# 智能航运感知数据集整理

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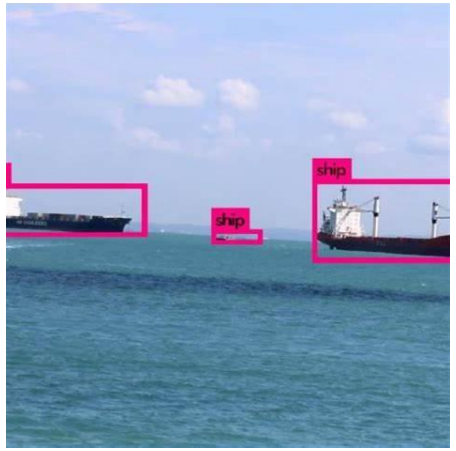
# 内容提要

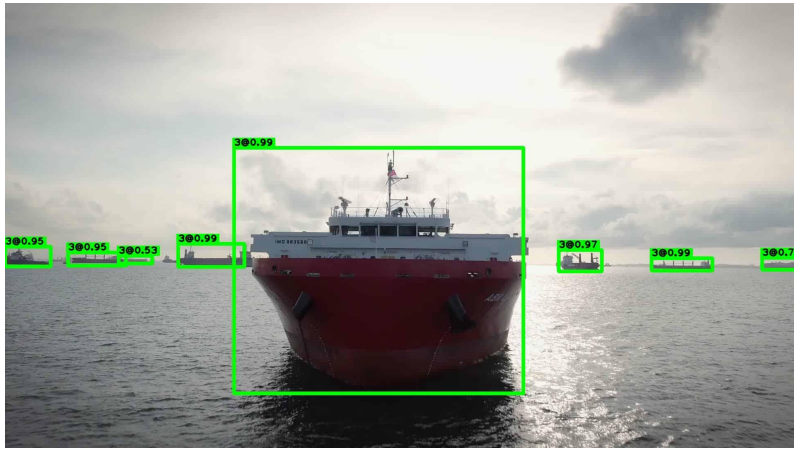
- 智能航运感知问题分类
- 智能航运感知数据集分类与整理
- 后续研究问题与计划

