4. Opencv application

4.1. Target detection

The main problem solved in this section is how to use the dnn module in OpenCV to import a trained target detection network. But there are requirements for the version of opencv.

Currently, there are three main methods for using deep learning for target detection:

- Faster R-CNNs
- You Only Look Once(YOLO)
  -Single Shot Detectors(SSDs)

Faster R-CNNs is the most commonly heard neural network based on deep learning. However, this method is technically difficult to understand (especially for deep learning novices), difficult to implement, and difficult to train.

In addition, even if the "Faster" method is used to implement R-CNNs (where R stands for Region Proposal), the algorithm is still relatively slow, about 7FPS.

If we are pursuing speed, we can turn to YOLO because it is very fast and can reach 40-90 FPS on TianXGPU, and the fastest version may reach 155 FPS. But the problem with YOLO is that its accuracy needs to be improved.

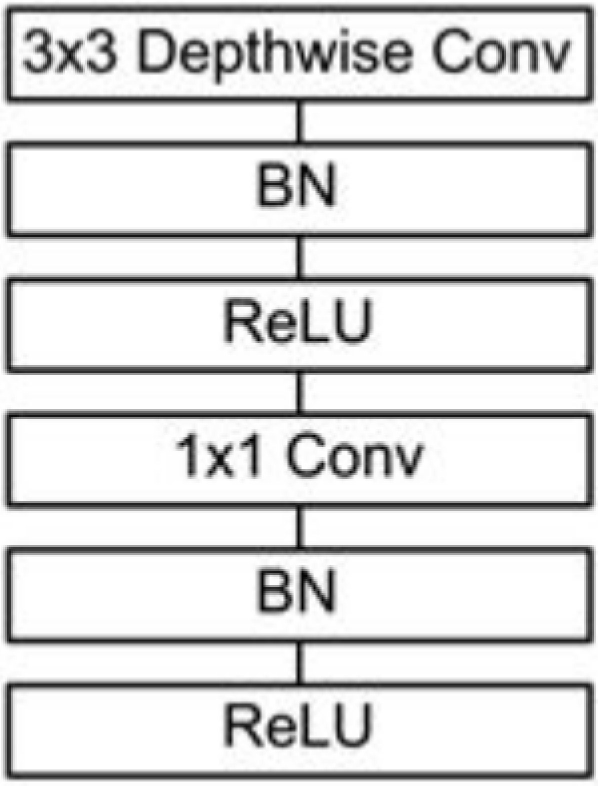
SSDs were originally developed by Google and can be said to be a balance between the above two. Compared with Faster R-CNNs, its algorithm is more straightforward. Compared with YOLO, it is more accurate.

4.1.1. Model structure

The main work of MobileNet is to use depthwise sparable convolutions (depth-level separable convolutions) to replace the past standard convolutions (standard convolutions) to solve the problems of computational efficiency and parameter volume of convolutional networks. The MobileNets model is based on depthwise sparable convolutions (depth-level separable convolutions), which can decompose standard convolutions into a depth convolution and a point convolution (1 × 1 convolution kernel). **Depthwise convolution applies each convolution kernel to each channel, while 1 × 1 convolution is used to combine the outputs of channel convolutions.**

Batch Normalization (BN) will be added to the basic components of MobileNet, that is, in each SGD (stochastic gradient descent), standardization processing will be performed so that the mean of the result (all dimensions of the output signal) is 0 and the variance is 1. Generally, when you encounter problems such as slow convergence or gradient explosion and other problems that cannot be trained during neural network training, you can try BN to solve the problem. In addition, in general use cases, BN can also be added to speed up training and improve model accuracy.

In addition, the model also uses the ReLU activation function, so the basic structure of depthwise separable convolution is as shown below:



The MobileNets network is composed of many depthwise separable convolutions as shown in the figure above. Its specific network structure is shown in the figure below:

