



西安电子科技大学
XIDIAN UNIVERSITY

MSSDet: A Multi-scale Ship Detection Framework in Optical Remote Sensing Images



Speaker: Weiming Chen

2021-10-28

Visual Information in Processing Lab(VIP Lab)



- Introduction
- HRSC2016-MS Dataset
- MSSDet
- Experimental Result
- Conclusion



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The significance of ship detection



Fishery management



Suppress smuggling



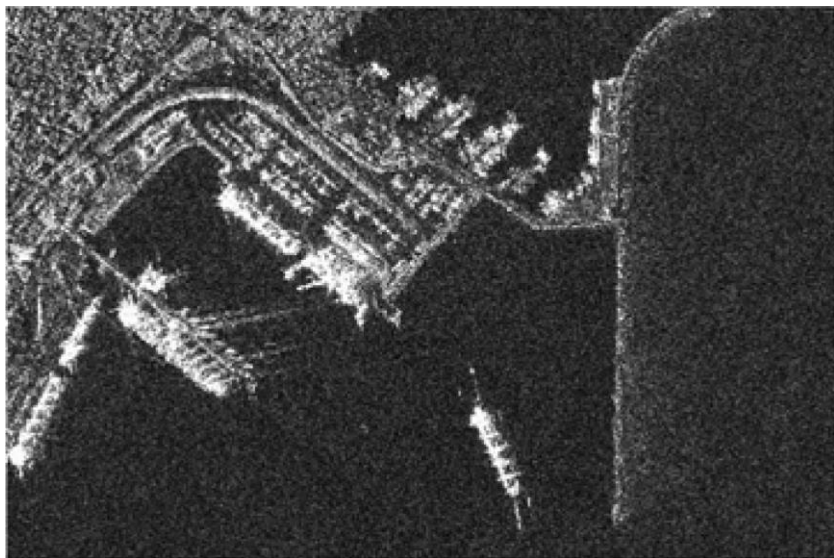
Maritime transportation



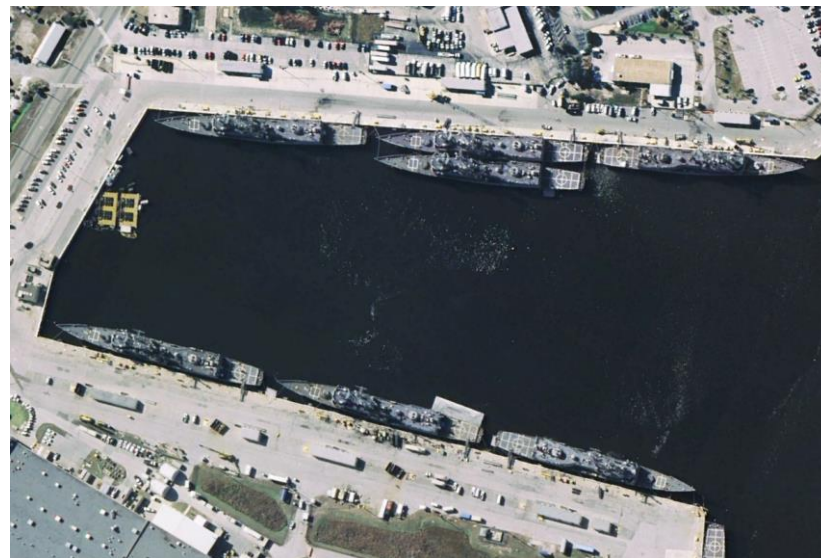
Naval warfare



Why is optical remote sensing images?



Synthetic Aperture Radar (SAR)



Optical Remote Sensing (ORS)



Dataset	Categories	Images	Instances	Year
TAS	1	30	1319	2008
SZTAKIINRIA	1	9	665	2012
*NWPU VHR10	10	800	3775	2014
VEDAI	9	1210	3640	2015
UCASAOD	2	910	6029	2015
DLR 3K Vehicle	2	20	14235	2015
*HRSC2016	1	1070	2976	2016
RSOD	4	976	6950	2017
*DOTA	15	2806	188282	2018
*DIOR	20	23463	192472	2019
*HRRSD	13	26722	55740	2019

*: the dataset contains the category of ship.



