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

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FUSION 2018 International Conference, Cambridge UK, July 2018

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Good morning, everyone. I am Jinwang Wang from Wuhan University. In the next few minutes, I will introduce our work “Bottle Detection in the Wild Using Low-Altitude Unmanned Aerial Vehicles”.

Outline

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

I will talk my work through the following sections.

Introduction

First, introduction.

Motivation

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

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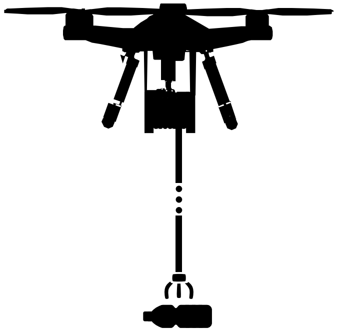

UAVs can help them!

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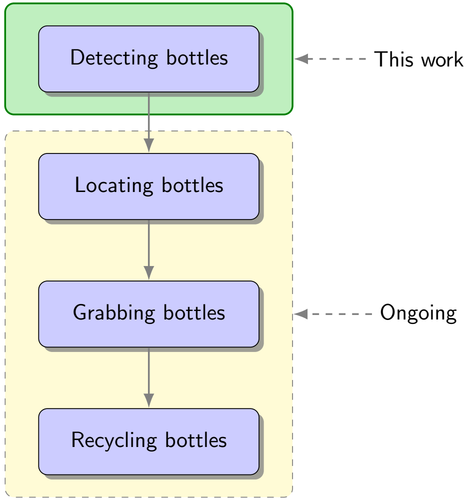
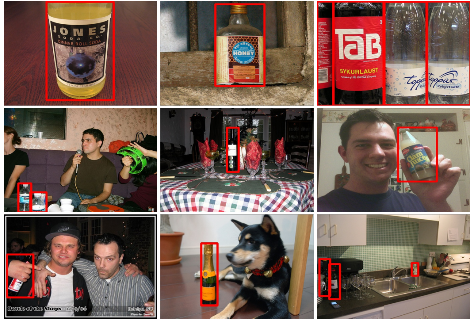
Pipeline



This work mainly focuses on bottles detection. The whole pipeline is shown as below. After detecting bottles, locating bottles, grabbing bottles and recycling bottles is ongoing.

challenges

In UAV images, the bottles look completely different from the bottles in datasets such as PASCAL VOC, ImageNet, Microsoft COCO, etc.



In order to detect bottles on UAV, a high quality bottle dataset is needed for training deep learning based detection models. There are exactly bottles in the PASCAL VOC, ImageNet, Microsoft COCO, etc. datasets, why don't we use these bottles to training models?

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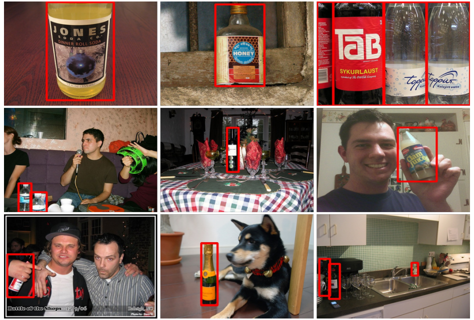

Because in UAV images, the bottles look completely different from the bottles in PASCAL VOC etc. datasets. As to UAV image, as you can see, detecting bottles exists several unique challenges.

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◎ The bottle size in image is very small, generally less than 50×50 pixels.

First, the bottle size in image is very small, generally less than 50×50 pixels;

Second, the backgrounds are very complex.

Third, in contrast to conventional object detection dataset, the bottles in UAV images often appear with arbitrary orientations.

Fourth, plastic bottles are often transparent, thus the background will can be seen through the bottles.

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UAV-Bottle Dataset

Dataset

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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 scale and aspect ratios.

