4. Target detection

4.1. Introduction

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

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

- 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 newcomers to deep learning), difficult to implement, and difficult to train.

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

If we pursue speed, we can turn to YOLO, because it is very fast, reaching 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.

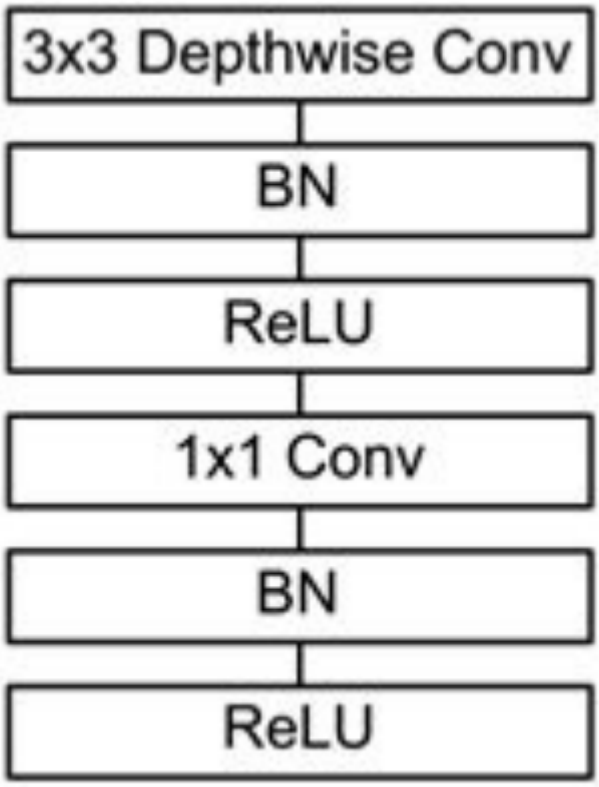
SSDs was originally developed by Google and can be said to be a balance between the above two. Compared with Faster R-CNNs, its algorithm is more direct. Compared with YOLO, it is more accurate.

4.1.1, Model Structure

The main work of MobileNet is to replace the past standard convolutions with depthwise sparable convolutions to solve the problems of computational efficiency and parameter quantity of convolutional networks. The MobileNets model is based on depthwise sparable convolutions, which can decompose the standard convolution into a depthwise convolution and a point convolution (1 × 1 convolution kernel). **Deep convolution applies each convolution kernel to each channel, while 1 × 1 convolution is used to combine the output of channel convolution.**

Batch Normalization (BN) is added to the basic components of MobileNet, that is, at each SGD (stochastic gradient descent), the standardization process is performed so that the result (each dimension of the output signal) has a mean of 0 and a variance of 1. Generally, when the convergence speed is very slow or the gradient explodes during neural network training, BN can be tried to solve the problem. In addition, BN can also be added to speed up training and improve model accuracy in general use.

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



The MobileNets network is composed of many depthwise separable convolutions shown in the figure above. The 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 path: ~/ascam_ws/src/ascam_visual/detection/target_detection.py

List of recognizable 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] ```python # 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 the 300x300 pixel blob, and pass this blob to 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, Startup

Start the camera

```
roslaunch ascamera hp60c.launch
```

Open a new terminal and input,

```
rosrun ascam_visual target_detection.py
```

After clicking the image box, use the keyboard [f] key to switch to human posture estimation.