Method

Advantages

Disadvantages

Non-oriented Ship
Detection

High accuracy;
Strong robustness

Cannot predict orientation;
Weak detection performance for
dense objects

Oriented Ship Detection

Can predict orientation;
Good detection performance
for dense objects

Hard to annotate;
Low efficiency



Non-oriented Ship Detection



Oriented Ship Detection



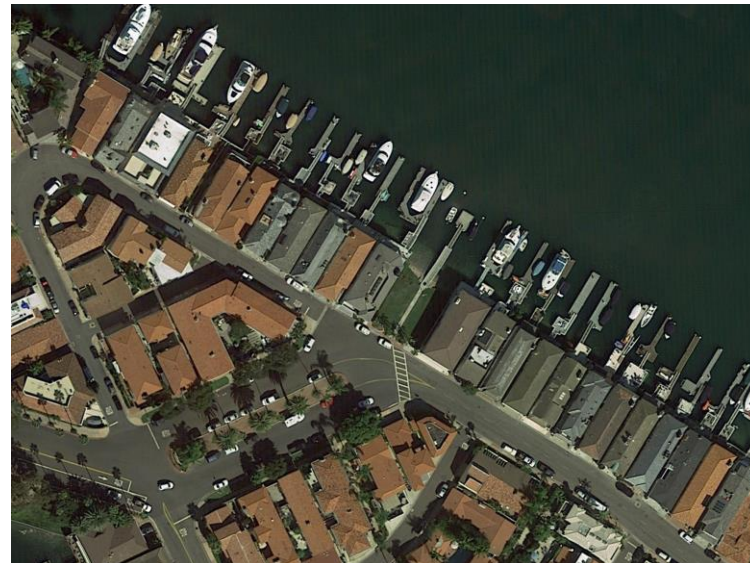
Natural Image



Moderate size

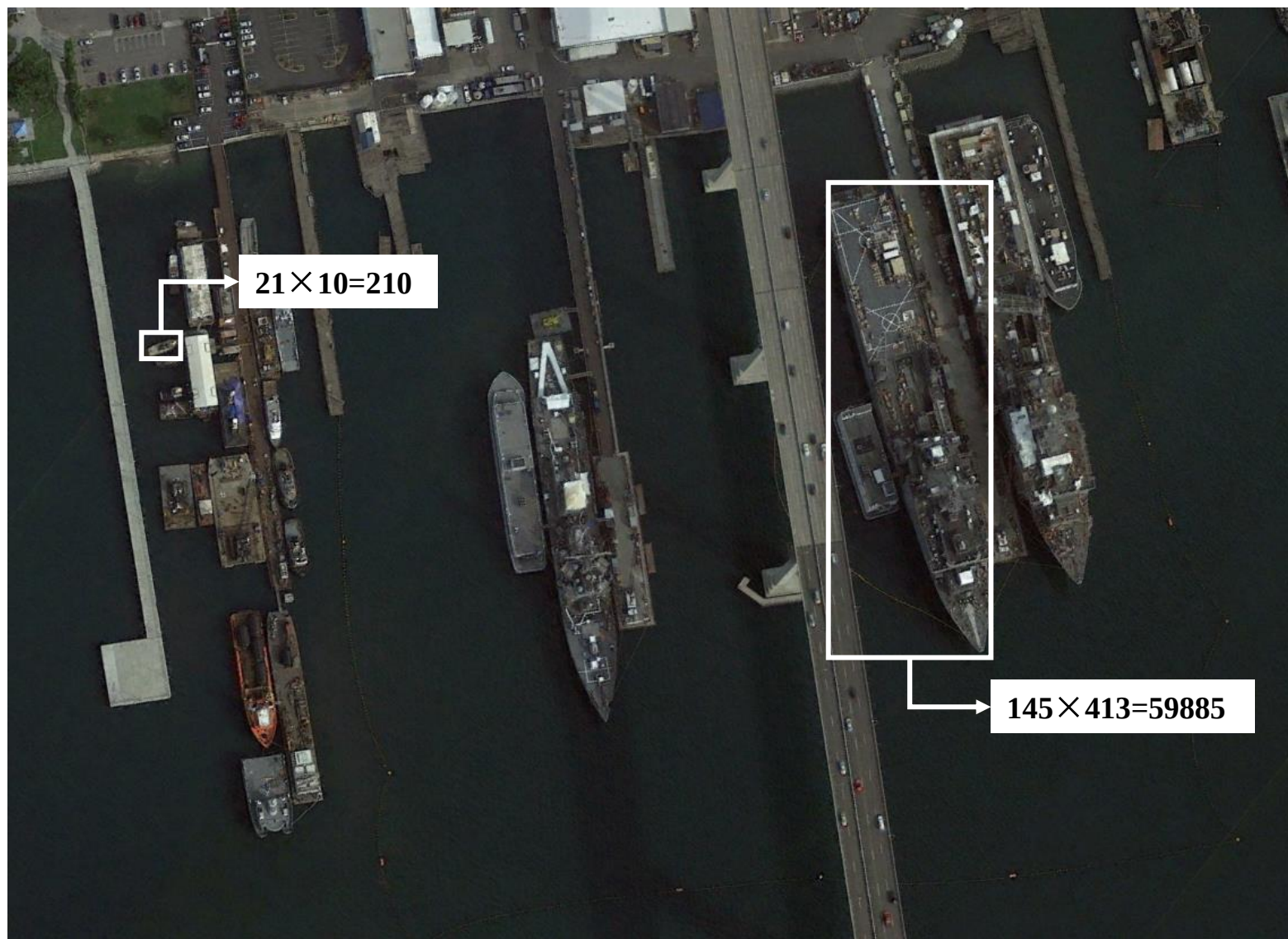
Pure scenario

Optical Remote Sensing Image



Large size

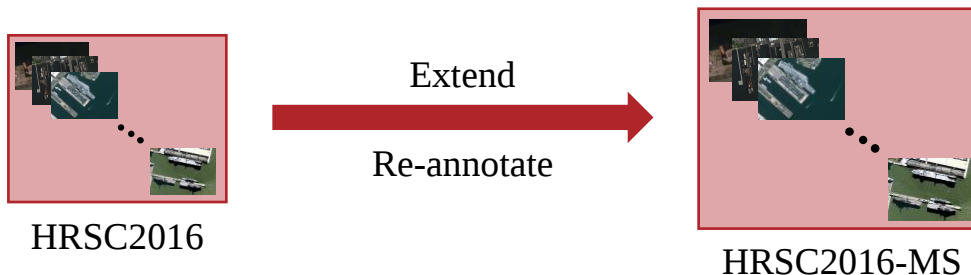
Complex scenario





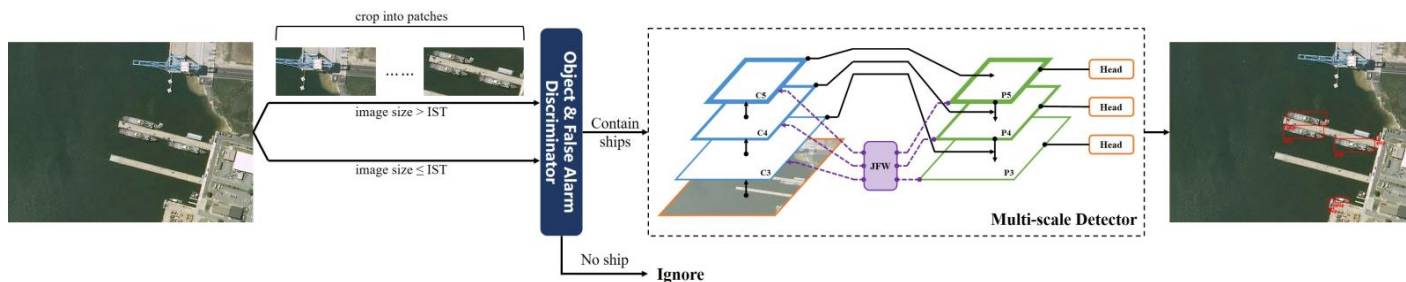
DATASET

- We build a new dataset with rich multi-scale ship instances based on HRSC2016.



ALGORITHM

- We propose **Adaptive Cropping Strategy** and **Objects and False Alarms Discriminator** to deal with the difficulty of size.
- We propose **Joint Recursive Feature Pyramid** to deal with the difficulty of scenario and multi-scale instances.

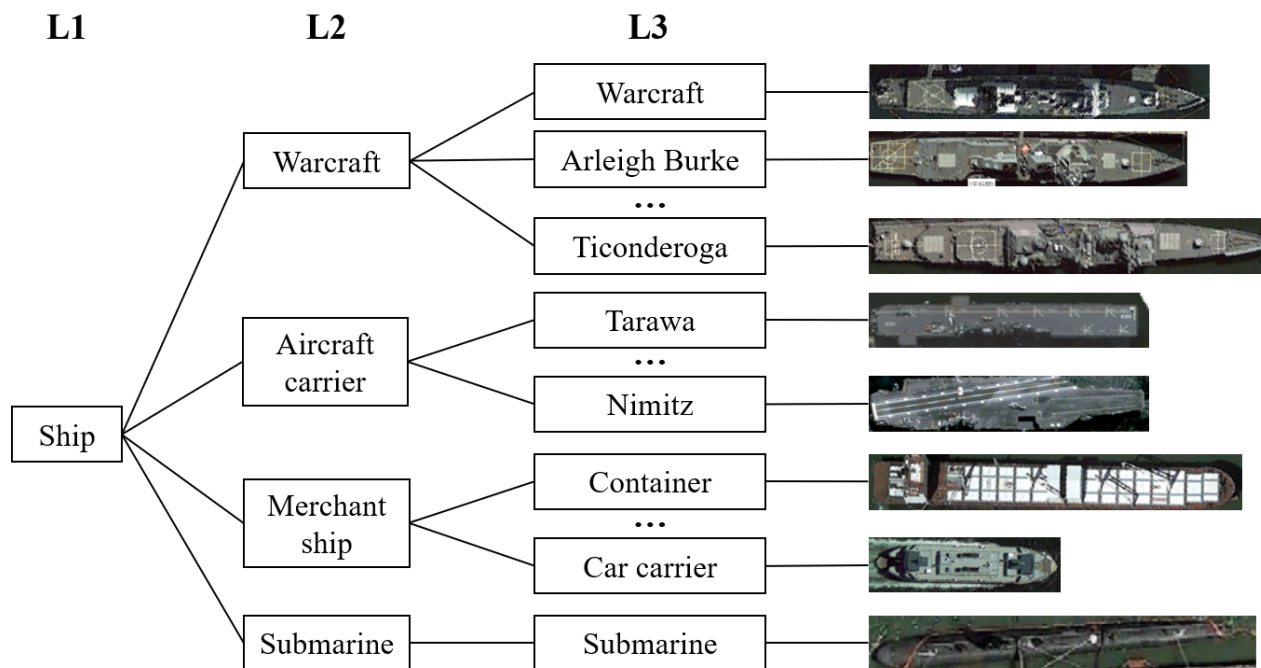




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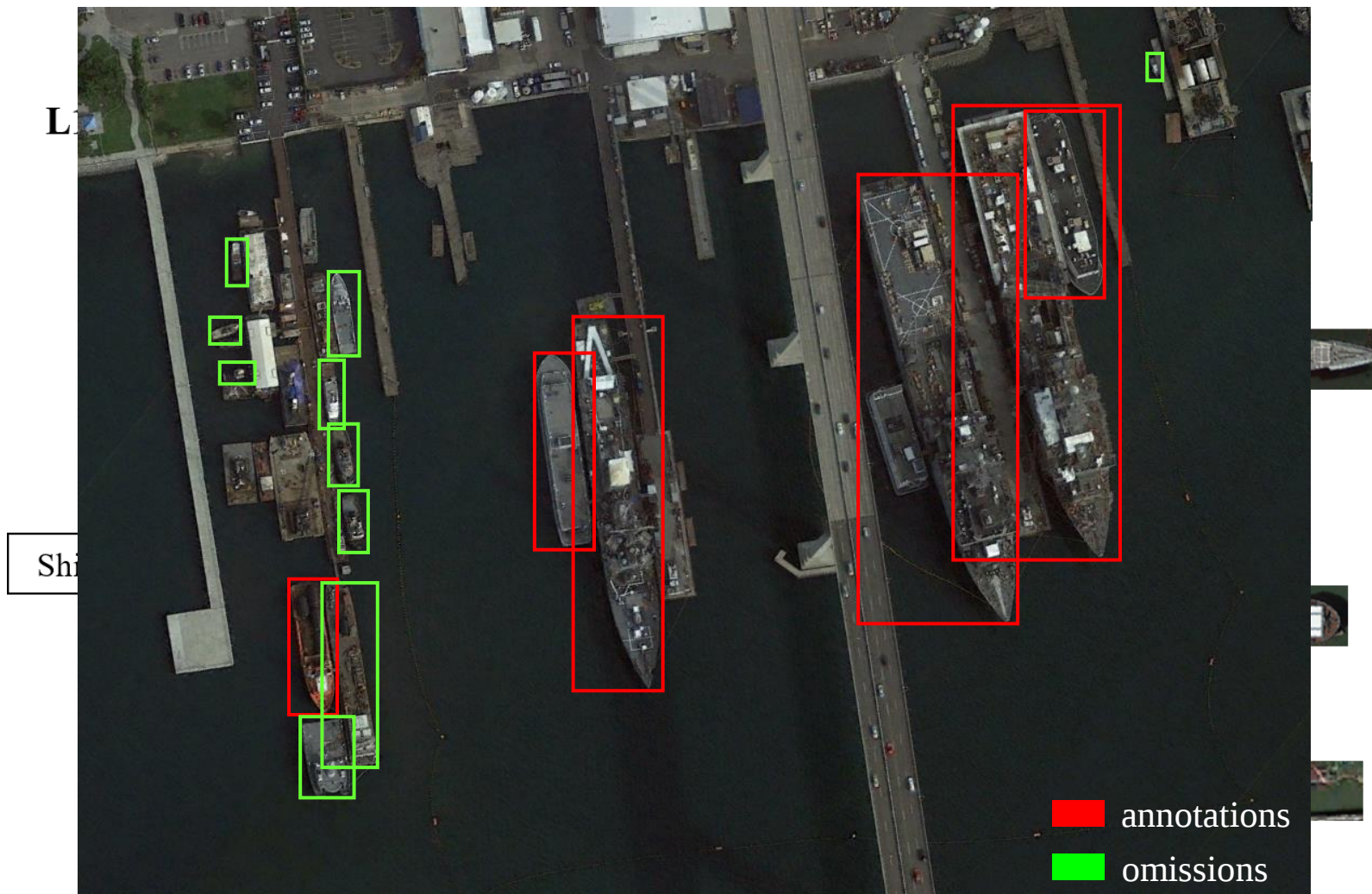


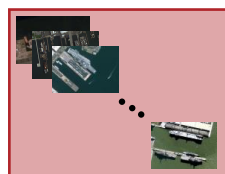
- **Data source:** Google Earth
- **Data volume:** 1070 images with 2976 ship instances
- **Image size:** 300×300 to 1500×900 (most of them are larger than 1000×600)
- **Spatial resolution:** between 2m and 0.4m
- **Scenario:** sea and sea-land
- **Annotation:** HBB and OBB
- **Label set:** cover 1, 4, 27 classes respectively.