We use DJI Phantom 4 Pro to collect images. The resolution of the captured images are 5472×3078 pixels. At the same time, we follow four key suggestions. First, collecting images including bottles a wide range of scale and aspect ratio. Second, collecting images including different backgrounds. Third, collecting images including bottles different orientations. Fourth, collecting as many types of bottles as possible.

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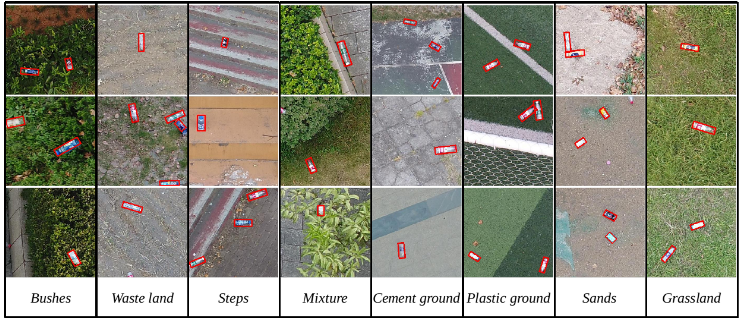
Dataset Collection

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

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



Eight scenes are chosen and annotated in our UAV-BD, including 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, θ) to describe bounding boxes, where θ is the angle from the vertical direction of the main-axis direction of the bottle.

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Dataset Statistics

The size of each original image(OI) in UAV-BD is 5472×3078 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 342×342 pixels. The numbers 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
Total	2204	44356	34779	25394

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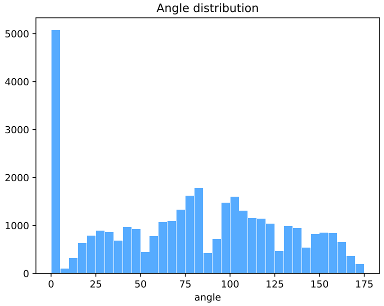

Angle distribution of UAV-BD. The angle ranges from $0°$ to $180°$.

For better training the CNN-based algorithms, we counted some dataset's data distribution. Including angle distribution, ratio distribution, size distribution.

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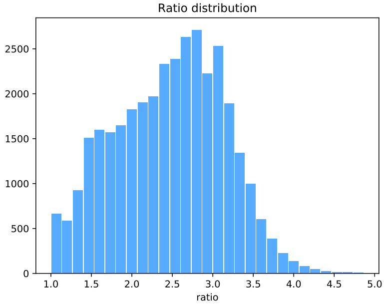

Ratio distribution of UAV-BD. The aspect ratio ranges from 1.0 to 5.0.

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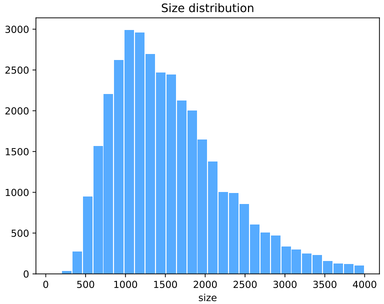
Dataset Statistics



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

For better training the CNN-based algorithms, we counted some dataset's data distribution. Including angle distribution, ratio distribution, size distribution.

Baselines and Methods

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.

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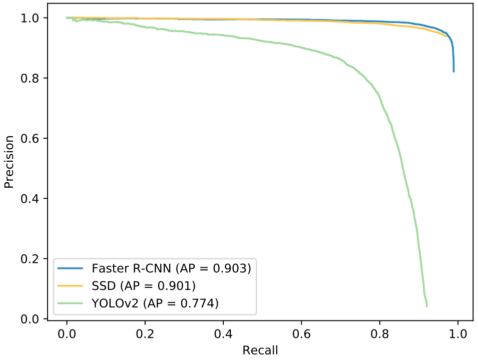
Baselines with Horizontal Bounding Boxes(HBB)

