

# Bottle Detection in the Wild Using Low-Altitude Unmanned Aerial Vehicles

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Jinwang Wang Wei Guo Ting Pan Huai Yu Lin Duan Wen Yang

Wuhan University, Wuhan, China

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武汉大学  
WUHAN UNIVERSITY



# Outline

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1. Introduction
2. UAV-Bottle Dataset
3. Baselines and Methods
4. Conclusion and Future Work



# Introduction

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# Motivation

It's very **dangerous** for the sanitation workers who pick up the waste bottles on the mountain. Can we help them? Yes!

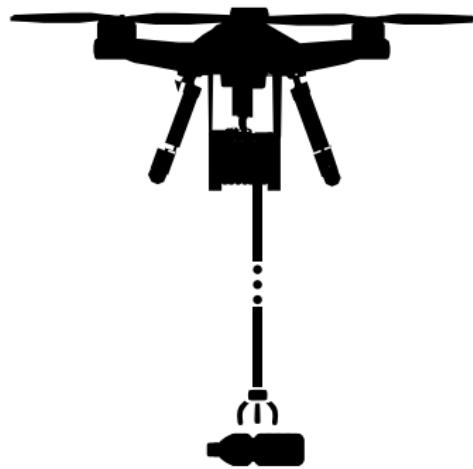


The sanitation workers were collecting the waste bottles at the Huashan Mountain.



# Motivation

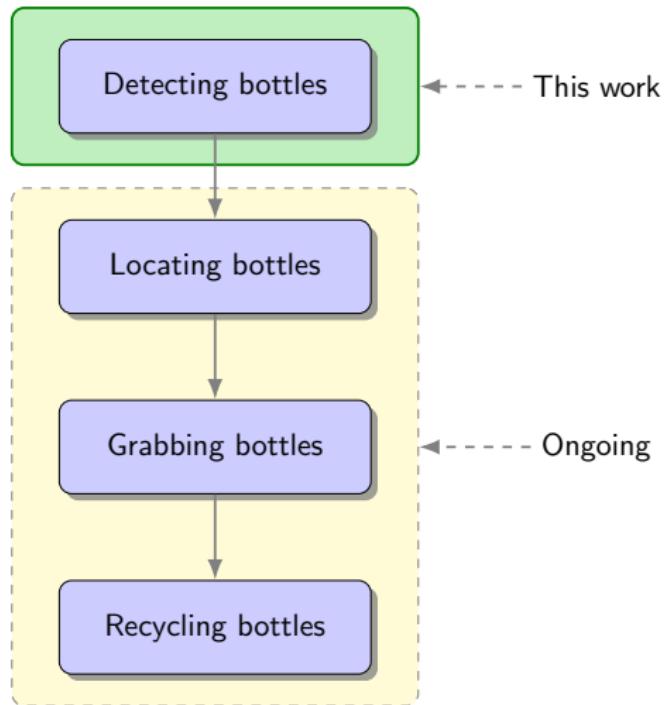
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UAVs can help them!