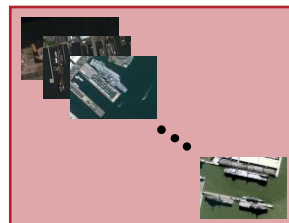
- **Defect 1:** the insufficiency of data
- **Defect 2:** annotation omission





HRSC2016

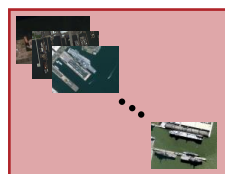
Extend
Re-annotate



HRSC2016-MS

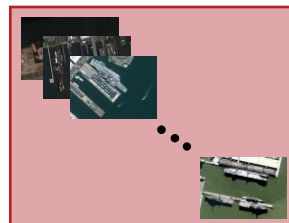
Extend

- **Data source:** Google Earth
- **Data volume:** 610 images
- **Image size:** 300×300 to 1500×900 (most of them are larger than 1000×600)
- **Spatial resolution:** between 2m and 0.4m
- **Scenario:** sea and sea-land



HRSC2016

Extend
Re-annotate



HRSC2016-MS

Re-annotate

HRSC2016-MS Dataset

Annotation Method

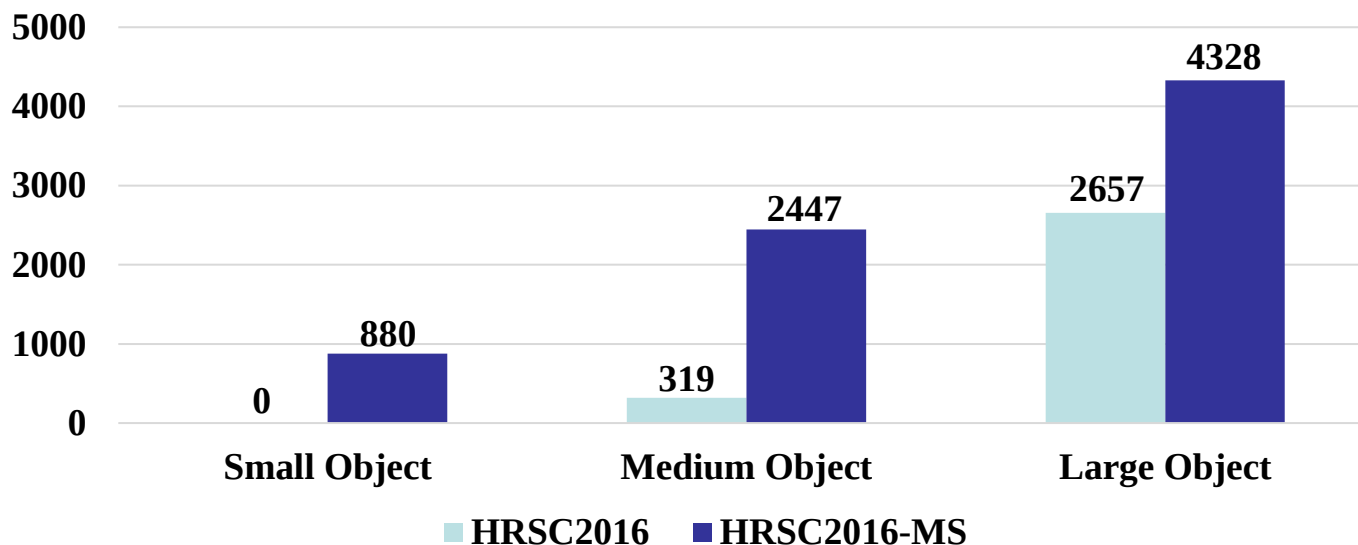


HRSC2016

HRSC2016-MS

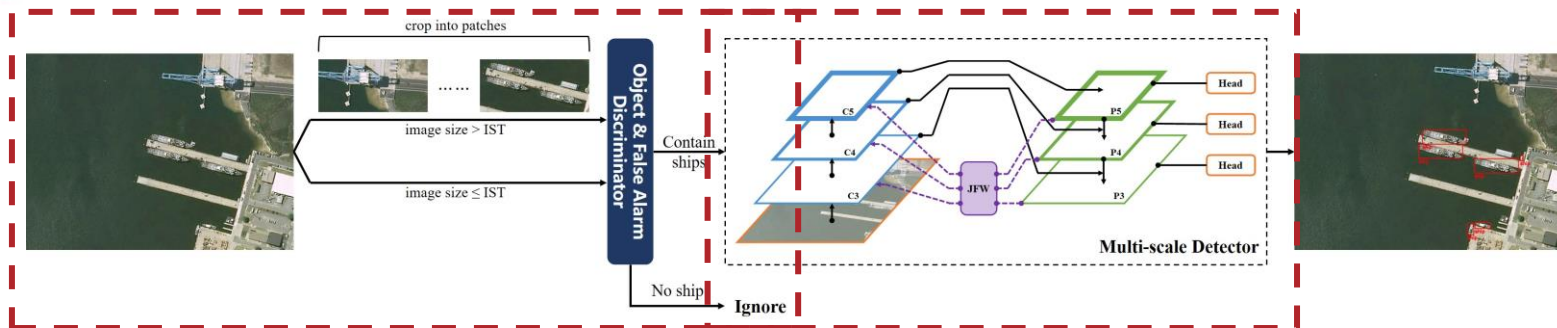
- **Data source:** Google Earth
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- **Scenario:** sea and sea-land
- **Annotation:** HBB and OBB
- **Label set:** cover 1, 4, 27 classes respectively

- **Data source:** Google Earth
- **Data volume:** 1680 images with 7655 instances
- **Image size:** 300×300 to 1500×900
- **Spatial resolution:** between 2m and 0.4m
- **Scenario:** sea and sea-land
- **Annotation:** HBB and OBB
- **Label set:** cover 1 class