# 智能航运感知任务分类

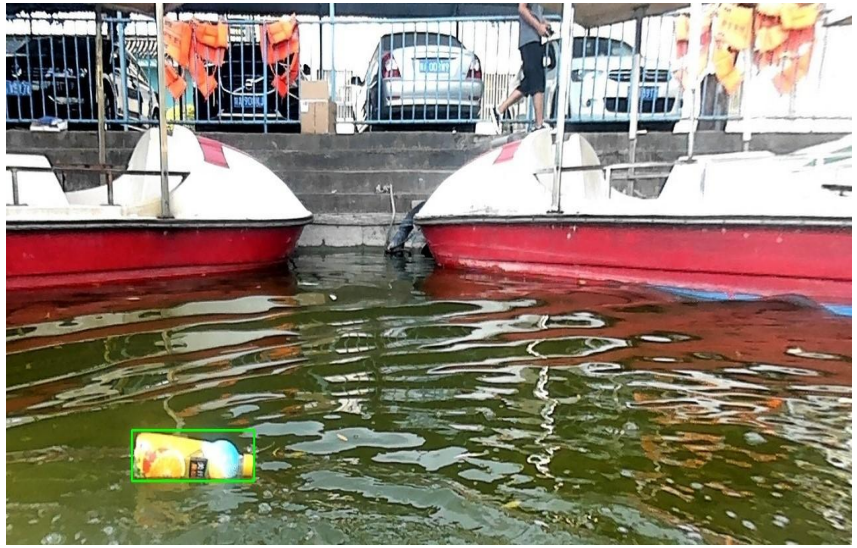
## 1. 目标检测任务

- 从图像中检测目标



### 1.1 船舶目标检测任务



### 1.2 其它目标检测任务

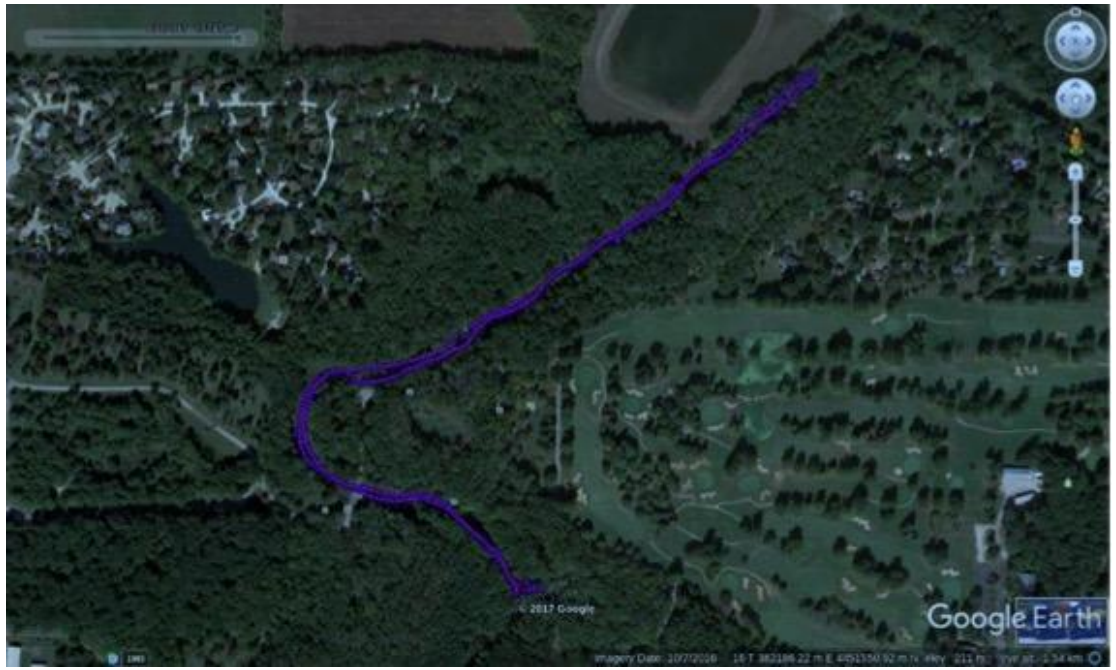
# 智能航运感知任务分类

## 2. SLAM与视觉里程计任务

### 2.1 同时完成自身定位和环境建图

**H05_7_Sequence_160_270**
Duration: 110s
Trajectory Length: 138m
Weather: Rain

### 2.2 通过视觉和惯导数据计算船舶的准确行驶轨迹

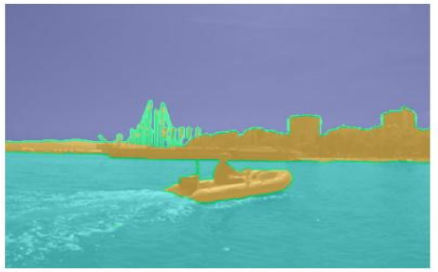


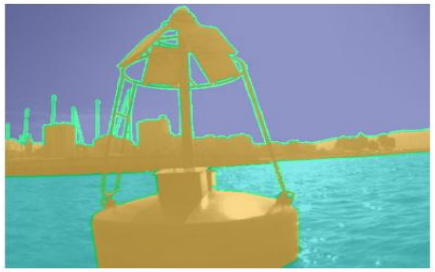
# 智能航运感知任务分类

## 3. 语义分割任务

### 3.1. 场景语义分割任务

- 通过图像分割、理解前视图





### 3.2 水岸分割任务

- 分割图像中的水面区域

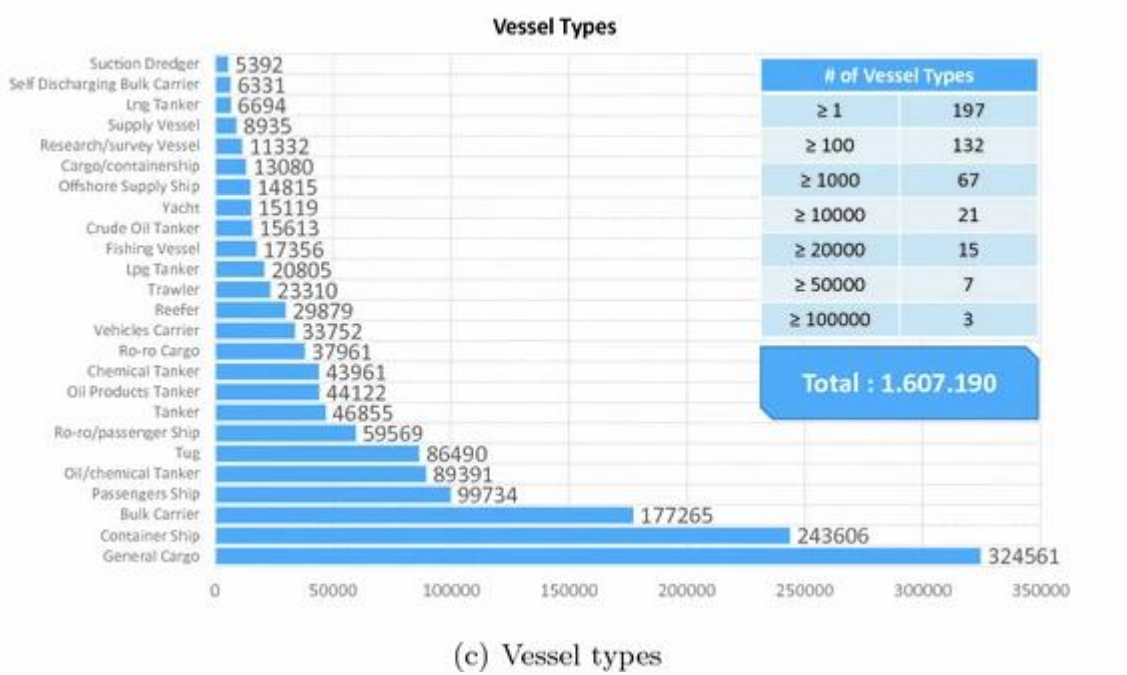
### 3.3. 实例分割任务

- 对图中的目标对象进行语义分割

# 智能航运感知任务分类

## 4. 船舶分类任务

- 确定检测到的船只究竟是什么类型的船只

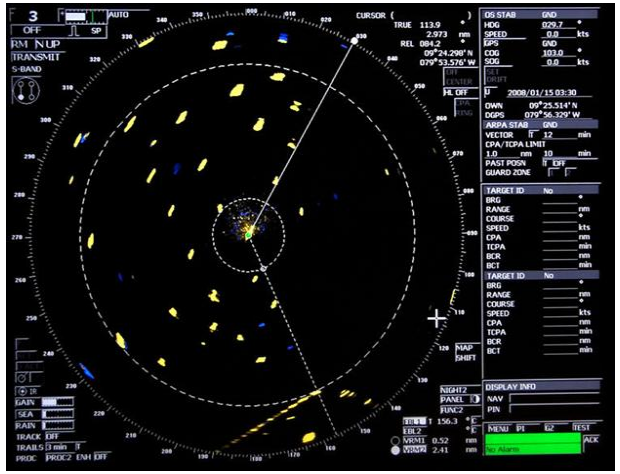


(c) Vessel types

# 智能航运感知任务分类

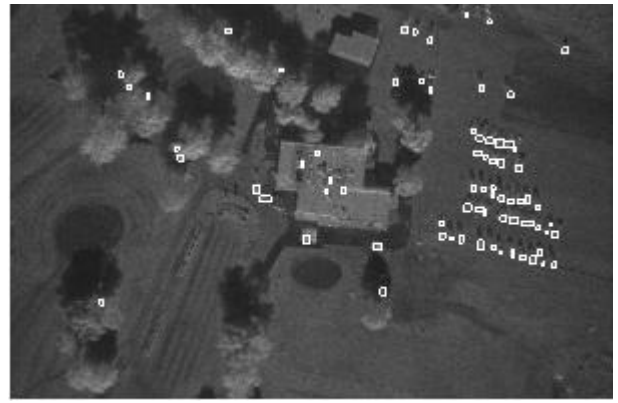
## 5. 雷达目标检测任务

- 基于雷达数据进行目标检测



## 6. SAR目标检测任务

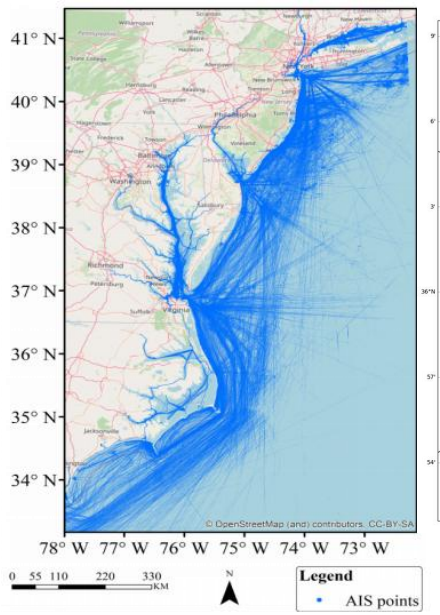
- 基于SAR数据进行目标检测

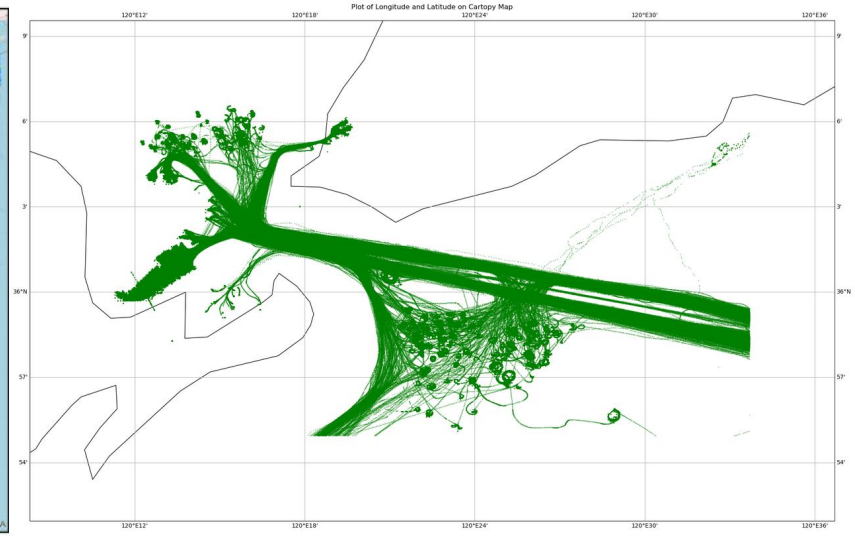



# 智能航运感知任务分类

## 7. AIS数据集相关任务

- 基于AIS数据进行船舶轨迹预测



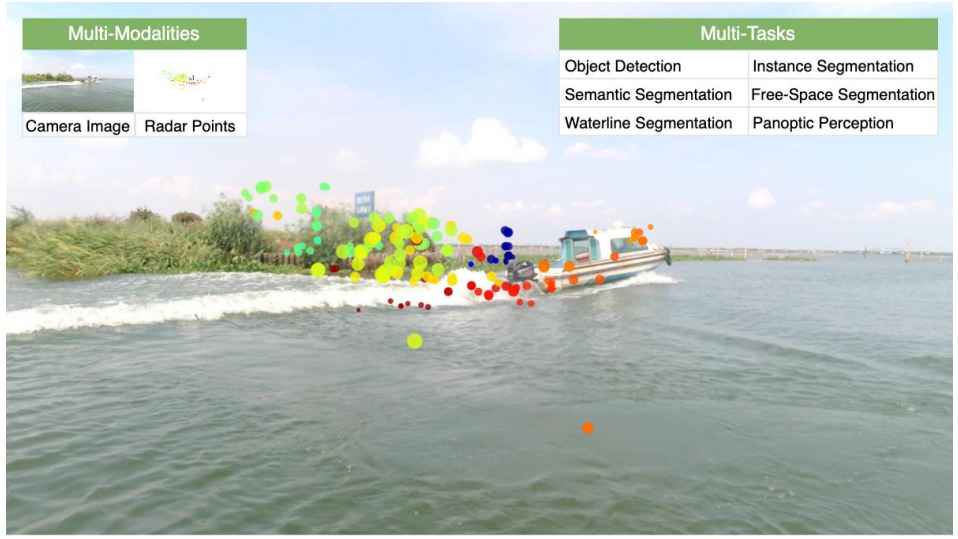




- 融合AIS和视觉的目标追踪