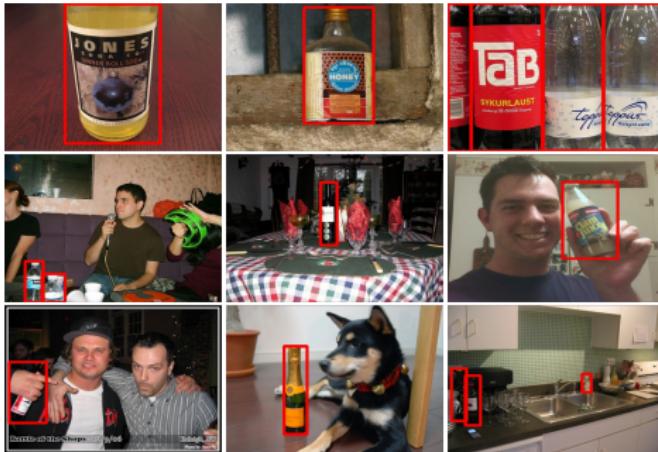


# Pipeline



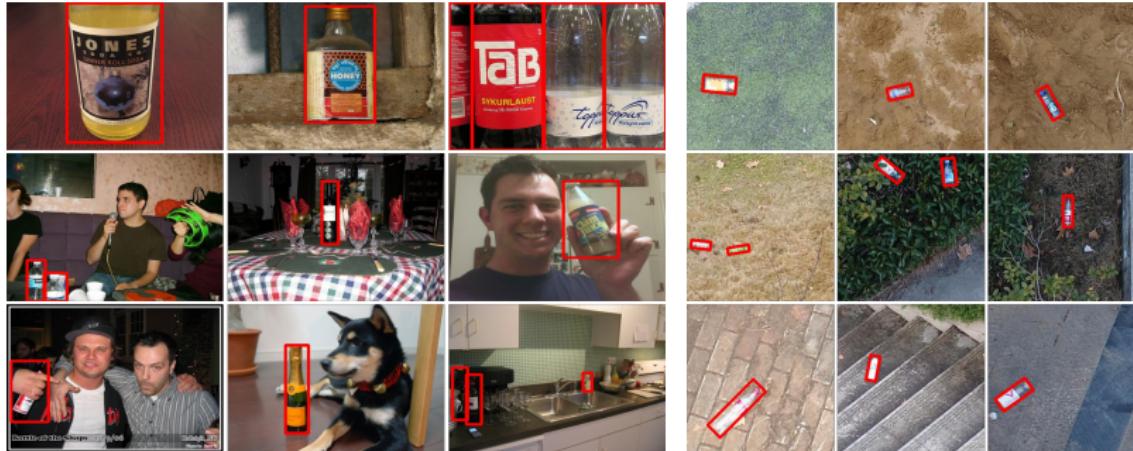
# challenges

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- The bottle size in image is very small, generally less than  $50 \times 50$  pixels.
- Backgrounds are very complex.
- Arbitrary orientations.
- Plastic bottles are often transparent.



# UAV-Bottle Dataset

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# Dataset

To build a baseline for bottle detection in UAV images, we first established a large scale dataset which called [UAV-Bottle Dataset\(UAV-BD\)](#).



# Dataset Collection

We used **DJI Phantom 4 Pro** to collect images. The resolution of the captured images are **5472 × 3078 pixels**.



- ◎ A wide range of scales and aspect ratios.



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# Dataset Collection

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- A wide range of scales and aspect ratios.
- Different backgrounds.
- Different orientations.
- As many types of bottles as possible.



# Dataset Collection

8 different scenes are chosen and annotated in our UAV-BD:

- Bushes
- Waste land
- Steps
- Mixture
- Cement ground
- Plastic ground
- Sands
- Grassland



# Annotation Method

A common description of horizontal bounding boxes is  $(c_x, c_y, h, w)$ , where  $(c_x, c_y)$  is the center location,  $h, w$  are the height and width, respectively.



However, horizontal bounding box cannot accurately or compactly outline oriented instances such as the bottles in UAV images. Instead we use  $(c_x, c_y, h, w, \theta)$  to describe bounding boxes, where  $\theta$  is the angle from the vertical direction of the main-axis direction of the bottle.



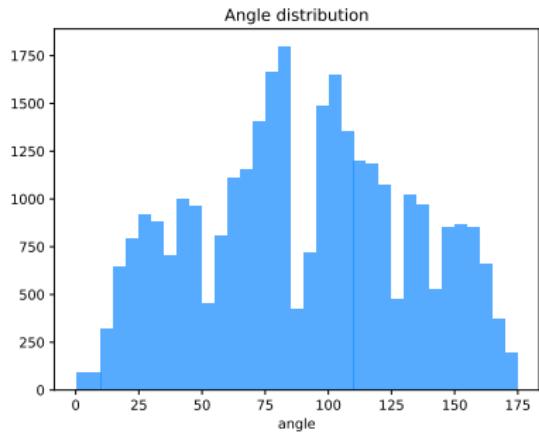
# Dataset Statistics

The size of each original image(OI) in UAV-BD is  $5472 \times 3078$  pixels, it's too large to be trained for CNN-based algorithms. Therefore we segment each OI into 144 small subimages(SIs), and the size of each SI is  $342 \times 342$  pixels. The number of images and instances in UAV-BD are shown in the table below.

Scenes	OI	SI	Instances in OI	Instances in SI
Bushes	230	4134	3047	1812
Waste land	379	7598	5800	4355
Steps	135	2691	2106	1325
Mixture	285	5724	4891	3702
Cement ground	134	2803	2142	1538
Plastic ground	336	6807	4998	4180
Sands	249	5570	4008	2704
Grassland	456	9029	7787	5778
<b>Total</b>	<b>2204</b>	<b>44356</b>	<b>34779</b>	<b>25394</b>



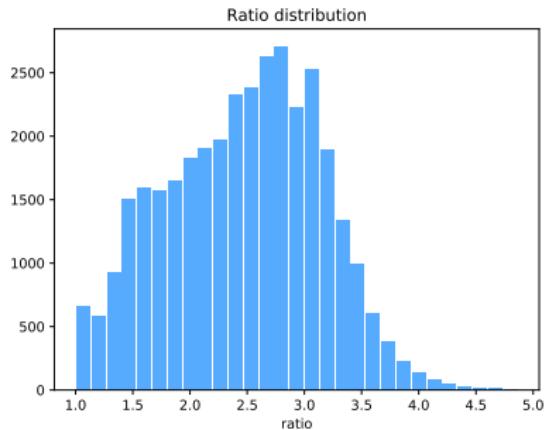
# Dataset Statistics



Angle distribution of UAV-BD.  
The angle ranges from  $0^\circ$  to  $180^\circ$ .