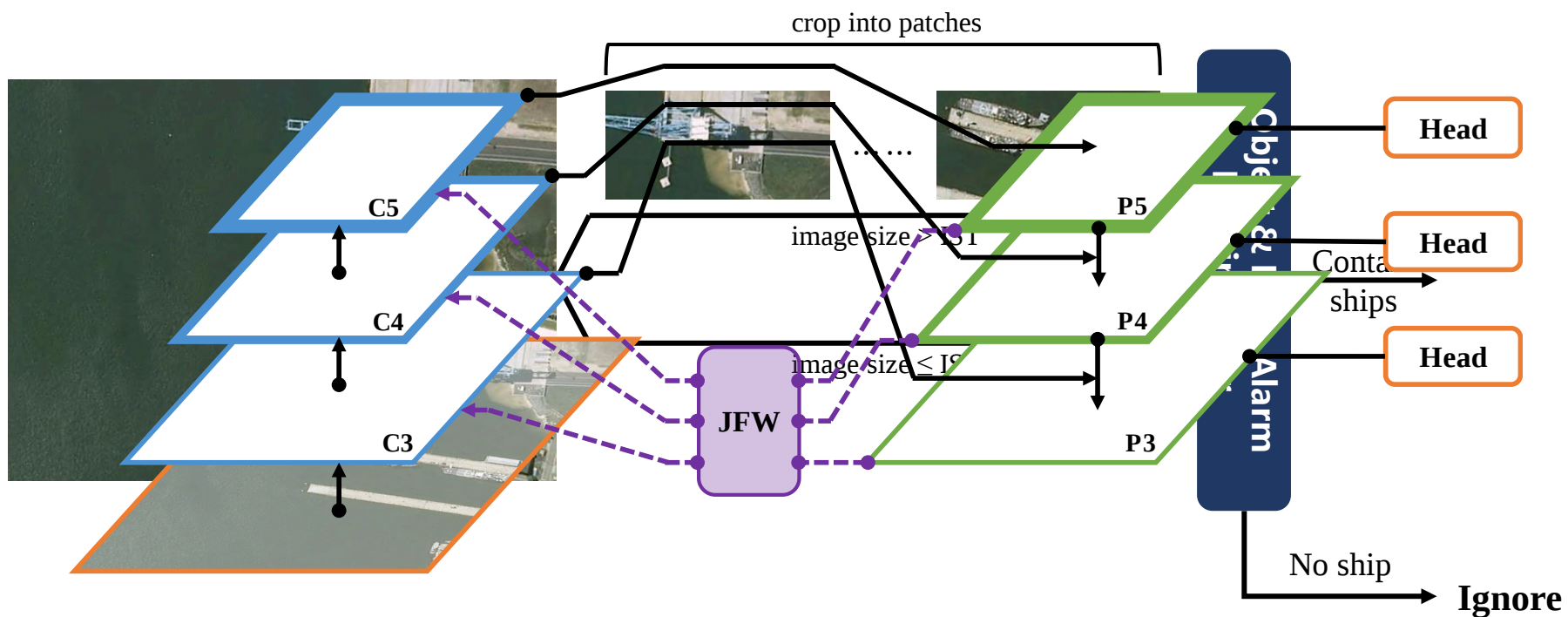




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Multi-scale processing

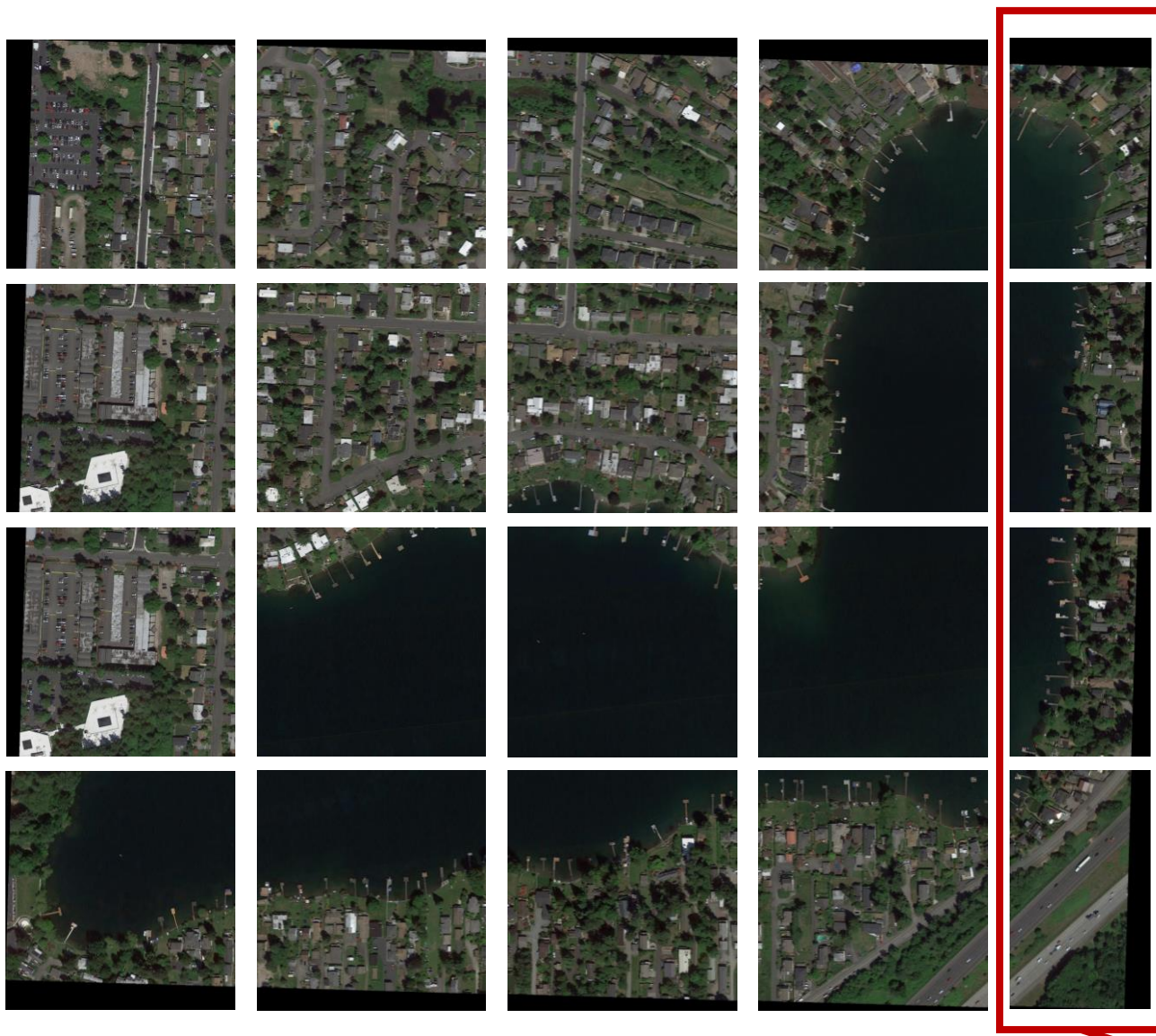




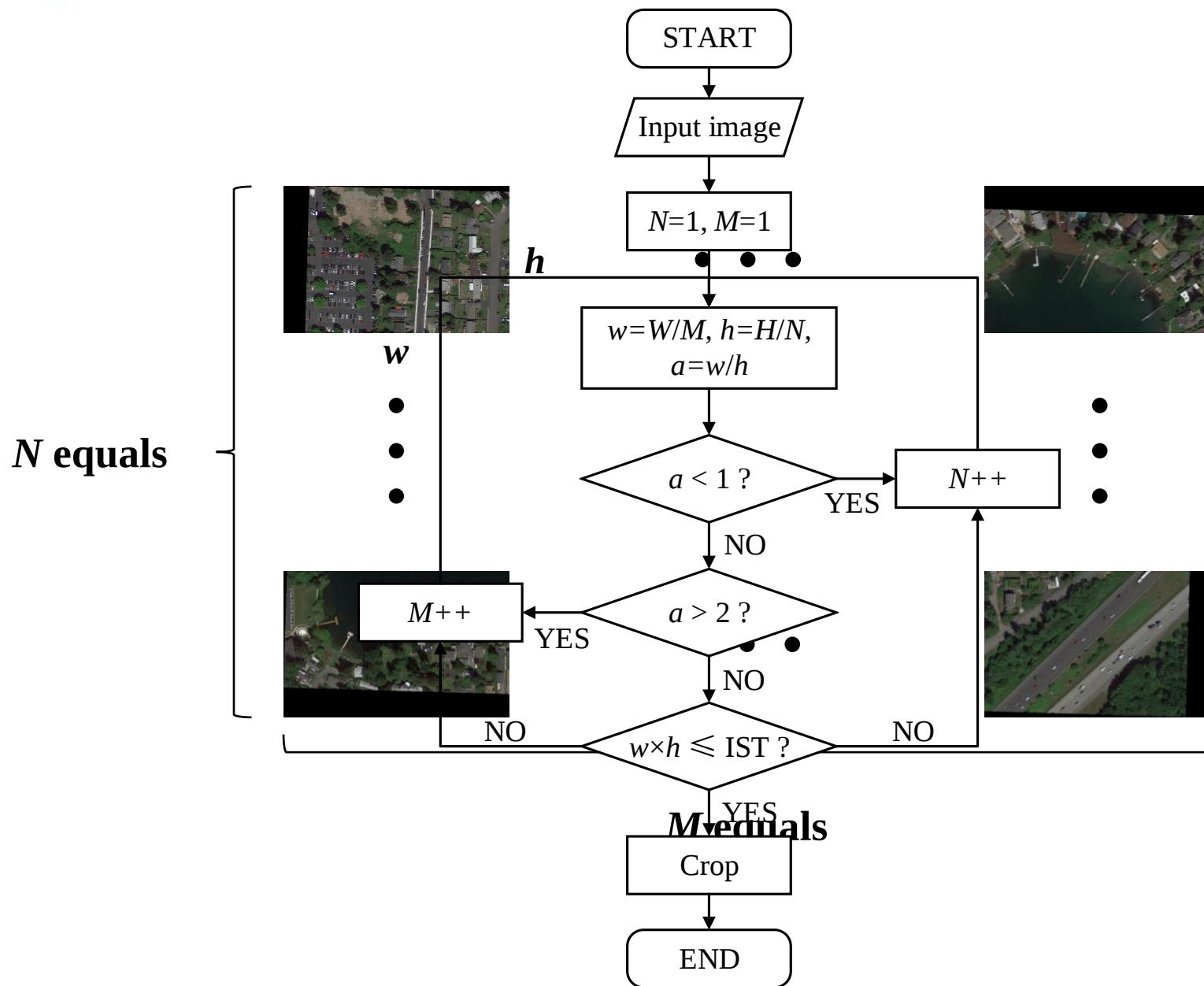
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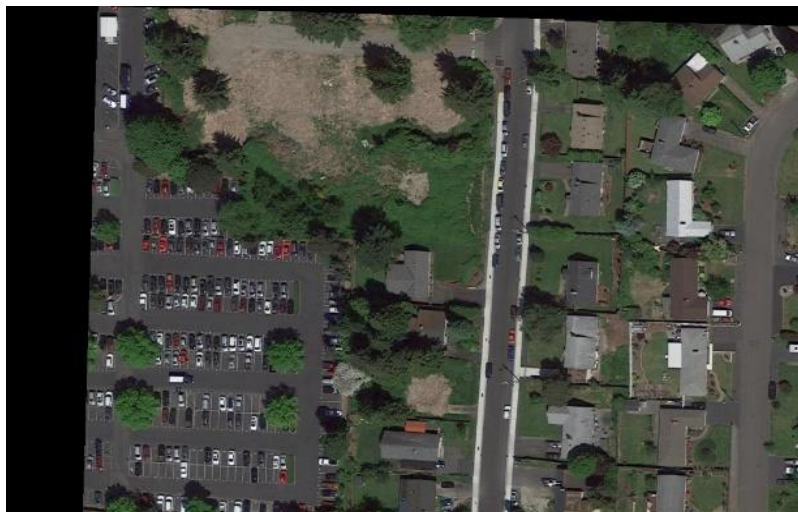
Data preprocessing





Unsuitable aspect ratio



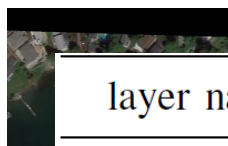


Blank Patch

- It is **waste of computing resources** when the detector is processing blank patches.
- It may **increase the risk of detecting false alarms** when input blank patches into the detector.