# 智能航运感知任务分类

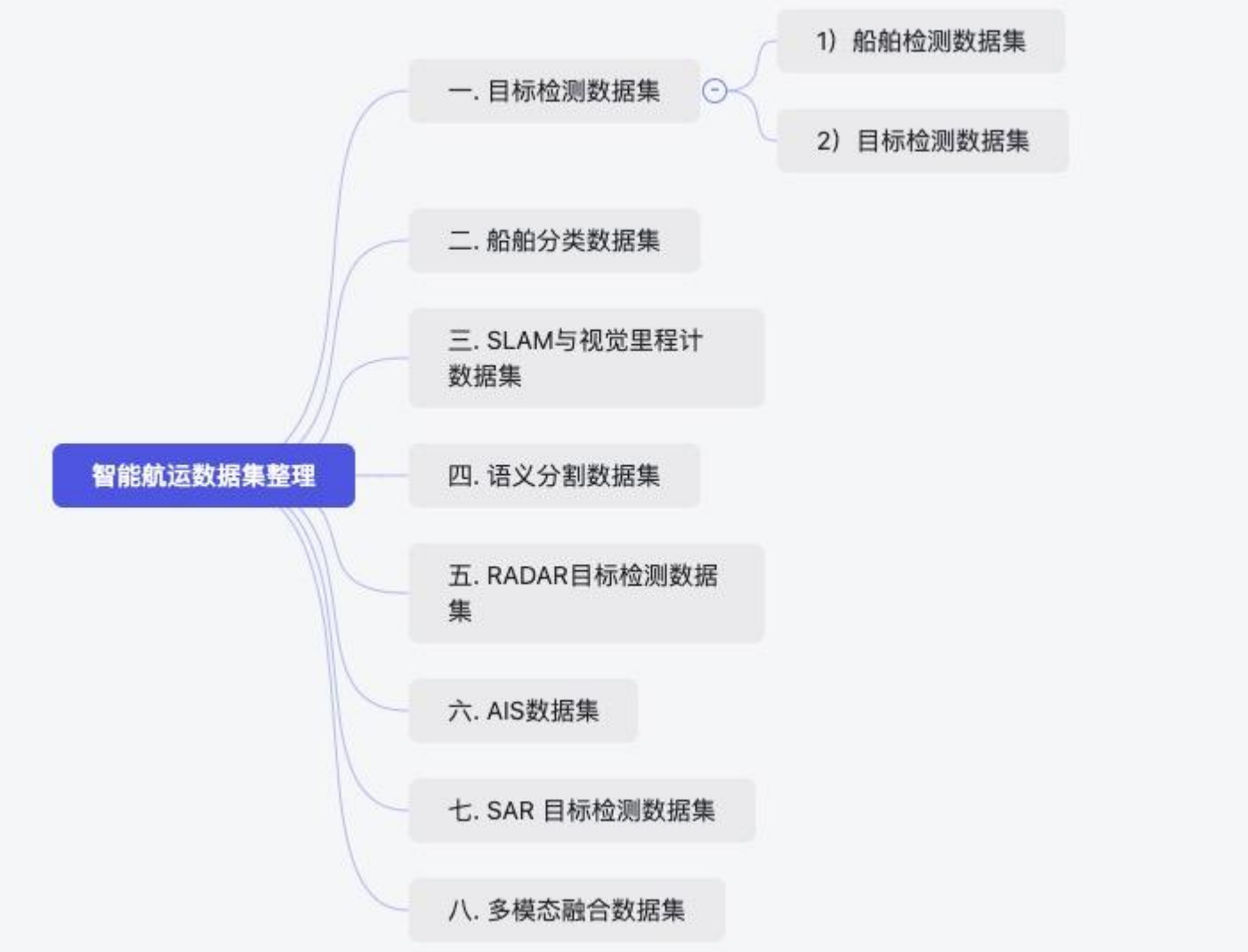
## 8. 多源信息融合类任务

### 1. 基于视觉数据与雷达融合进行目标检测




### 2. 基于视觉数据与雷达融合进行SLAM

# 我们整理的智能航运感知数据集




| 数据集类别 | 数据集数量 |
| --- | --- |
| 目标检测数据集 | 11 |
| 船舶分类数据集 | 2 |
| SLAM与视觉里程计数据集 | 3 |
| 语义分割数据集 | 4 |
| RADAR目标检测数据集 | 1 |
| AIS数据集 | 7 |
| SAR目标检测数据集 | 4 |
| 多模态融合数据集 | 3 |
| 总计 | 35 |

目标检测数据集

船舶检测数据集

目标检测数据集

## 一. 目标检测数据集

### 1）船舶检测数据集

1. ABOShips
2. Seaships
3. McShips
4. MVDD13
5. Singapore Maritime Dataset (SMD)

### 2）目标检测数据集

1. FloW（漂浮物检测数据集）
2. Water Surface Object Detection Dataset （WSODD 数据集）
3. Marine Image Dataset (MID)
4. Multi-modal Marine Obstacle Detection Dataset (MODD 2)
5. Marine Obstacle Detection Dataset (MODD)
6. Sea Situational Awareness (SeaSAw) Dataset （超大规模数据集，但未开源）

# 船舶检测的几个数据集对比

| Datasets for Ship Detection | | | |
|---|---|---|---|
| **Name** | **Total Images** | **Annotations** | **Ship Types Included** |
| SeaShips | 31,455 | 40,077 | 6 |
| Singapore | 17,450 | 192,980 | 6 |
| MCShips | 14,709 | 26,529 | 13 |
| ABOShips | 9880 | 41,967 | 9 |

