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

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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.

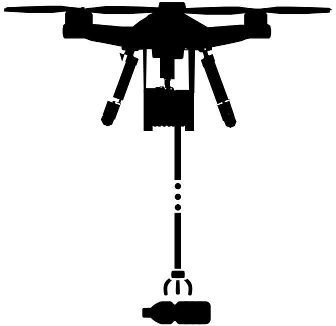
Motivation

dangerous

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

As we all know, It's very dangerous for the sanitation workers who pick up the waste bottles on the mountain. This image shows that the sanitation workers were collecting the waste bottles at the Huanshan Mountain. So can we help them? Yes! We can use UAV to pick up bottles.

dangerous



UAVs can help them!

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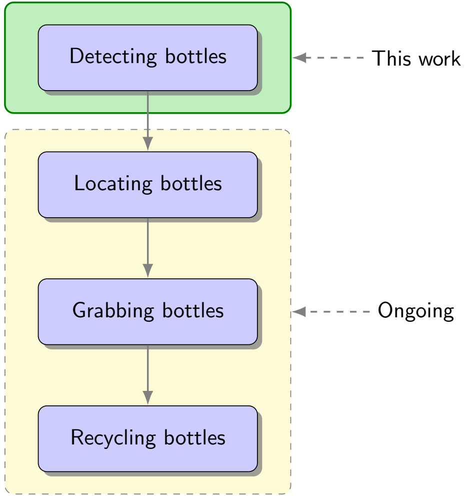
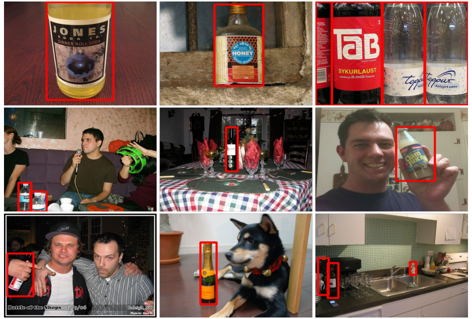
Pipeline



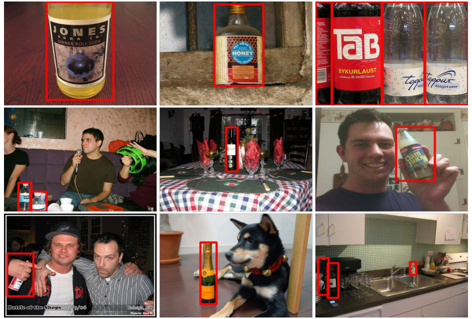
This work mainly focuses on bottles detection. The whole pipeline is shown as below. After detecting bottles, locating bottles, grabbing bottles and recycling bottles is ongoing.

challenges



In 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?

challenges



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.

challenges

- 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

Next section, UAV-Bottle Dataset

Dataset

UAV-Bottle Dataset(UAV-BD).

To build a baseline for bottle detection in UAV images, we established a large scale bottle detection dataset, we call UAV-Bottle Dataset(UAV-BD).

Dataset Collection

DJI Phantom 4 Pro

5472×3078 pixels

- A wide range of scales 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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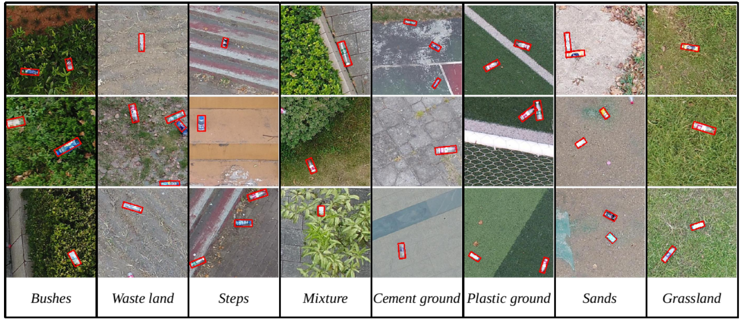
Dataset Collection

8 different scenes

- 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

(c_x, c_y, h, w)

(c_x, c_y, h, w, θ)

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. However, horizontal bounding boxes 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.

Dataset Statistics

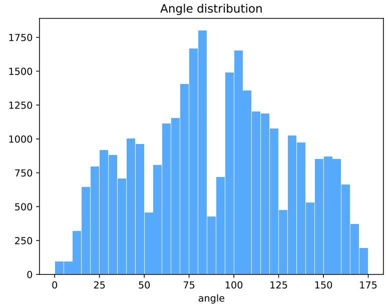
5472×3078 pixels

342×342 pixels

Bushes
Waste land
Steps
Mixture
Cement ground
Plastic ground
Sands
Grassland

In our dataset, the size of original image is 5472×3078 pixels, they are too large to be trained for CNN-based algorithms. So we segment each original image into 144 small subimages, and the size of subimages is 342×342 pixels. Images and instances number in UAV-BD are shown in the table below.