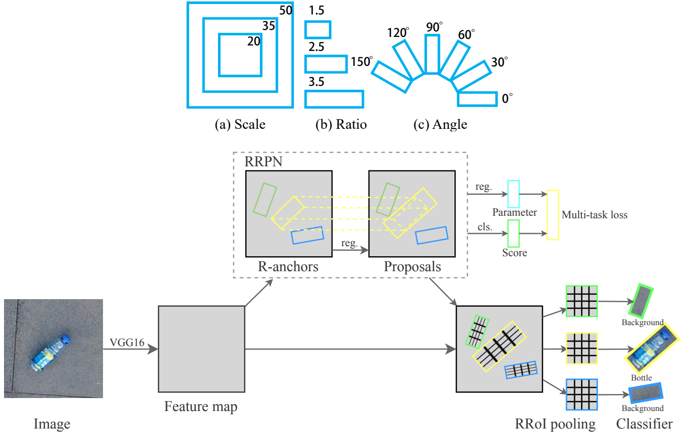
We select Faster R-CNN[1], SSD[2], YOLOv2[3] as baselines for bottle detection with horizontal bounding box. The experimental results of HBB prediction are shown in figure below.



We select Faster R-CNN, SSD, YOLOv2 as our baseline for horizontal object detection. 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 algorithm to predict properly oriented bounding boxes. The RRPN's network structure is shown in figure below.



For oriented object detection, wo modify the original Rotation Region Proposal Network(RRPN) algorithm to predict properly oriented bounding boxes. RRPN's network structure is shown in figure below. The scale, ratio and angle settings are came from dataset's distribution.

Baseline with Oriented Bounding Boxes(OBB)

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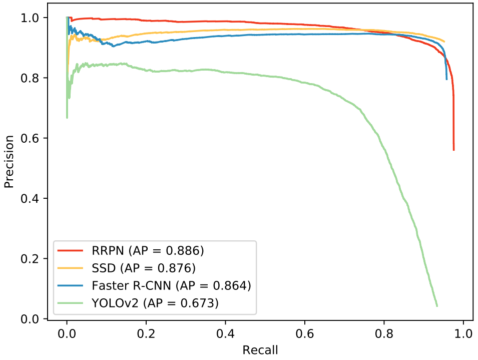

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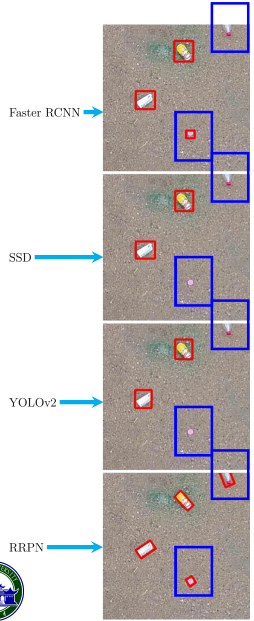
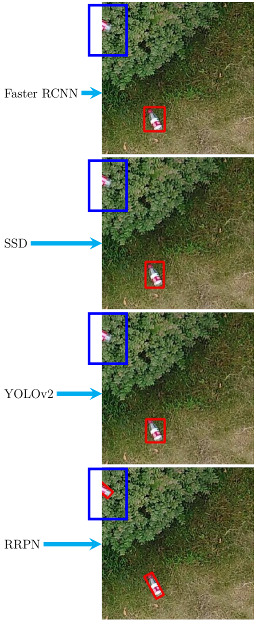
Experimental Analysis

Bottles detection results in our dataset. As you can see, RRPN's performance is highest.

Some Details





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Conclusion and Future Work

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Contribution

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

Future Work

Our contributions including built a large-scale dataset for bottle detection in UAV images named UAV-BD, annotated a huge number of well-distributed bottles with oriented bounding boxes, established a benchmark for bottle detection. In the future, we will focus on locating and recycling bottles in the real-world using UAV.

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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

You can download our dataset from Google Drive and download develop kit from Github.

References

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There are some references.

Comments and Questions!

Welcome to make comments and ask Questions