以ABOShips数据集为例，数据集中各类船舶的数量

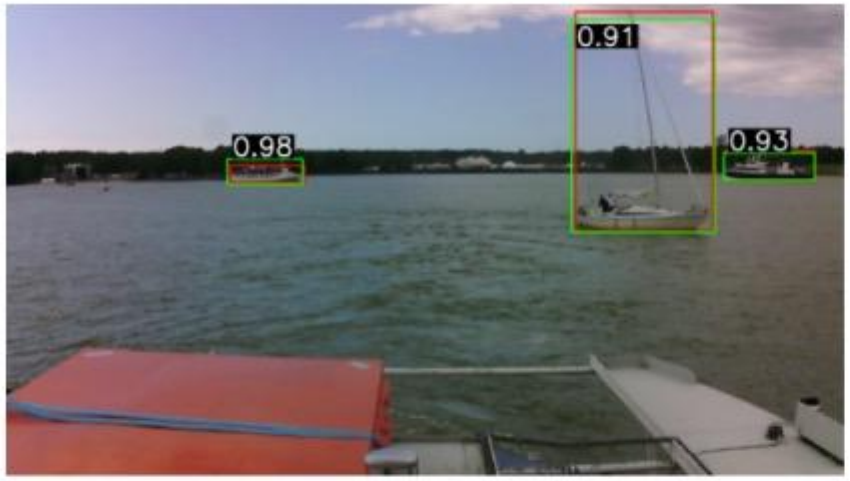
| Number of Images and Annotations for Every Object Category | | | | |
|---|---|---|---|---|
| **Class** | **Images** | **Percentage** | **Objects** | **Percentage** |
| Seamark | 3744 | 37.89% | 7670 | 18.27% |
| Boat | 2034 | 20.58% | 2913 | 6.94% |
| Sailboat | 3842 | 38.88% | 8147 | 19.41% |
| Motorboat | 4062 | 41.11% | 7092 | 16.89% |
| Passengership | 2639 | 26.71% | 4464 | 10.63% |
| Cargoship | 157 | 1.58% | 161 | 0.38% |
| Ferry | 945 | 9.56% | 1046 | 2.49% |
| Miscboat | 2797 | 28.30% | 4642 | 11.06% |
| Miscellaneous | 129 | 1.30% | 200 | 0.47% |
| Militaryship | 2559 | 25.90% | 4128 | 9.83% |
| Cruiseship | 1347 | 13.63% | 1504 | 3.58% |

# 常用目标检测算法在ABOShips数据集上对船舶检测的准确性

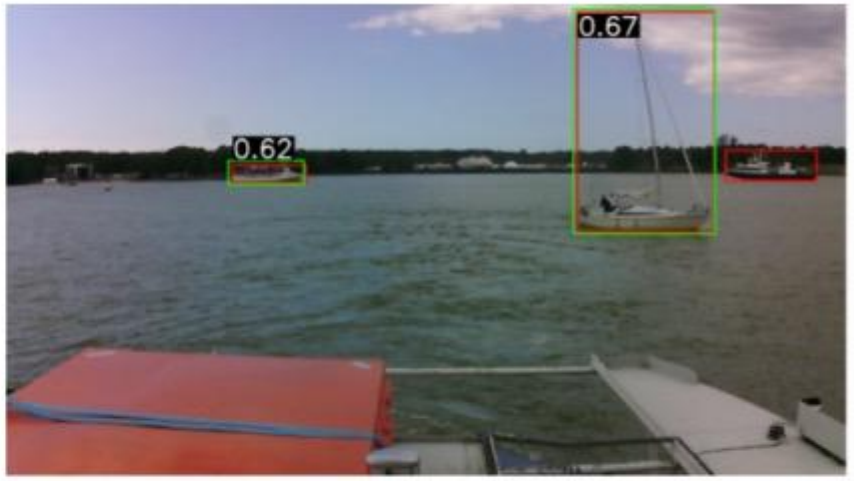
| Detection Performance of Different Detectors on the ABOships Dataset | | | | | |
|---|---|---|---|---|---|
| **Method** | **Feature Extractor** | $AP_S$ | $AP_M$ | $AP_L$ | $AP$ |
| Faster RCNN | Inception ResNet V2 | 23.16 | 30.86 | 46.84 | **35.18** |
| | ResNet50 V1 | 9.76 | 20.94 | 41.65 | 26.49 |
| | ResNet101 | 18.42 | 25.07 | 38.17 | 30.26 |
| SSD | ResNet101 V1 FPN | 21.39 | 31.18 | 42.07 | 30.03 |
| | MobileNet V1 FPN | 12.34 | 27.61 | 37.83 | 28.59 |
| | MobileNet V2 | 3.01 | 17.05 | 27.37 | 17.48 |
| EfficientDet | EfficientNet D1 | 10.94 | 29.68 | **55.48** | 33.83 |
| RFCN | ResNet101 | 18.05 | 26.20 | 41.61 | 32.46 |

检测的准确度普遍不高

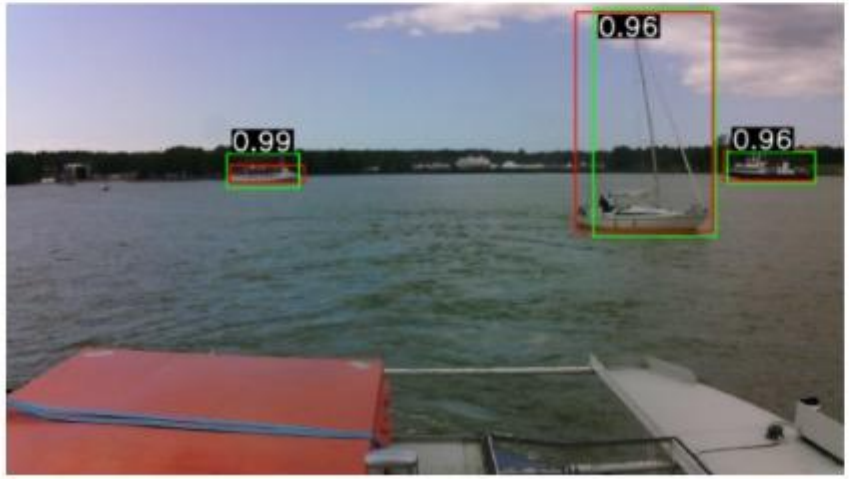
# 常用目标检测算法在ABOShips数据集上对船舶检测示例

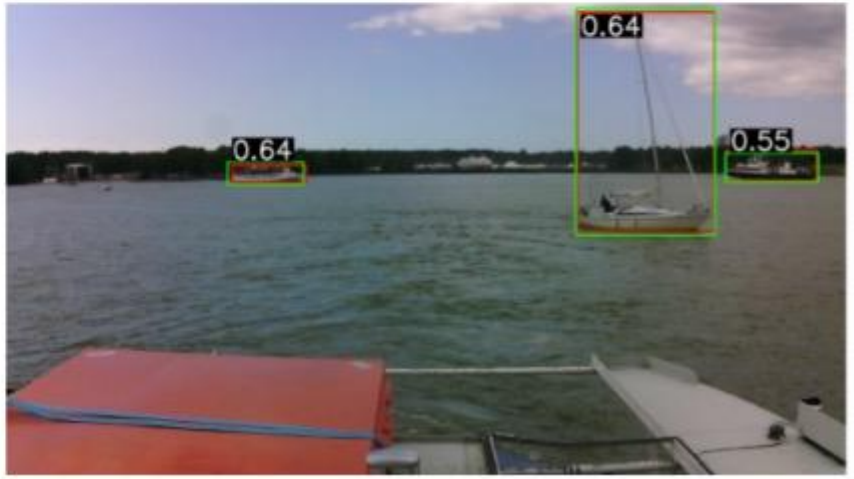



a




b



# （二）目标检测数据集

1. FloW（漂浮物检测数据集）

2. Water Surface Object Detection Dataset （WSODD 数据集）

3. Marine Image Dataset (MID) （海事目标检测数据集）

4. Marine Obstacle Detection Dataset (MODD)

5. Multi-modal Marine Obstacle Detection Dataset (MODD 2)

6. Sea Situational Awareness (SeaSAw) Dataset （超大规模数据集，但未开源）

# 以WSODD为例，介绍目标检测数据集

| Dataset | Dataset's type | Main categories | Main environments | Weather conditions | Shooting time | Images |
|---|---|---|---|---|---|---|
| MSCOCO | Generic | 1 | Sea<br>Lake | Sunny<br>Cloudy | Daytime | 3,146 |
| ImageNet | | 4 | Sea<br>Lake | Sunny<br>Foggy | Daytime | 1,996 |
| Places2 | | 5 | Lake<br>River | Sunny | Daytime | 6,514 |
| Boat-types-recognition | Specialized | 3 | Sea<br>Lake<br>River | Sunny | Daytime<br>Twilight<br>Night | 1,462 |
| WSODD | | 14 | Sea<br>Lake<br>River | Sunny<br>Foggy<br>Cloudy | Daytime<br>Twilight<br>Night | 7,467 |