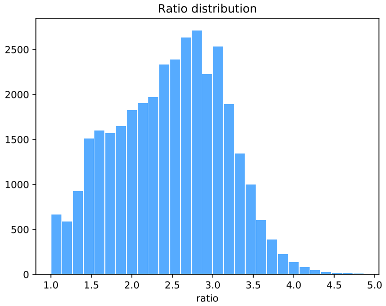
Dataset Statistics



Angle distribution of UAV-BD.

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

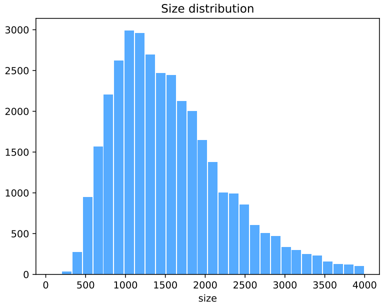
Dataset Statistics



Ratio distribution of UAV-BD.

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

Dataset Statistics



Size distribution of UAV-BD.

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

Baselines and Methods

Next section, Baselines and Methods

Dataset Partition

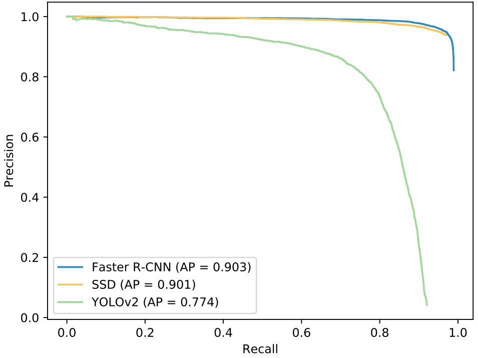
64% 16% 20%

training validation testing

We randomly select 64%, 16% and 20% of the UAV-BD as the training, validation and testing data. So 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)

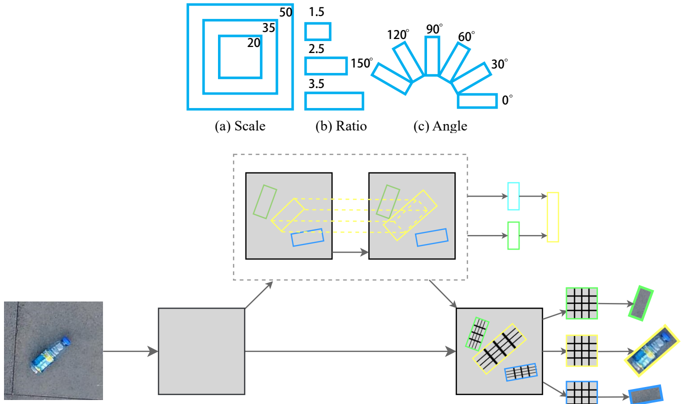
Faster R-CNN[1] SSD[2] YOLOv2[3]



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.

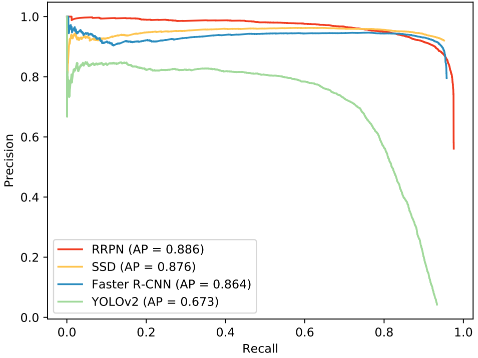
Baselines with Oriented Bounding Boxes(OBB)

Rotation Region Proposal Network(RRPN)[4]



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)

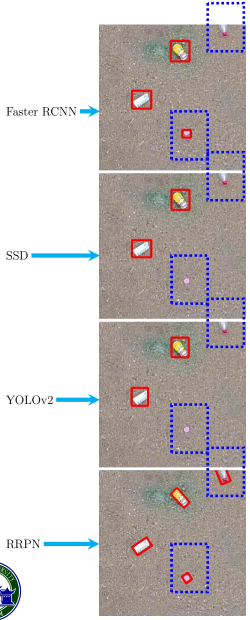


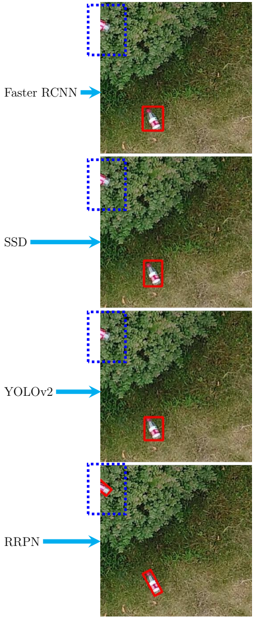
The experimental results of OBB prediction are shown in figure below.

Experimental Analysis

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

Some Details





There some details of detection results.

Conclusion and Future Work

Next section, Conclusion and Future Work

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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Future Work

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

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Get UAV-Bottle Dataset

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

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