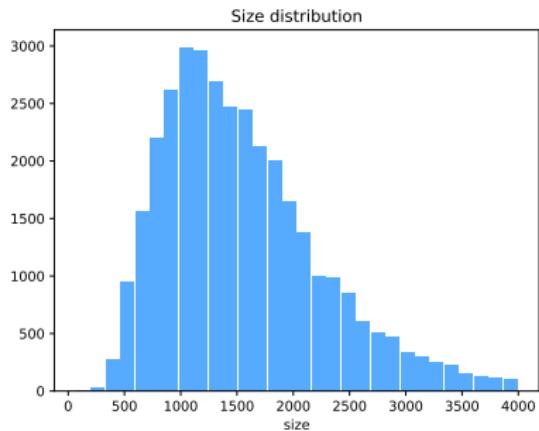
# Dataset Statistics



Ratio distribution of UAV-BD.  
The aspect ratio ranges from 1.0 to 5.0.



# Dataset Statistics



Size distribution of UAV-BD. The size ranges from 64 to 4000 pixels.



## Baselines and Methods

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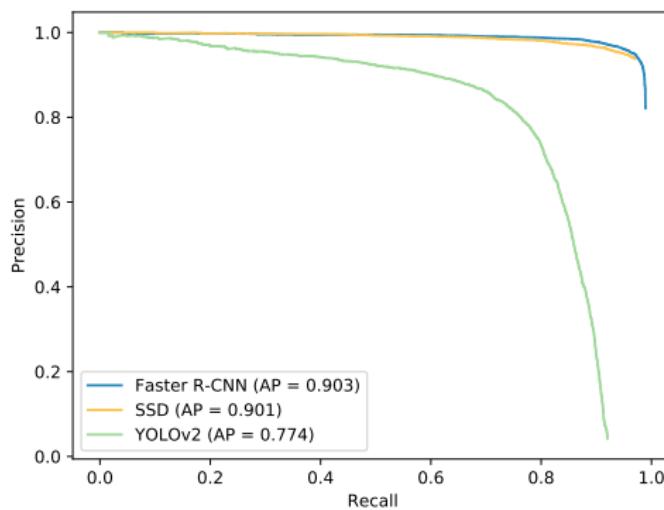
# Dataset Partition

We randomly select **64%**, **16%** and **20%** of the UAV-BD as the **training**, **validation** and **testing** data. The whole UAV-BD contains 16,258 images with 22,211 instances for training, 4,055 images with 5,624 instances for validation and 5,081 images with 6,944 instances for testing.



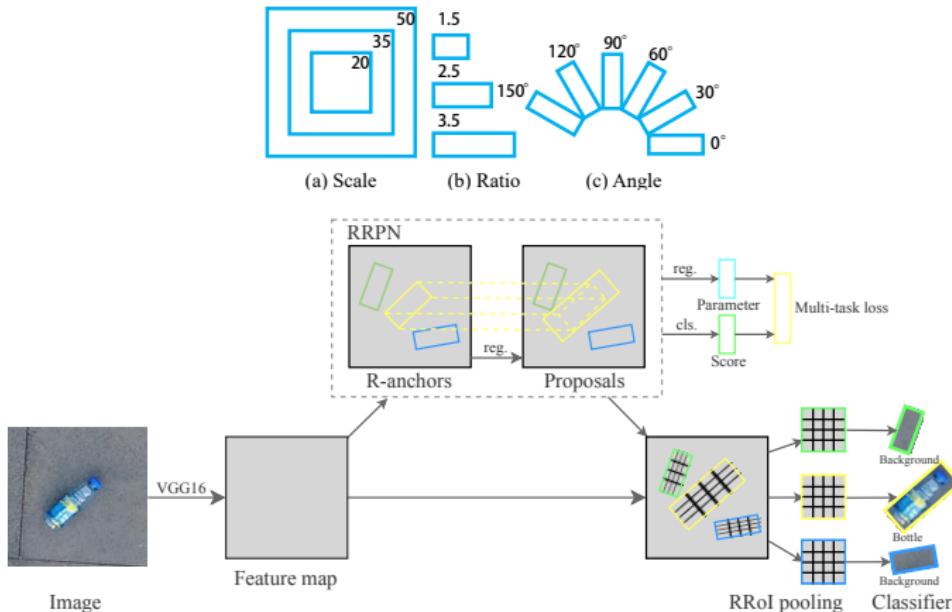
# Baselines with Horizontal Bounding Boxes(HBB)

We select [Faster R-CNN\[1\]](#), [SSD\[2\]](#), [YOLOv2\[3\]](#) as baselines for bottle detection with horizontal bounding box. The experimental results of HBB prediction are shown in figure below.



