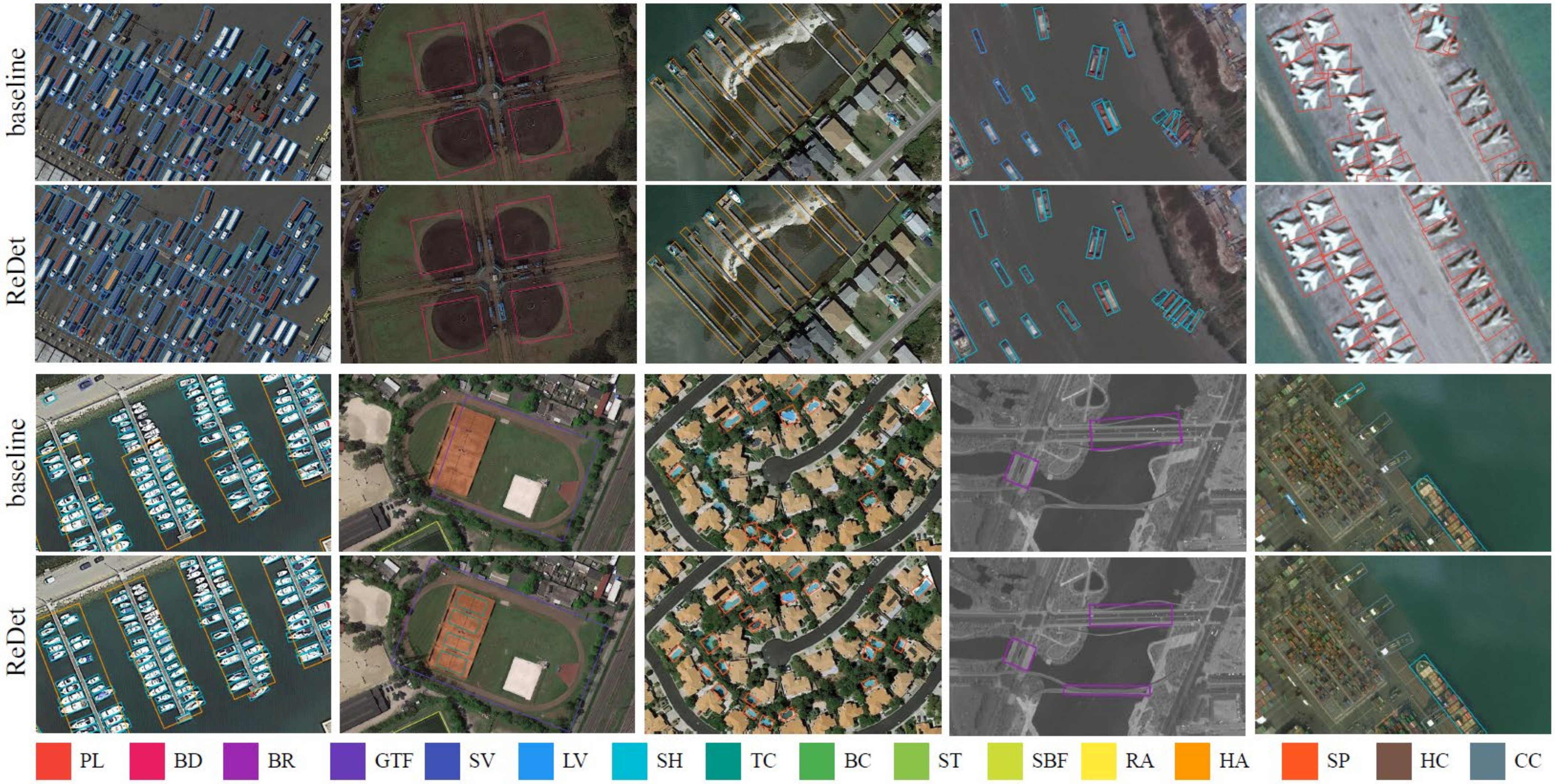
method	PL	BD	BR	GTF	SV	LV	SH	TC	BC	ST	SBF	RA	HA	SP	HC	CC	mAP
OBB results:																	
RetinaNet-O [18]	71.43	77.64	42.12	64.65	44.53	56.79	73.31	90.84	76.02	59.96	46.95	69.24	59.65	64.52	48.06	0.83	59.16
FR-O [27]	71.89	74.47	44.45	59.87	51.28	68.98	79.37	90.78	77.38	67.50	47.75	69.72	61.22	65.28	60.47	1.54	62.00
Mask R-CNN [11]	76.84	73.51	49.90	57.80	51.31	71.34	79.75	90.46	74.21	66.07	46.21	70.61	63.07	64.46	57.81	9.42	62.67
HTC [2]	77.80	73.67	51.40	63.99	51.54	73.31	80.31	90.48	75.12	67.34	48.51	70.63	64.84	64.48	55.87	5.15	63.40
OWSR* [15]	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	74.90
ReDet (Ours)	79.20	82.81	51.92	71.41	52.38	75.73	80.92	90.83	75.81	68.64	49.29	72.03	73.36	70.55	63.33	11.53	66.86
ReDet* (Ours)	88.51	86.45	61.23	81.20	67.60	83.65	90.00	90.86	84.30	75.33	71.49	72.06	78.32	74.73	76.10	46.98	**76.80**
HBB results:																	
RetinaNet-O [18]	71.66	77.22	48.71	65.16	49.48	69.64	79.21	90.84	77.21	61.03	47.30	68.69	67.22	74.48	46.16	5.78	62.49
FR-O [27]	71.91	71.60	50.58	61.95	51.99	71.05	80.16	90.78	77.16	67.66	47.93	69.35	69.51	74.40	60.33	5.17	63.85
HTC [2]	78.41	74.41	53.41	63.17	52.45	63.56	79.89	90.34	75.17	67.64	48.44	69.94	72.13	74.02	56.42	12.14	64.47
Mask R-CNN [11]	78.36	77.41	53.36	56.94	52.17	63.60	79.74	90.31	74.28	66.41	45.49	71.32	70.77	73.87	61.49	17.11	64.54
OWSR* [15]	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	77.90
ReDet (Ours)	79.51	82.63	53.81	69.82	52.76	75.64	87.82	90.83	75.81	68.78	49.11	71.65	75.57	75.17	58.29	15.36	67.66
ReDet* (Ours)	88.68	86.57	61.93	81.20	73.71	83.59	90.06	90.86	84.30	75.56	71.55	71.86	83.93	80.38	75.62	49.55	**78.08**

- SOTA on HRSC2016.

method	RC2 [19]	RRPN [22]	R^2PN [43]	RRD [16]	RoI Trans. [7]	Gliding Vertex [36]
mAP	75.7	79.08	79.6	84.3	86.2	88.2
method	R^3Det [37]	DRN [24]	CenterMap [30]	CSL [38]	S^2A-Net [10]	ReDet (Ours)
mAP	89.26	92.7*	92.8*	89.62	90.17 / 95.01*	**90.46 / 97.63***

Experiments

■ Visualization



Thank you

ReDet: A Rotation-equivariant Detector for Aerial Object Detection

Paper

Code

Website