

## 中国科学技术大学 University of Science and Technology of China

### Cascade Saliency Attention Network for Object Detection in Remote Sensing Images

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#### 01 | Introduction

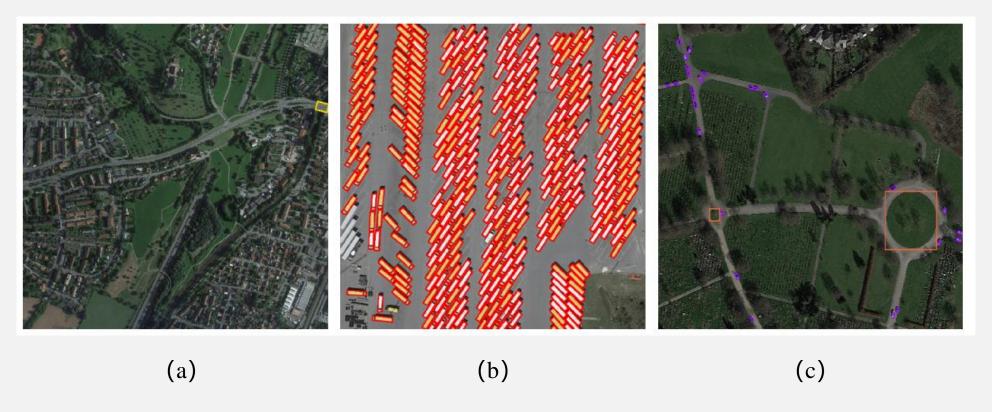


Fig 1. Three difficulties in remote sensing image object detection. (a) The bridge is overwhelmed by the complex backgrounds. (b) Large vehicles are densely arranged in the parking lot. (c) There is a large-scale variations within roundabout, and between roundabout and small vehicle.

#### 02 | Methodology

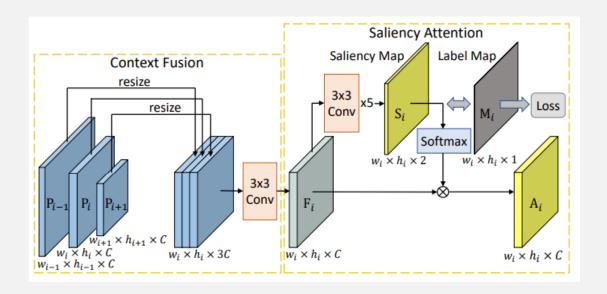


Fig 2. The architecture of Context Fusion Saliency Attention module. This module first fuses multi-layer features and then performs pixel attention on the context fusion feature map

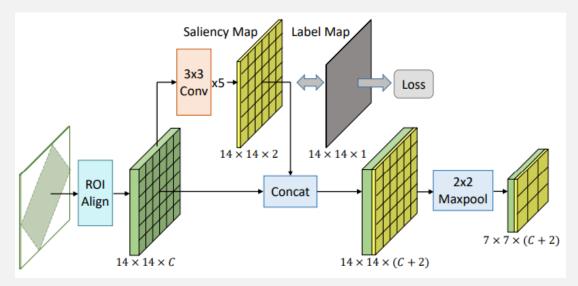


Fig 3. The architecture of cascade network with Saliency Attention ROI Align. At cascade stage, the instance segmentation is used on ROIs extracted by ROI Align.

#### 02 | Methodology

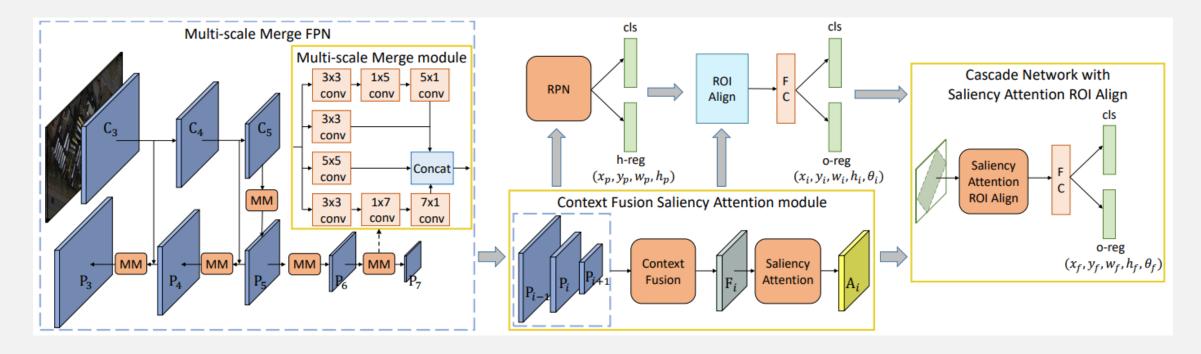


Fig 4. The framework of proposed network. The network contains three main subparts: Multi-scale Merge module in FPN, Context Fusion Saliency Attention module, and cascade network with Saliency Attention ROI Align.

