

9.Target detection

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

At present, there are three main methods for object 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 deep learning novices), 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.

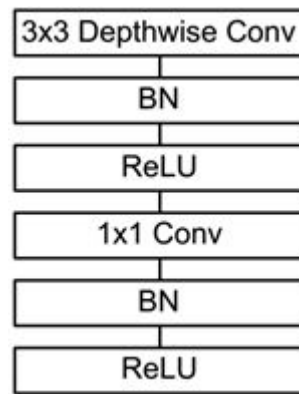
SSDs was originally developed by Google and can be said to be a balance between the above two. Compared with Faster R-CNNs, its algorithm is more direct. Compared with YOLO, it is more accurate.

9.1. Model structure

The main work of MobileNet is to replace the previous standard convolutions with depthwise separable convolutions to solve the problems of computational efficiency and parameter quantity of convolutional networks. The MobileNets model is based on depthwise separable convolutions, which can decompose standard convolutions into a depth 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 mean of the result (each dimension of the output signal) is 0 and the variance is 1. Generally, when you encounter a situation where the convergence speed is very slow or the gradient explodes and you cannot train, you can try to solve it with BN. In addition, in general use, you can also add BN to speed up the training speed and improve the model accuracy.

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



The MobileNets network is composed of many depthwise separable convolutions 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×	Conv dw / s1	$3 \times 3 \times 512$ dw
	Conv / s1	$1 \times 1 \times 512 \times 512$
	Conv dw / s2	$3 \times 3 \times 512$ dw
	Conv / s1	$1 \times 1 \times 512 \times 1024$
	Conv dw / s1	$3 \times 3 \times 1024$ dw
	Conv / s1	$1 \times 1 \times 1024 \times 1024$
	Avg Pool / s1	Pool 7×7
	FC / s1	1024×1000
	Softmax / s1	Classifier

9.2, Code Analysis

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]

```
# Load COCO class name Load COCO class name
with open('object_detection_coco.txt', 'r') as f: class_names =
f.read().split('\n')
# Display different colors for different targets
COLORS = np.random.uniform(0, 255, size=(len(class_names), 3))
# Load DNN image model
model = cv.dnn.readNet(model='frozen_inference_graph.pb',
config='ssd_mobilenet_v2_coco.txt', framework='TensorFlow')
```

Import the image, extract the height and width, calculate the 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 through each detection
    for detection in output[0, 0, :, :]:
        # Extract the confidence of the detection
        confidence = detection[2]
        # Draw bounding box only if detection confidence is above a certain threshold,
        otherwise skip
        if confidence > .4:
            # Get class ID
            class_id = detection[1]
            # Map class id to class
            class_name = class_names[int(class_id) - 1]
            color = COLORS[int(class_id)]
            # Get bounding box coordinates
            box_x = detection[3] * image_width
            box_y = detection[4] * image_height
            # Get the width and height of the bounding box
            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)
            # Write 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
```

9.3 Startup

Note: The following commands require vnc login to the robot.

```
cd /home/pi/project_demo/07.AI_Visual_Recognition/detection
```

```
python target_detection_USB.py
```

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

```
if action == ord('f') or action == ord('F'):state = not state # 功能切换
```