*The main categories refer to the number of categories related to water surface object detection. The boat-types-recognition dataset includes many kinds of boats, which are all considered as boat here. Similarly. Images in this Table refer to the number of images related to water surface object detection.*

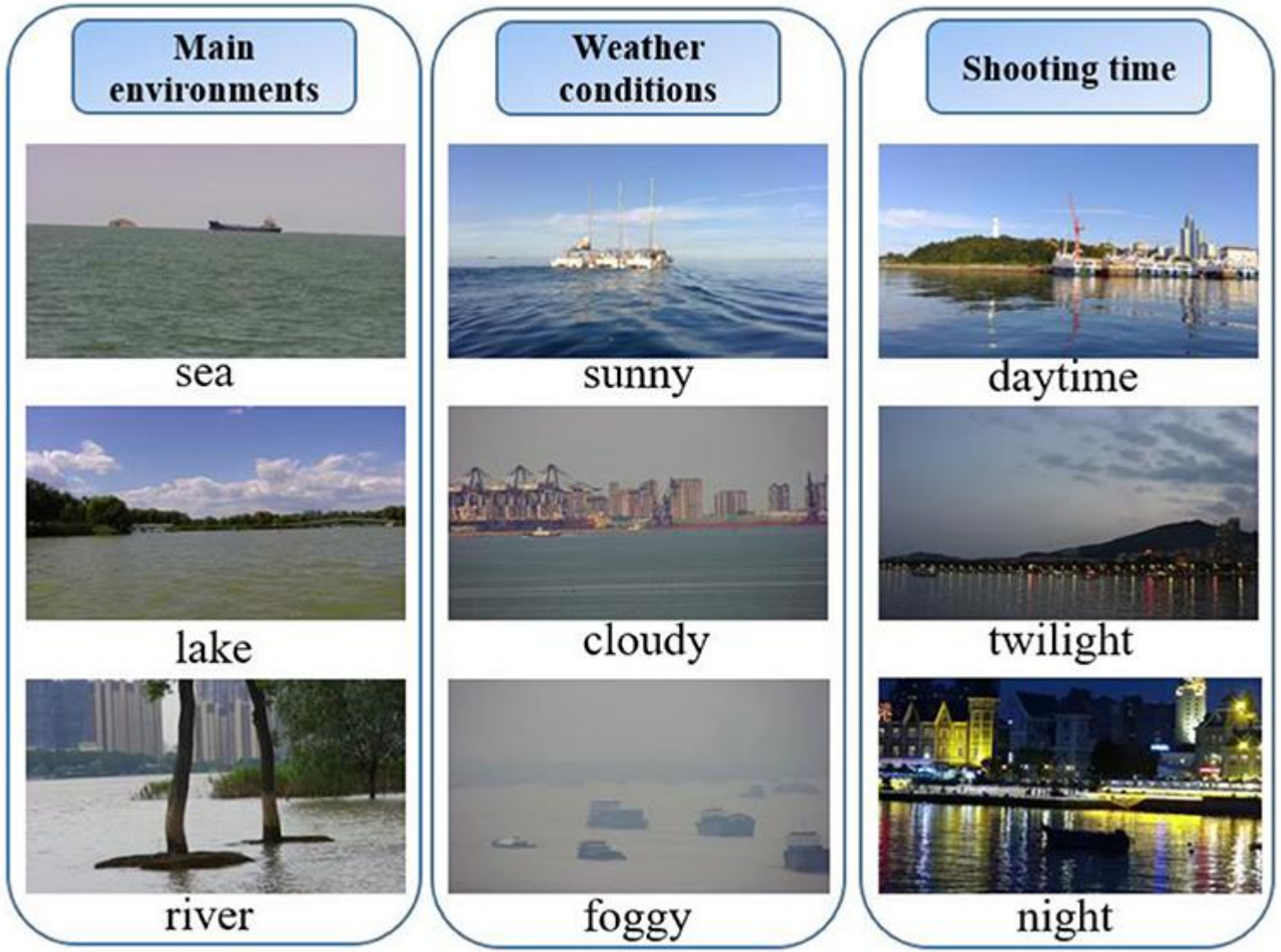
WSODD有7467张标注图像，有14中水面物体类别，包含三种天气情况

# 以WSODD为例，介绍目标检测数据集

不同环境

不同天气

不同时间



# 主要的水面目标类别14种


| Label | Images | Instances |
|---|---|---|
| Boat | 4,325 | 8,179 |
| Ship | 1,832 | 3,423 |
| Ball | 652 | 2,609 |
| Bridge | 1,827 | 2,014 |
| Rock | 696 | 1,540 |
| Person | 357 | 695 |
| Rubbish | 461 | 669 |
| Mast | 177 | 354 |
| Buoy | 153 | 167 |
| Platform | 480 | 614 |
| Harbor | 1,211 | 1,224 |
| Tree | 72 | 219 |
| Grass | 103 | 110 |
| Animal | 50 | 94 |
| **Total** | **7,467** | **21,911** |