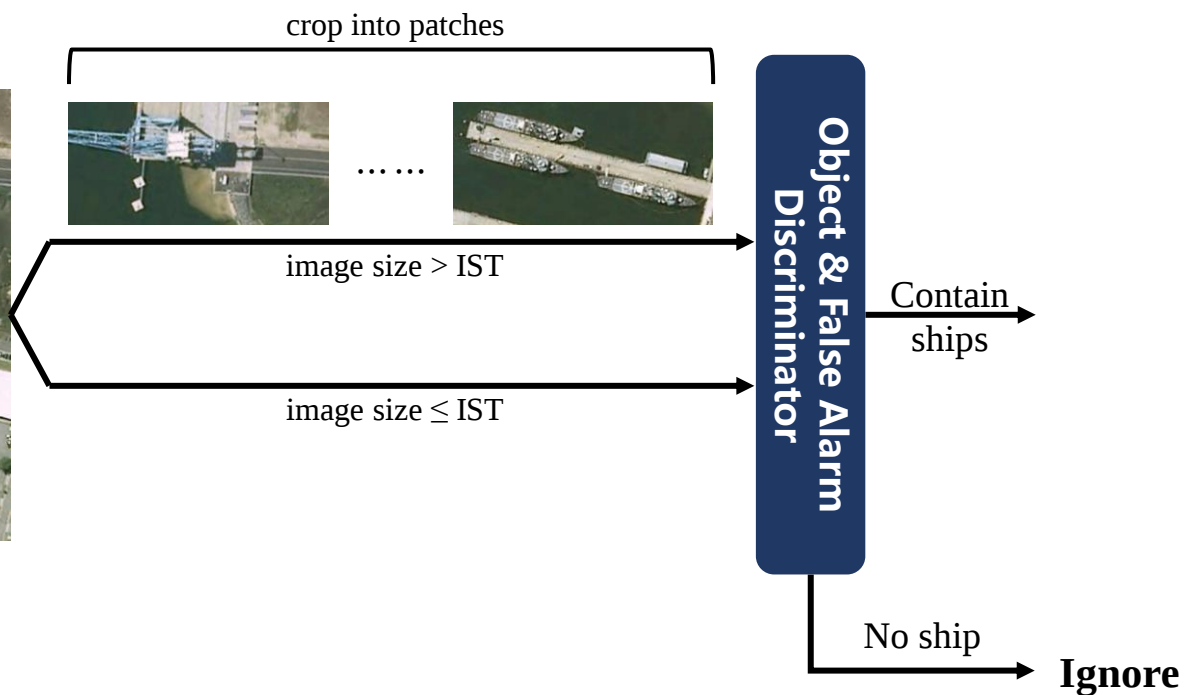
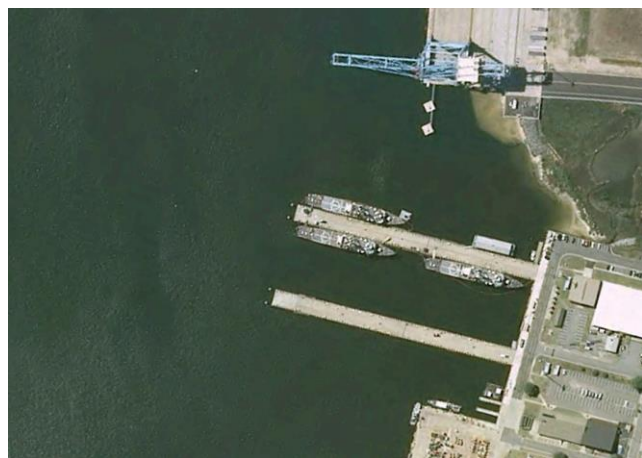
ResNet34



layer name	architecture
conv1	conv, 7×7, 64, stride 2 max pooling, 3×3, stride 2
conv2	$\begin{bmatrix} 3 \times 3, 64 \\ 3 \times 3, 64 \end{bmatrix} \times 3$
conv3	$\begin{bmatrix} 3 \times 3, 128 \\ 3 \times 3, 128 \end{bmatrix} \times 4$
conv4	$\begin{bmatrix} 3 \times 3, 256 \\ 3 \times 3, 256 \end{bmatrix} \times 6$
conv5	$\begin{bmatrix} 3 \times 3, 512 \\ 3 \times 3, 512 \end{bmatrix} \times 3$
	global average pooling fc, 2-d softmax

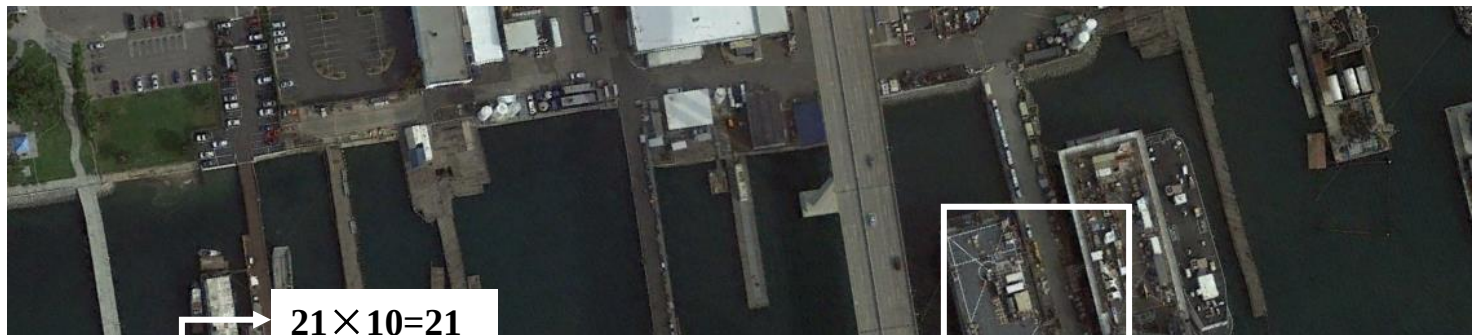
- OFAD act as a filter to
- A good OFAD should
- and **strong generaliz**