#### 03 | Experiments and Results

TABLE I
RESULTS ON DIFFERENT OBJECTS AND OVERALL PERFORMANCES ON DOTA DATASET

TABLE II RESULTS ON HRSC2016 DATASET

Method	PL	BD	BR	GTF	SV	LV	SH	TC	BC	ST	SBF	RA	HA	SP	HC	mAP
FR-H [17]*	47.16	61.00	9.80	51.74	14.87	12.80	6.88	56.26	59.97	57.32	47.83	48.70	8.23	37.25	23.05	36.29
FR-O [13]*	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	52.93
R <sup>2</sup> CNN [27]	80.94	65.67	35.34	67.44	59.92	50.91	55.81	90.67	66.92	72.39	55.06	52.23	55.14	53.35	48.22	60.67
ICN [12]*	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
ROI Trans [11]*	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
CAD-Net [9]*	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
R <sup>2</sup> CNN++ [10]	89.66	81.22	45.50	75.10	68.27	60.17	66.83	90.90	80.69	86.15	64.05	63.48	65.34	68.01	62.05	71.16
R3Det [28]	89.24	80.81	51.11	65.62	70.67	76.03	78.32	90.83	84.89	84.42	65.10	57.18	68.10	68.98	60.88	72.81
Zhu et al. [22]	89.67	76.77	51.28	71.65	73.11	77.18	79.54	90.79	79.01	84.54	66.51	64.71	73.97	67.73	58.40	73.66
Ours	89.86	83.52	51.98	71.58	75.68	80.34	87.26	90.50	80.92	86.61	66.11	67.44	74.53	69.55	57.84	75.58

Method	mAP
BL2 [29]	69.60
R <sup>2</sup> CNN [27]	73.07
RC1 & RC2 [29]	75.70
R2PN [30]	79.60
RRD [31]	84.30
ROI Trans [11]	86.20
R3Det [28]	89.33
Ours	93.43

#### 03 | Experiments and Results

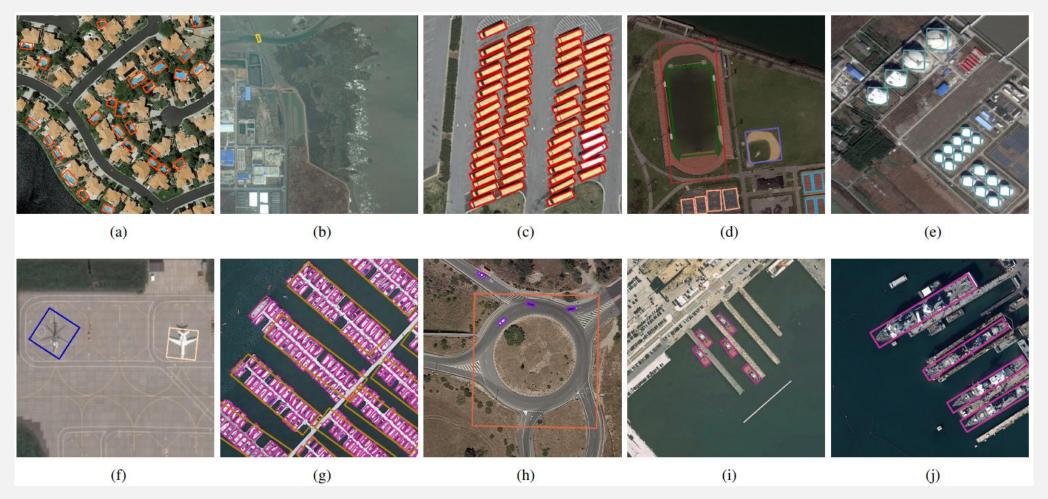


Fig 5. Some detection results on DOTA and HRSC2016. (a)-(h) Detection results on DOTA. (i)-(j) Detection results on HRSC2016. In the case of complex backgrounds, dense arrangement, and large-scale variations, our method can still accurately detect objects in remote sensing images.

# Thank you very much