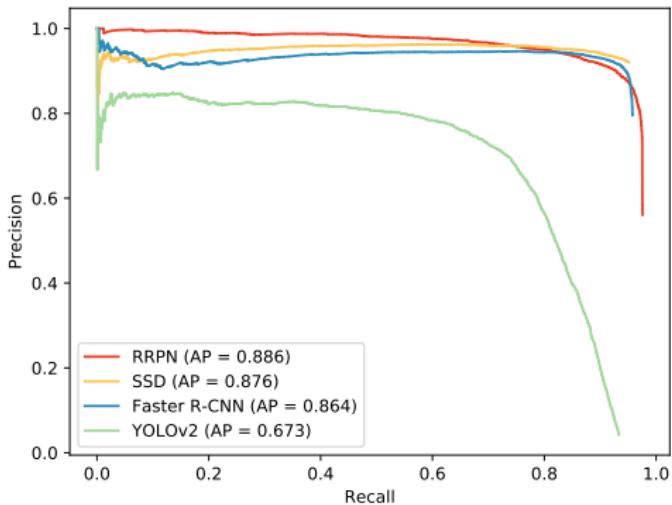
# Baselines with Oriented Bounding Boxes(OBB)

For oriented object detection, we employ the [Rotation Region Proposal Network\(RRPN\)\[4\]](#) algorithm to predict properly oriented bounding boxes. The RRPN's network structure is shown in figure below.



# Baseline with Oriented Bounding Boxes(OBB)

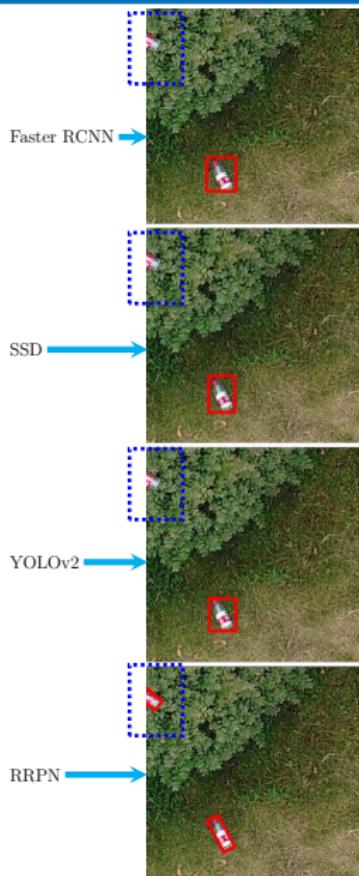
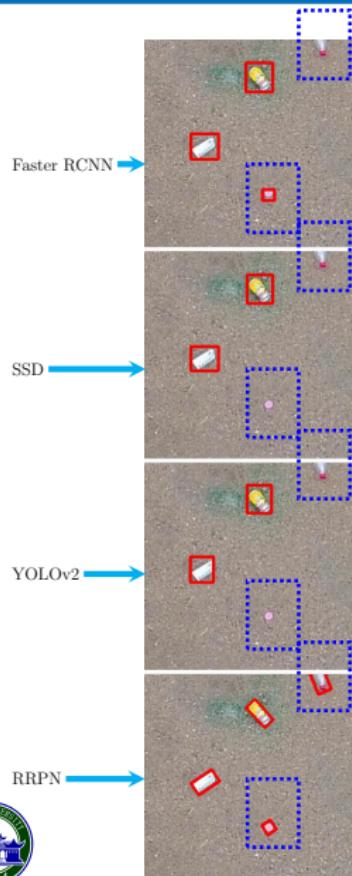
The experimental results of OBB prediction are shown in figure below.



# Experimental Analysis



# Some Details



## Conclusion and Future Work

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## Contribution

- ⑤ Built a large-scale dataset for bottle detection in UAV images named UAV-BD.

## Future Work



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- ⑤ Established a benchmark for bottle detection in UAV images.

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## Future Work

- ⑤ Locating and recycling bottles in the real-world using UAVs.



# Get UAV-Bottle Dataset

UAV-Bottle Dataset and Development Kit can be downloaded on the Webpage and Github.

UAV-Bottle Dataset

<https://jwwangchn.github.io/UAV-BD/>

Development Kit

<https://github.com/jwwangchn/UAV-BD.git>



# References

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# Comments and Questions!