# 测试的17种目标检测方法的性能

| Method | FPS | mAP (%) | $AP_{50}$ | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | Boat (%) | Ship (%) | Ball (%) | Bridge (%) | Rock (%) | Person (%) | Rubbish (%) | Mast (%) | Buoy (%) | Platform (%) | Harbor (%) | Tree (%) | Grass (%) | Animal (%) |
| DPM | 42.16 | 21.9 | 9 | 28 | 12 | 34 | 17 | 27 | 29 | 14 | 29 | 32 | 40 | 19 | 15 | 2 |
| RANSAC-SVM | 43.51 | 27.1 | 11 | 49 | 6 | 32 | 33 | 29 | 34 | 7 | 41 | 31 | 27 | 36 | 23 | 20 |
| Faster R-CNN | 19.42 | 32.3 | 1 | 73 | 19 | 70 | 14 | 13 | 24 | 14 | 29 | 44 | 53 | 50 | 14 | 4 |
| Mask R-CNN | 17.79 | 35.7 | 7 | 79 | 18 | 88 | 27 | 16 | 40 | 22 | 28 | 42 | 61 | 46 | 17 | 8 |
| Cascade R-CNN | 29.56 | 41.1 | 6 | 82 | 22 | 91 | 31 | 19 | 42 | 34 | 31 | 37 | 67 | 63 | 38 | 12 |
| TridentNet | 10.16 | 62.2 | 51 | 77 | 37 | 93 | 47 | 57 | 48 | 57 | 66 | 71 | 77 | 70 | 58 | 62 |
| SSD | 43.02 | 41.5 | 41 | 78 | 7 | 79 | 28 | 13 | 28 | 20 | 31 | 47 | 64 | 72 | 29 | 45 |
| RetinaNet | 33.84 | 27.9 | 54 | 73 | 12 | 62 | 26 | 18 | 20 | 7 | 17 | 28 | 31 | 26 | 4 | 11 |
| Yolov3 | 45.34 | 56.1 | 0 | 83 | 25 | 95 | 40 | 59 | 45 | 60 | 56 | 65 | 89 | 71 | 49 | 48 |
| RFBNet | 44.61 | 35.7 | 45 | 69 | 6 | 77 | 24 | 12 | 24 | 15 | 35 | 36 | 56 | 25 | 14 | 62 |
| M2Det | 40.63 | 39.3 | 0 | 73 | 5 | 83 | 22 | 22 | 25 | 28 | 39 | 46 | 74 | 74 | 20 | 39 |
| CenterNet | 43.42 | 53.5 | 70 | 85 | 19 | 93 | 44 | 12 | 44 | 20 | 46 | 61 | 82 | 73 | 48 | 53 |
| EfficientDet | 30.83 | 31.3 | 50 | 75 | 14 | 49 | 26 | 20 | 21 | 16 | 30 | 41 | 25 | 58 | 12 | 0 |
| Yolov4 | 46.25 | 57.2 | 0 | 85 | 39 | 94 | 51 | 61 | 46 | 60 | 60 | 62 | 83 | 65 | 51 | 45 |
| Yolov3-2SMA | 50.46 | 56.9 | 0 | 84 | 25 | 92 | 47 | 62 | 46 | 57 | 55 | 69 | 88 | 73 | 44 | 54 |
| ShipYolo | 49.81 | 58.4 | 0 | 87 | 41 | 93 | 52 | 66 | 45 | 63 | 59 | 71 | 78 | 59 | 57 | 56 |
| CRB-Net | **43.76** | **65.0** | **0** | **90** | **69** | **96** | **70** | **71** | **49** | **49** | **59** | **75** | **88** | **72** | **47** | **74** |

*The last 14 columns show the $AP_{50}$ for each category on WSODD. The first two methods are traditional machine learning method, the middle four methods belong to two-stage object detection method and the last nine methods are dedicated to one-stage object detection method.*

识别难度比较大的物体：　　垃圾　　桅栏　　草

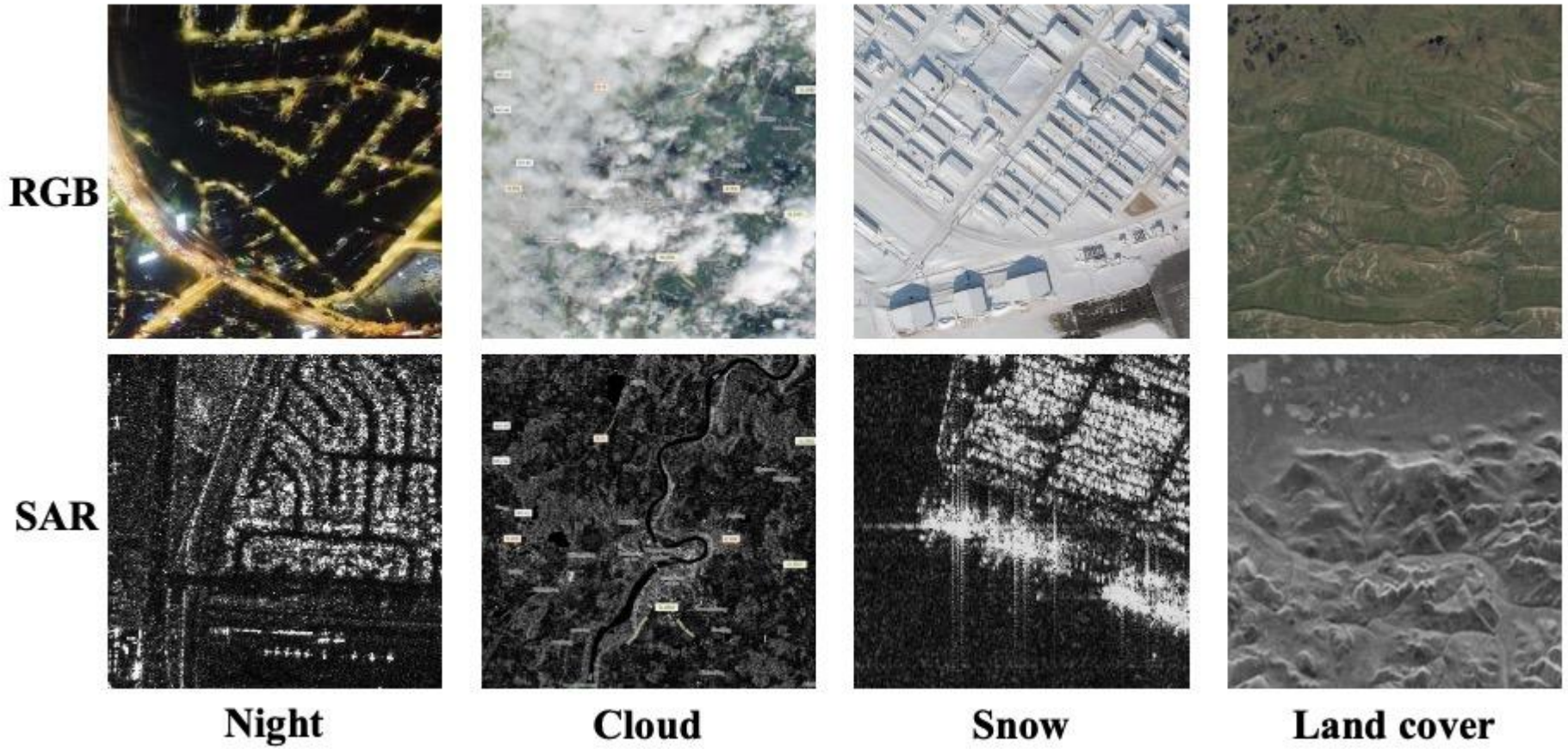
# 三．SAR目标检测数据集

**合成孔径雷达（SAR）**是一种微波传感器，通过向目标发射射频信号并接收反射信号来获取 SAR 图像。由于具有全天候成像、不受天气影响、观测范围广、高成像分辨率等特点，SAR 船舶检测在海洋开发、海洋监测、海上交通监控等民用和军事领域的重要性，成为当前研究的热点问题。

| Method | Year | Experiment Datasets | Results(mAP) |
|---|---|---|---|
| SSDD [33] | 2017 | 1,160 | 2,456 |
| SAR-Ship-Dataset [34] | 2019 | 43,819 | 59,535 |
| AIR-SARShip-1.0 [35] | 2019 | 31 | 461 |
| HRSID [36] | 2020 | 5,604 | 16,951 |
| RSDD-SAR [37] | 2022 | 7,000 | 10,263 |
| MSAR [38] | 2022 | 28,449 | 39,858 |
| SARDet-100k [39] | 2024 | 1,165,988 | 119,261 |