, **fast inference speed**

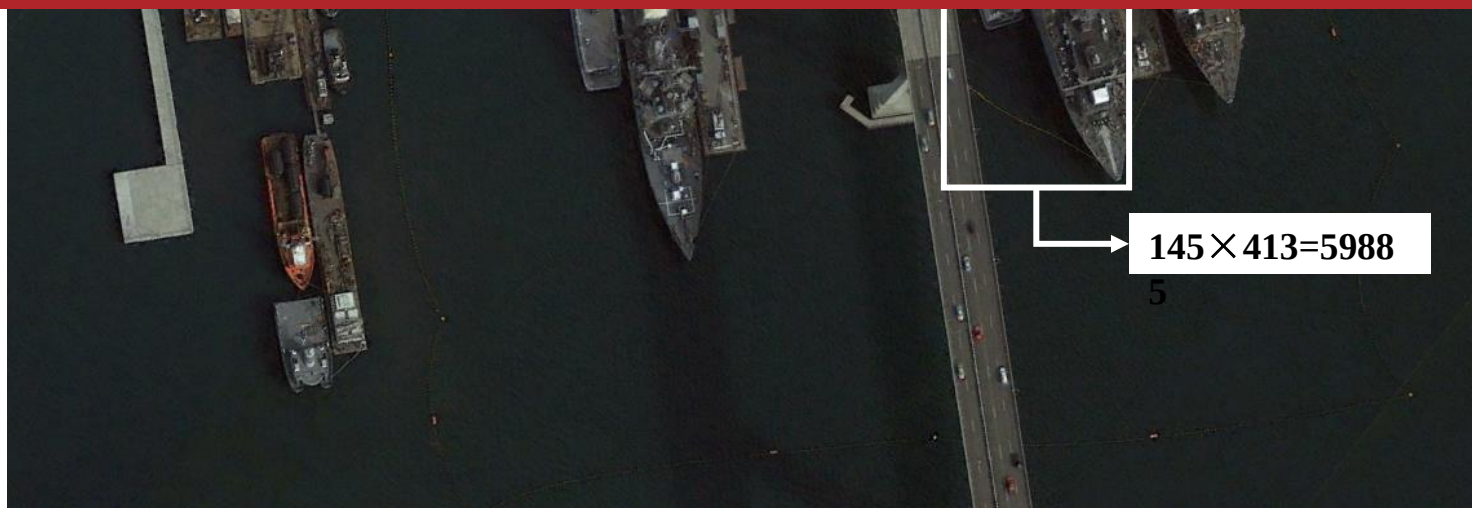




Learning the pattern of multi-scale objects is huge challenge

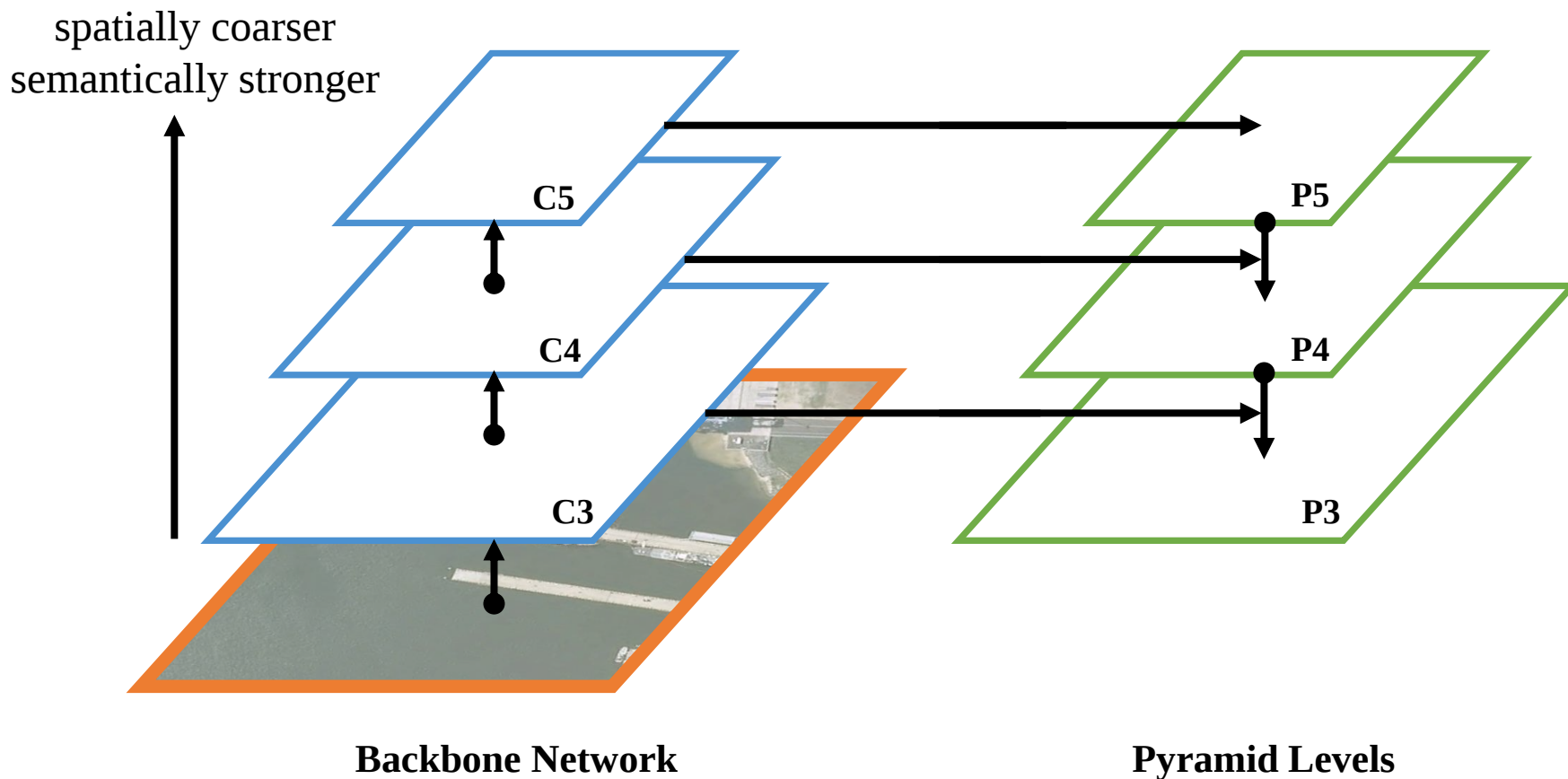


Improve multi-scale feature representation capability



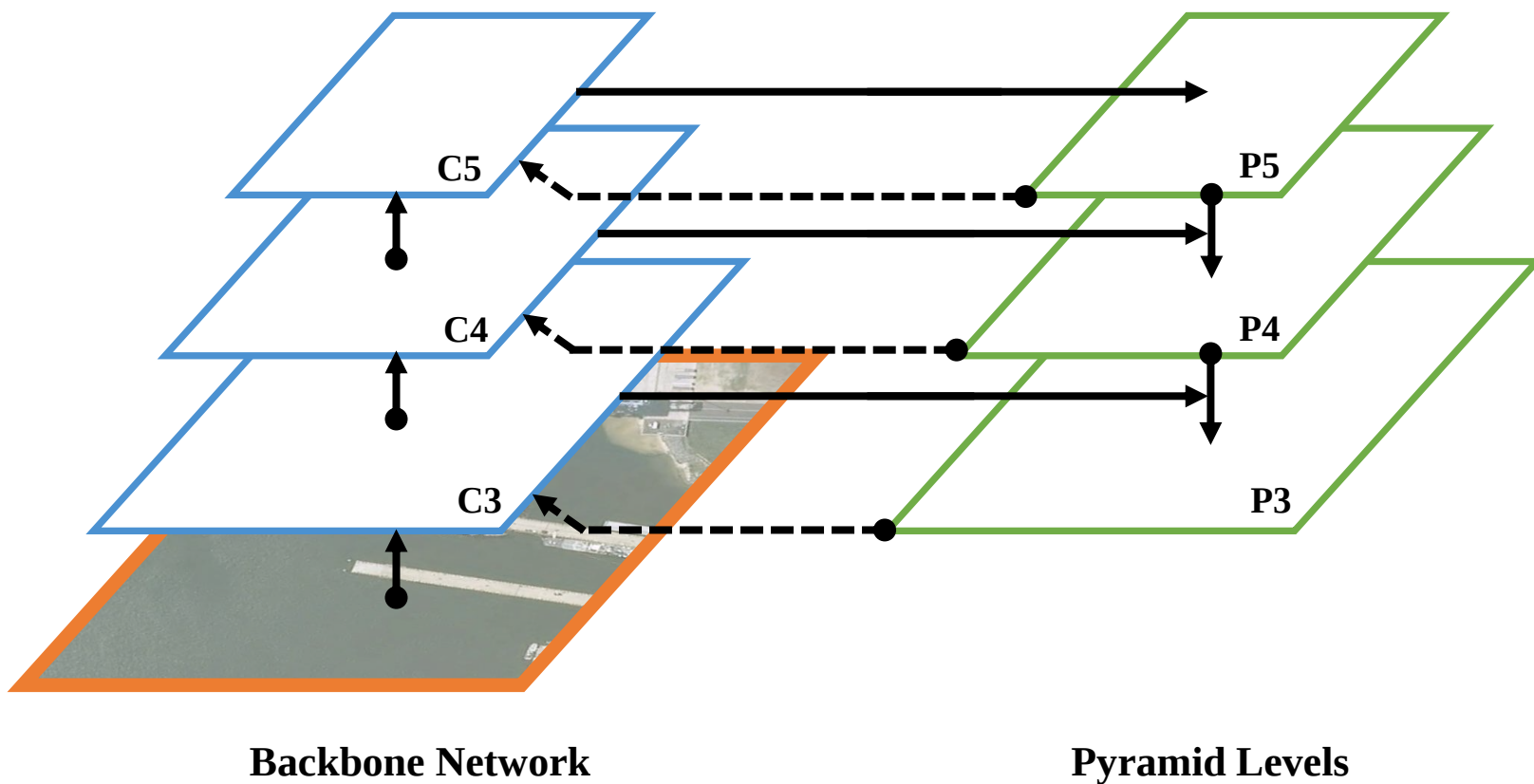


Feature Pyramid Network (FPN)



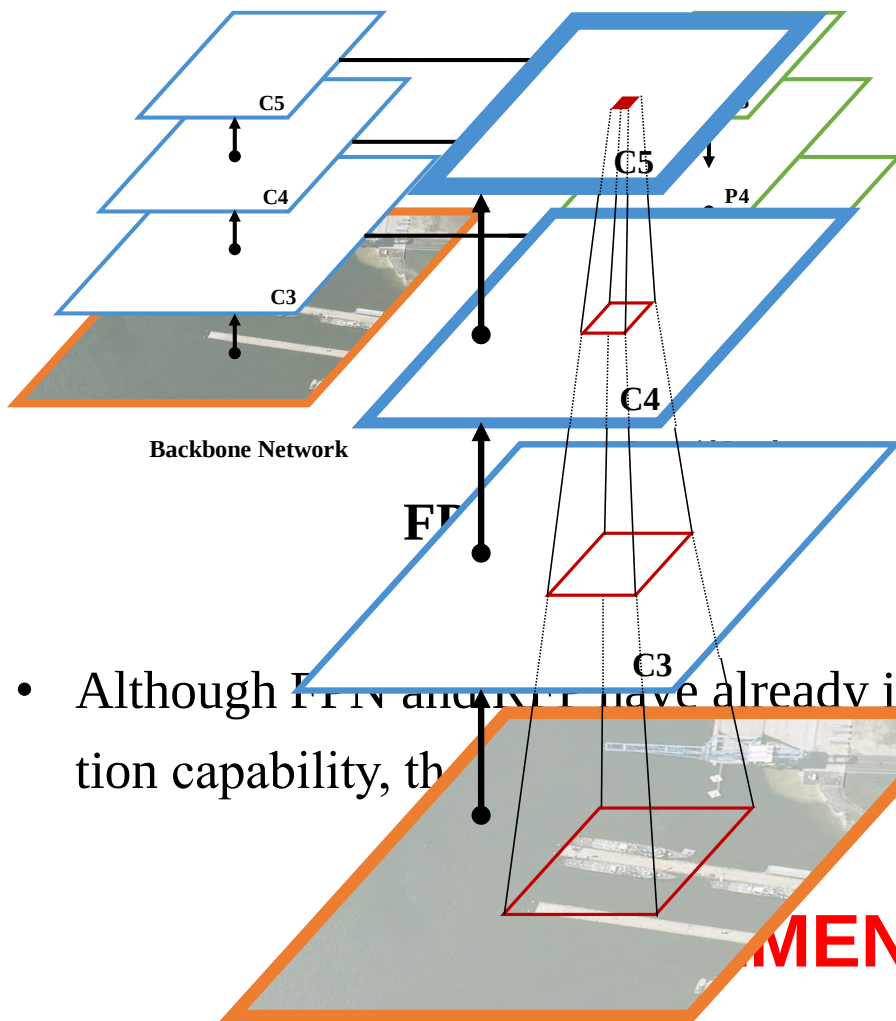


Recursive Feature Pyramid (RFP)