Type / Stride	Filter Shape	Input Size
Conv / s2	$3 \times 3 \times 3 \times 32$	$224 \times 224 \times 3$
Conv dw / s1	$3 \times 3 \times 32$ dw	$112 \times 112 \times 32$
Conv / s1	$1 \times 1 \times 32 \times 64$	$112 \times 112 \times 32$
Conv dw / s2	$3 \times 3 \times 64$ dw	$112 \times 112 \times 64$
Conv / s1	$1 \times 1 \times 64 \times 128$	$56 \times 56 \times 64$
Conv dw / s1	$3 \times 3 \times 128$ dw	$56 \times 56 \times 128$
Conv / s1	$1 \times 1 \times 128 \times 128$	$56 \times 56 \times 128$
Conv dw / s2	$3 \times 3 \times 128$ dw	$56 \times 56 \times 128$
Conv / s1	$1 \times 1 \times 128 \times 256$	$28 \times 28 \times 128$
Conv dw / s1	$3 \times 3 \times 256$ dw	$28 \times 28 \times 256$
Conv / s1	$1 \times 1 \times 256 \times 256$	$28 \times 28 \times 256$
Conv dw / s2	$3 \times 3 \times 256$ dw	$28 \times 28 \times 256$
Conv / s1	$1 \times 1 \times 256 \times 512$	$14 \times 14 \times 256$
$5\times$ Conv dw / s1 Conv / s1	$3 \times 3 \times 512$ dw $1 \times 1 \times 512 \times 512$	$14 \times 14 \times 512$ $14 \times 14 \times 512$
Conv dw / s2	$3 \times 3 \times 512$ dw	$14 \times 14 \times 512$
Conv / s1	$1 \times 1 \times 512 \times 1024$	$7 \times 7 \times 512$
Conv dw / s1	$3 \times 3 \times 1024$ dw	$7 \times 7 \times 1024$
Conv / s1	$1 \times 1 \times 1024 \times 1024$	$7 \times 7 \times 1024$
Avg Pool / s1	Pool 7×7	$7 \times 7 \times 1024$
FC / s1	1024×1000	$1 \times 1 \times 1024$
Softmax / s1	Classifier	$1 \times 1 \times 1000$

4.1.2. Source code analysis

Source code location: ~/orbbec_ws/src/astra_visual/detection/target_detection.py

list of recognized objects,

```
[person, bicycle, car, motorcycle, airplane, bus, train,truck, boat, traffic
light, fire hydrant, street sign,stop sign, parking meter, bench, bird, cat,
dog, horse,sheep, cow, elephant, bear, zebra, giraffe, hat, backpack,umbrella,
shoe, eye glasses, handbag, tie, suitcase, frisbee, skis, snowboard, sports
ball, kite, baseball bat,baseball glove, skateboard, surfboard, tennis
racket,bottle, plate , wine glass, cup, fork, knife, spoon, bowl,banana, apple,
sandwich, orange, broccoli, carrot, hot dog,pizza, donut, cake, chair, couch,
potted plant, bed, mirror,dining table, window , desk, toilet, door, tv, laptop,
mouse,remote, keyboard, cell phone, microwave, oven, toaster,sink, refrigerator,
blender, book, clock, vase, scissors,teddy bear, hair drier, toothbrush]
```

Load the category [object_detection_coco.txt], import the model [frozen_inference_graph.pb], and specify the deep learning framework [TensorFlow]

```
# load the COCO class names
with open('object_detection_coco.txt', 'r') as f: class_names =
f.read().split('\n')
# get a different color array for each of the classes
COLORS = np.random.uniform(0, 255, size=(len(class_names), 3))
# load the DNN modelimage
model =
cv.dnn.readNet(model='frozen_inference_graph.pb',config='ssd_mobilenet_v2_coco.t
xt',framework='TensorFlow')
```

Import the image, extract the height and width, calculate a 300x300 pixel blob, and pass this blob into the neural network

```
def Target_Detection(image):
     image_height, image_width, _ = image.shape
     # create blob from image
     blob = cv.dnn.blobFromImage(image=image, size=(300, 300), mean=(104, 117,
123), swapRB=True)
     model.setInput(blob)
     output = model.forward()
     # loop over each of the detections
     for detection in output[0, 0, :, :]:
         # extract the confidence of the detection
         confidence = detection[2]
         # draw bounding boxes only if the detection confidence is above...
         # ... a certain threshold, else skip
         if confidence > .4:
             # get the class id
             class_id = detection[1]
             # map the class id to the class
             class_name = class_names[int(class_id) - 1]
             color = COLORS[int(class_id)]
             # get the bounding box coordinates
             box_x = detection[3] * image_width
             box_y = detection[4] * image_height
             # get the bounding box width and height
             box_width = detection[5] * image_width
             box_height = detection[6] * image_height
             # draw a rectangle around each detected object
             cv.rectangle(image, (int(box_x), int(box_y)), (int(box_width),
int(box_height)), color, thickness=2)
             # put the class name text on the detected object
             cv.putText(image, class_name, (int(box_x), int(box_y - 5)),
cv.FONT_HERSHEY_SIMPLEX, 1, color, 2)
     return image
```

4.1.3. Start

Terminal input,

```
cd ~/orbbec_ws/src/astra_visual/detection
python target_detection.py
```


frame
FPS : 17
person
person
person
person
person
bicycle
motorcycle
(x=33, y=457) ~ R:247 G:250 B:255