SARDet—100k 是目前最大的SAR目标检测数据集

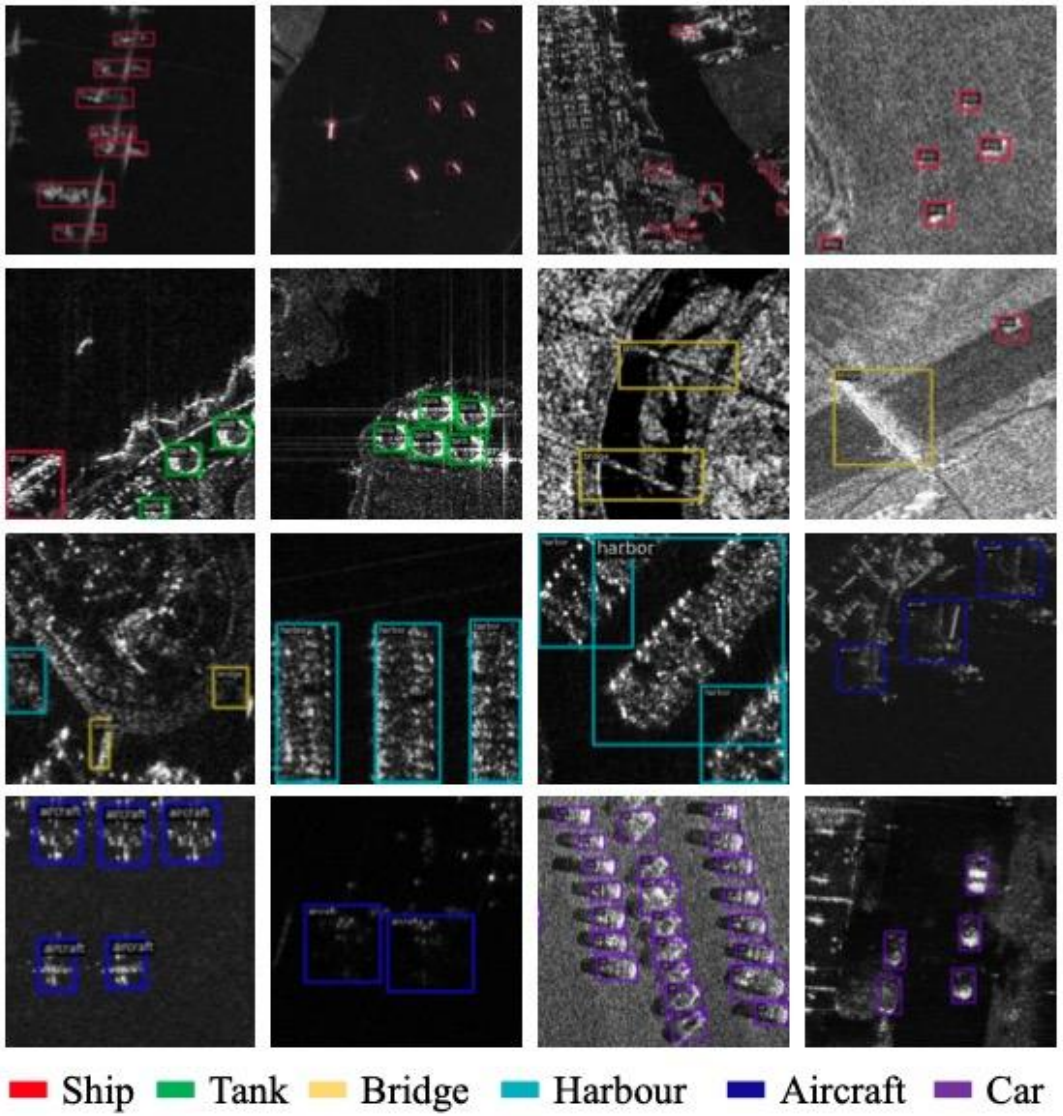
# 三．SAR目标检测数据集




SAR具有全天候的优势，但是是黑白图，有噪声

# 三．SAR目标检测数据集

SARDet—100k数据集可视化




不同检测算法在SAR数据集上检测效果

| | Detectors | Open Source | Year | $mAP_{50}$ ↑ | |
|---|---|---|---|---|---|
| | | | | SSDD | HRSID |
| General Detectors | Grid R-CNN [43] | ✓ | 2019 | 88.9 | 79.4 |
| | Faster R-CNN [53] | ✓ | 2015 | 89.7 | 80.7 |
| | Cascade R-CNN [4] | ✓ | 2019 | 90.5 | 81.3 |
| | Free-Anchor [87] | ✓ | 2019 | 91.0 | 81.8 |
| | Double-Head R-CNN [72] | ✓ | 2020 | 91.1 | <u>82.1</u> |
| | PANET [40] | ✓ | 2018 | 91.2 | 81.6 |
| | DCN [14] | ✓ | 2017 | 92.3 | <u>82.1</u> |
| SAR Detectors | NNAM [7] | ✗ | 2019 | 79.8 | - |
| | DCMSNM [25] | ✗ | 2018 | 89.6 | - |
| | ARPN [89] | ✗ | 2020 | 89.9 | 81.8 |
| | DAPN [13] | ✗ | 2019 | 90.6 | 81.8 |
| | HR-SDNet [70] | ✗ | 2020 | 90.8 | 82.5 |
| | SER Faster R-CNN [37] | ✗ | 2018 | 91.5 | 81.5 |
| | FBR-Net [20] | ✗ | 2020 | 94.1 | - |
| | NRENet [44] | ✗ | 2024 | 94.6 | 75.6 |
| | CenterNet++ [21] | ✗ | 2021 | 95.1 | - |
| | CRTransSar [74] | ✗ | 2022 | 97.0 | - |
| | SARATR-X [77] | ✗ | 2024 | <u>97.3</u> | 80.3 |
| Faster R-CNN + VAN-B | | ✓ | 2023 | 92.9 | 81.8 |
| **MSFA** (Faster R-CNN + VAN-B) | | ✓ | 2024 | **97.9**(+5.0) | **83.7**(+1.9) |