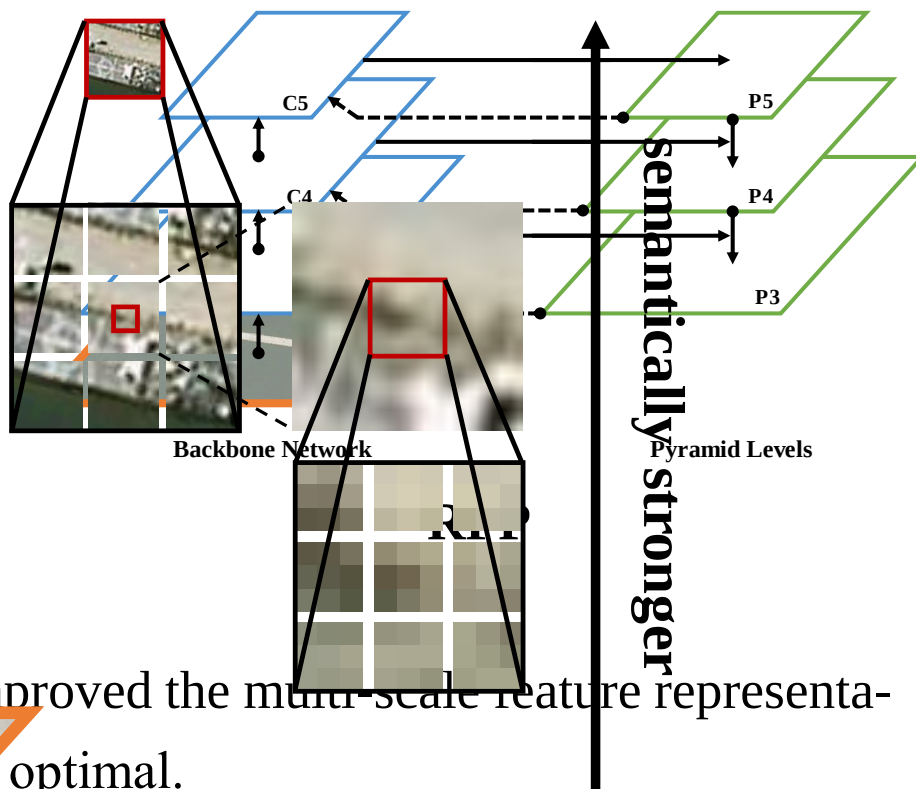




Backbone Network



Reception Field Visualization

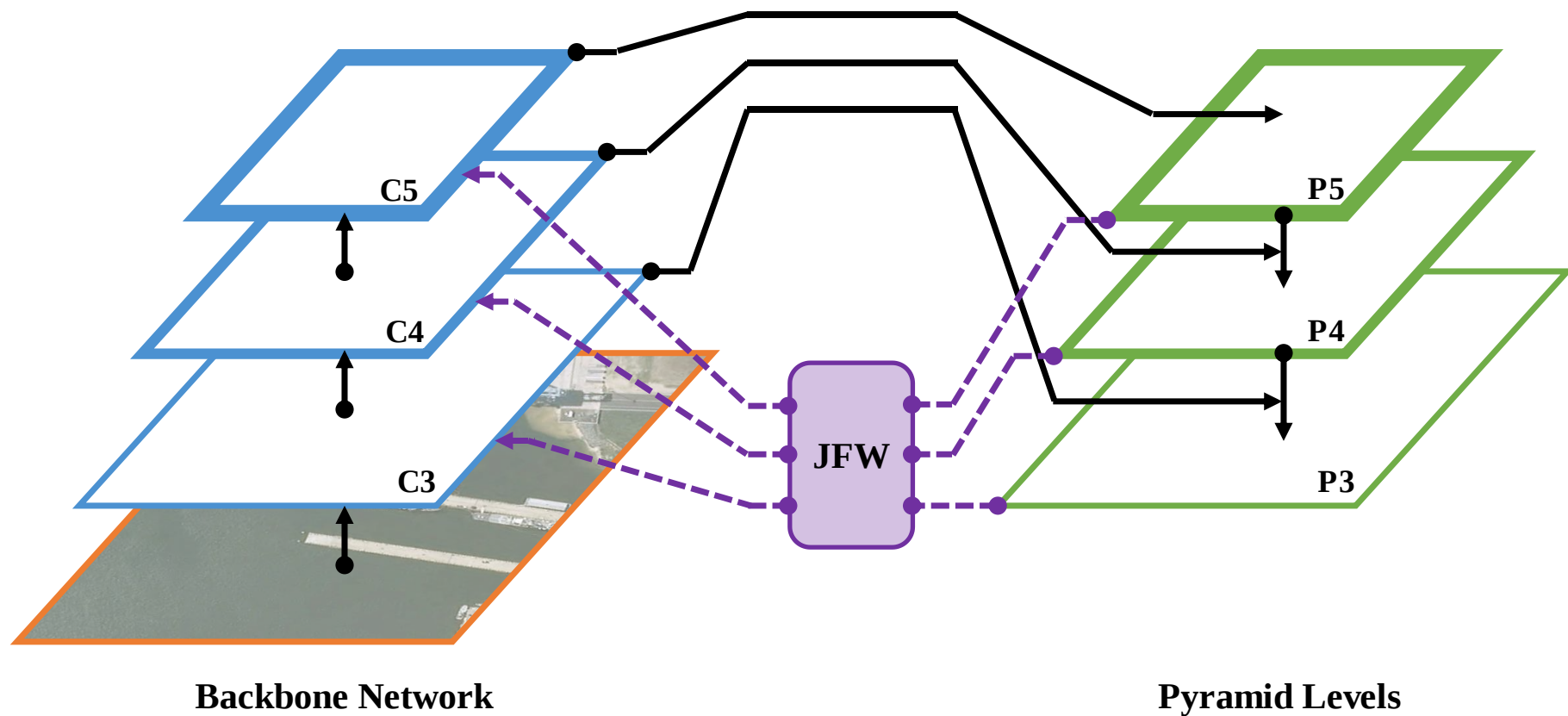


- Although FPN and N3DNet have already improved the multi-scale feature representation capability, they are not optimal.

SEMANTIC GAP

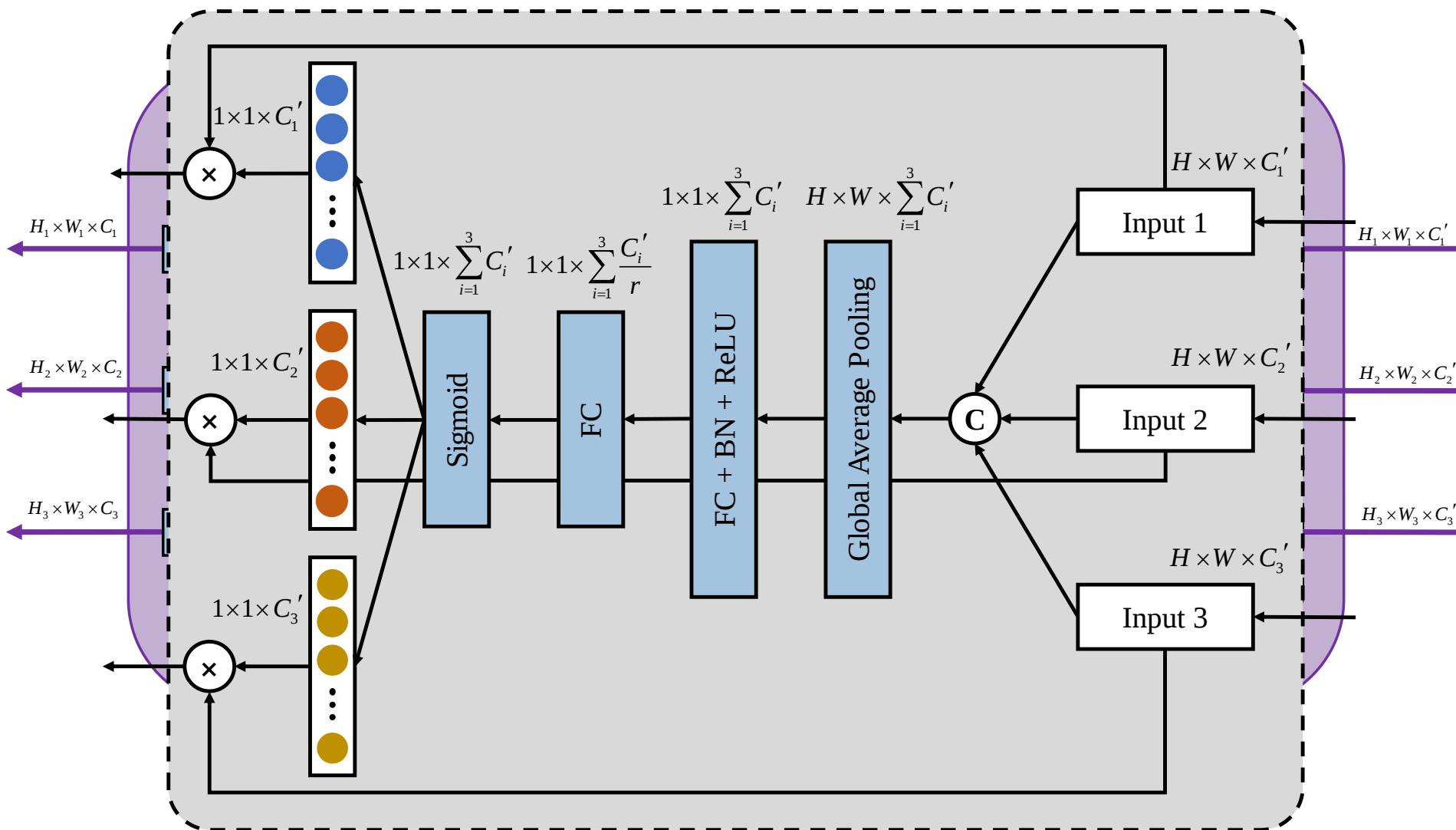


Joint Recursive Feature Pyramid (JRFP)





Joint Feedback Worker (JFW)