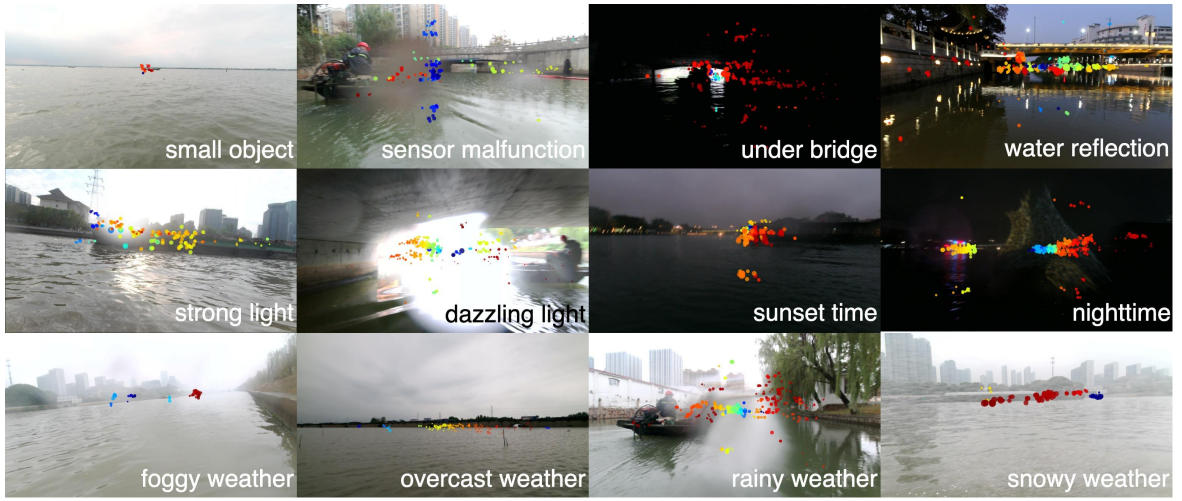
# 四．多模态融合数据集

## 视觉AIS融合

FVessel［TITS 2023］（视觉AIS融合的船舶检测与追踪）

## 视觉与雷达融合

WaterScenes［TITS 2024］（图像与4D雷达融合的多任务数据集）



# 四．多模态融合数据集

WaterScenes［TITS 2024］（图像与4D雷达融合的多任务数据集）

| Name | Year | Camera | Radar | GPS, IMU | Tasks | Annotations | Classes † | Annotated Frames | Adverse Lighting | Adverse Weather |
|---|---|---|---|---|---|---|---|---|---|---|
| MODD [41] | 2015 | Mono | - | - | OD, LS | 2D Box, 2D Line | 2 | 4,454 | ✓ | - |
| MODD2 [42] | 2018 | Stereo | - | GPS, IMU | OD, LS | 2D Box, 2D Line | 2 | 11,675 | ✓ | ✓ |
| SMD [43] | 2019 | Mono | - | - | OD, OT | 2D Box | 10 | 31,653 | ✓ | - |
| MaSTr1325 [4] | 2019 | Mono | - | IMU | SS | 2D Pixel | 4 | 1,325 | ✓ | ✓ |
| MODS [3] | 2021 | Stereo | - | IMU | OD, SS | 2D Box, 2D Line | 3 | 24,090 | ✓ | ✓ |
| MID [44] | 2021 | Mono | - | - | OD | 2D Box | 2 | 2,655 | ✓ | ✓ |
| USVInland [19] | 2021 | Stereo | - | GPS, IMU | SS, FS | 2D Line | 1 | 700 | ✓ | ✓ |
| FloW [27] | 2021 | Mono | 3D | - | OD | 2D Box | 1 | 2,000 | ✓ | - |
| LaRS [45] | 2023 | Mono | - | - | SS, PS | 2D Line | 11 | 4,006 | - | - |
| MVDD13 [46] | 2024 | Mono | - | - | OD | 2D Box | 13 | 35,474 | ✓ | ✓ |
| **WaterScenes** (Ours) | 2023 | Mono | 4D | GPS, IMU | OD, IS, SS, FS, LS, PP | 2D Box, 2D Pixel, 2D Line, 3D Point | 7 | 54,120 | ✓ | ✓ |

WaterScenes数据集与同类型数据集的对比：多任务的、多标签的、更大规模

# 四．多模态融合数据集

WaterScenes［TITS 2024］（图像与4D雷达融合的多任务数据集）

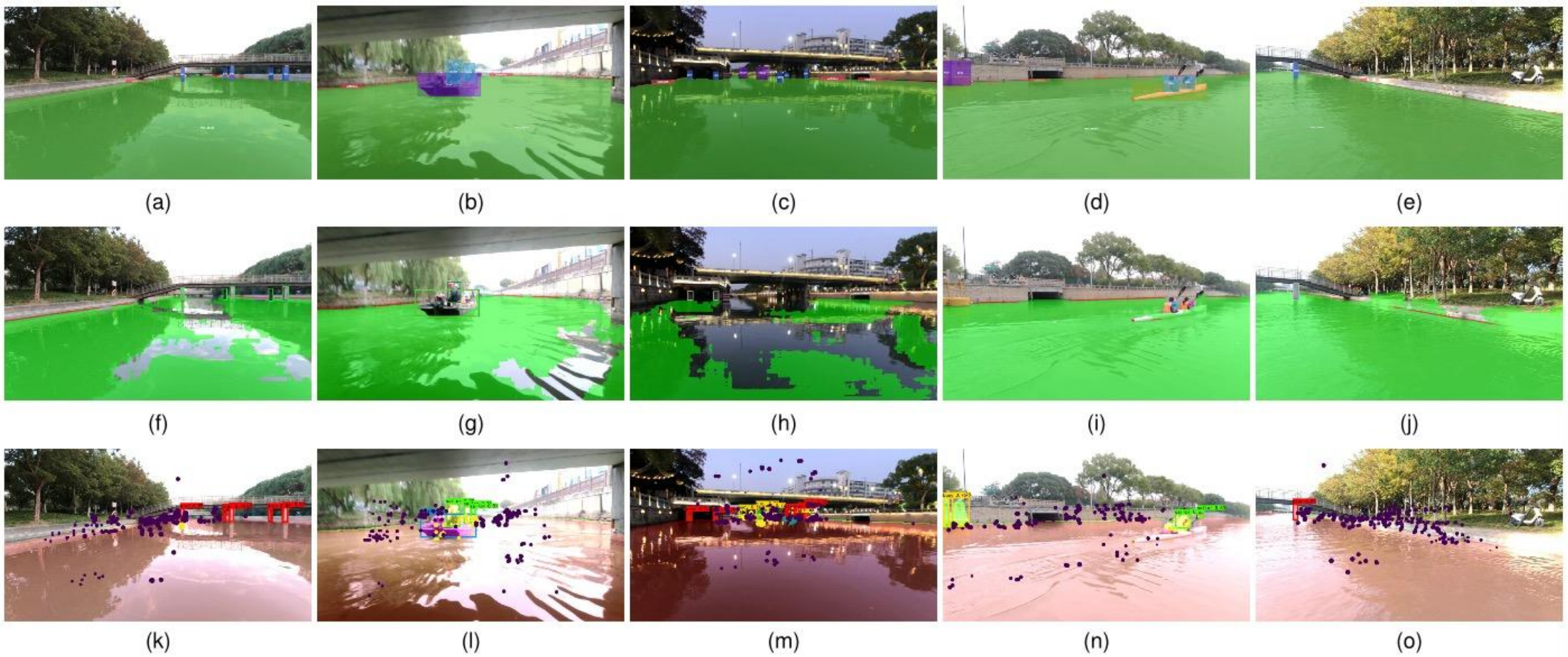
BENCHMARK RESULTS OF PANOPTIC PERCEPTION ON WATERSCENES. IN THE MODALITIES COLUMN, C DENOTES THE IMAGE MODALITY FROM THE CAMERA SENSOR, AND R DENOTES A SINGLE FRAME POINT CLOUD MODALITY FROM THE 4D RADAR SENSOR

| Model | Modalities | Params (M) | Object Detection | | Free-Space Segmentation | | Waterline Segmentation | | FPS |
|---|---|---|---|---|---|---|---|---|---|
| | | | $mAP_{50}$ | $mAP_{50-95}$ | OA | mIoU | OA | mIoU | |
| YOLOP [70] | C | 7.9 | 68.0 | 42.6 | 99.5 | 99.0 | 67.6 | 72.1 | 50.5 |
| HybridNets [71] | C | 12.8 | 69.8 | 49.5 | 97.2 | 98.0 | 65.3 | 69.8 | 45.8 |
| Achelous-MV-GDF-S0 [72] | C + R | 1.6 | 81.1 | 51.0 | 99.6 | 99.3 | 68.3 | 65.0 | **70.3** |
| Achelous-MV-GDF-S1 [72] | C + R | 2.8 | 83.5 | 54.1 | 99.6 | 99.4 | 69.5 | 68.7 | 69.6 |
| Achelous-MV-GDF-S2 [72] | C + R | 5.3 | **85.5** | **56.0** | **99.7** | **99.6** | **70.3** | **72.2** | 68.5 |

现有方法在WaterScenes数据集上，在多种任务上的效果

# 四．多模态融合数据集

WaterScenes［TITS 2024］（图像与4D雷达融合的多任务数据集）




融合方法相比纯视觉显然有更好的效果

# 总结

- 智能感知是智慧航运的基础。
- 感知数据集是研究智能感知方法的基础。
- 虽然现有多种智能航运感知数据集出现，但是规模仍然较小，数量较少，是限制智能航运感知快速发展的主要瓶颈之一。
- 智能航运感知的仿真平台也较少，如何构建智能航运感知的大数据平台，仍然是急需解决的问题。

# 谢谢，Q&A

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