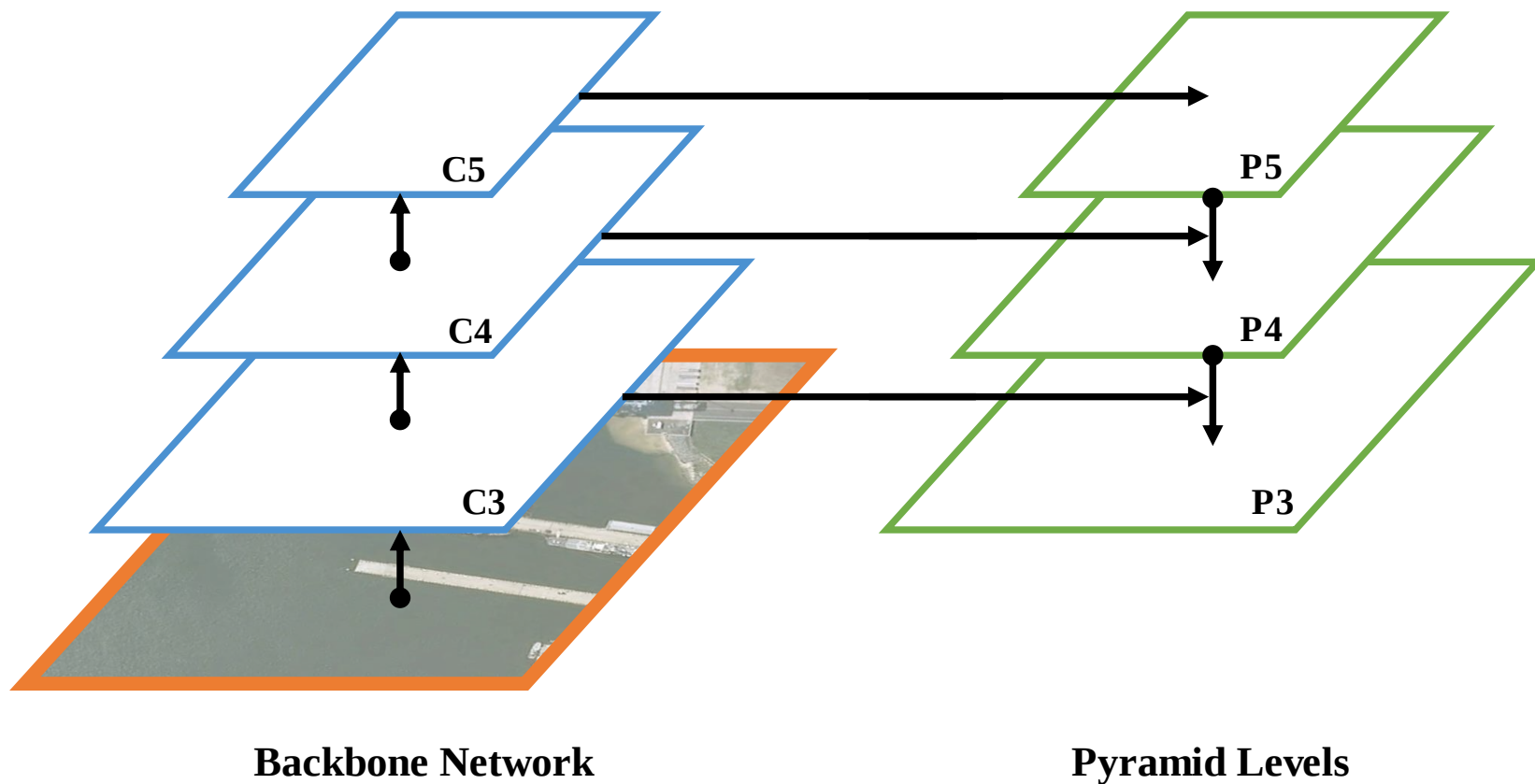
Specificity $\xleftrightarrow{\text{BALANCE}}$ Uniformity



Recursive Index (RI)

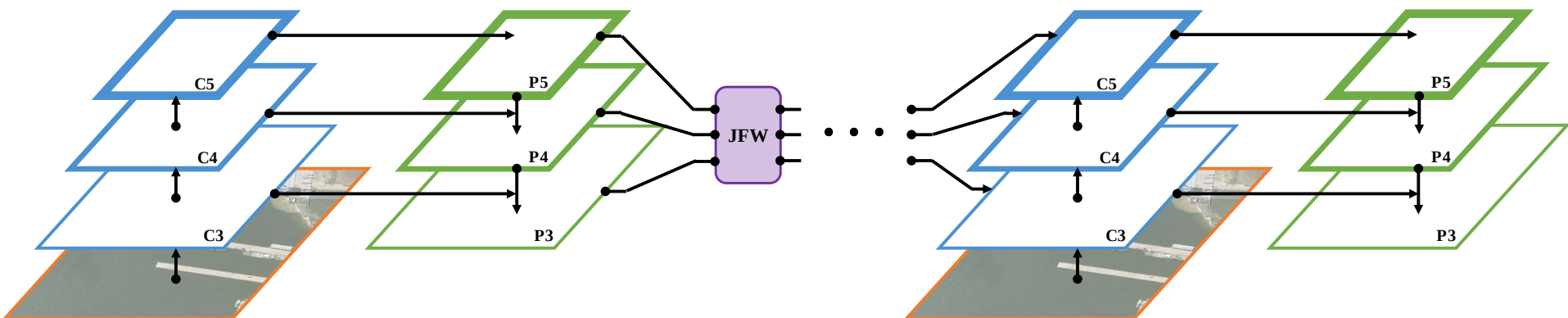


Unrolled JRFP (RI=0)





Unrolled JRFP (RI>0)





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Method	mAP (VOC2012 fashion)
Faster R-CNN [1]	0.246
Cascade R-CNN [2]	0.617
DetectoRS [3]	0.637
MSSDet (ours)	0.721

[1] S. Ren, et al. Faster R-CNN: Towards real-time object detection with region proposal networks. IEEE TPAMI, 2015.

[2] Z. Cai, et al. Cascade R-CNN: Delving into High Quality Object Detection. CVPR, 2018.

[3] S. Qiao, et al. DetectoRS: Detecting Objects with Recursive Feature Pyramid and Switchable Atrous Convolution. arXiv:2006.02334, 2020



Method	mAP (VOC2012 fashion)
BL1 [1]	0.797
Faster R-CNN (soft NMS) [2]	0.845
Faster R-CNN (dilated conv) [3]	0.709
Cascade R-CNN [4]	0.904
DetectoRS [5]	0.920
MSSDet (ours)	0.946

- [1] Z. Liu, et al. A High Resolution Optical Satellite Image Dataset for Ship Recognition and Some New Baselines. ICPRAM, 2017.
- [2] X. Tan, et al. Inshore ship detection based on improved faster R-CNN. Proc. SPIE 11429, MIPPR 2019.
- [3] S. Wei, et al. Ship Detection in Remote Sensing Image based on Faster R-CNN with Dilated Convolution. Proceedings of the 39th Chinese Control Conference, 2020
- [4] Z. Cai, et al. Cascade R-CNN: Delving into High Quality Object Detection. CVPR, 2018.
- [5] S. Qiao, et al. DetectoRS: Detecting Objects with Recursive Feature Pyramid and Switchable Atrous Convolution. arXiv:2006.02334, 2020



	Method	mAP (VOC2012 fashion)	
	R-CNN	0.377	
TAS	RICNN	0.442	
SZT	RICAOD	0.509	
NW	RIFD-CNN	0.561	
VEI	Faster R-CNN	0.651	
UC	SSD	0.586	
DLF	YOLOv3	0.571	
HRS	Mask R-CNN	0.652	
RSC	RetinaNet	0.661	
DO	PANet	0.661	
DIO	CornerNet	0.649	
HRE	MSSDet (ours)	0.778	



Method	mAP (VOC2012 fashion)
MSSDet (RI=0)	0.660
MSSDet (RI=1)	0.667
MSSDet (RI=2)	0.721
MSSDet (RI=3)	0.674

*: The ablation study was done on HRSC2016-MS dataset

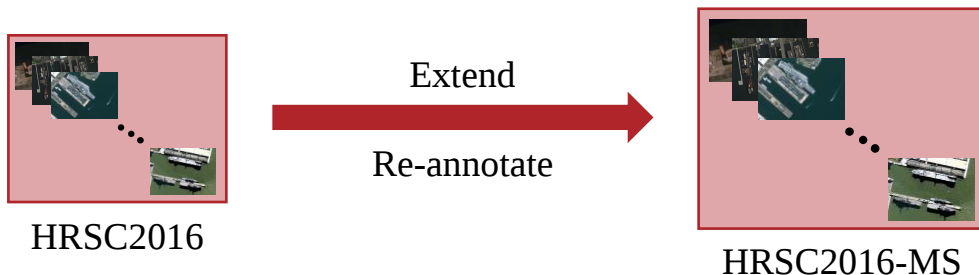


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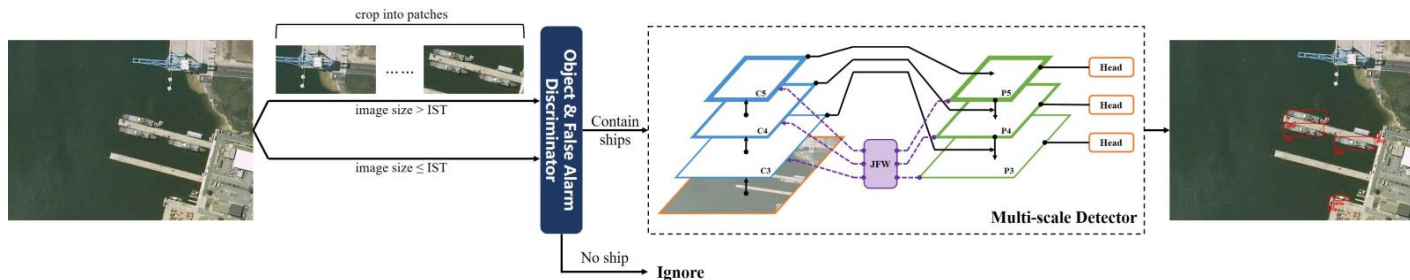
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THANKS FOR LISTENING

Q & A