5. Opencv application

5.1. Overview

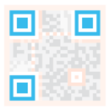
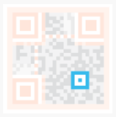
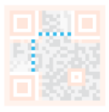
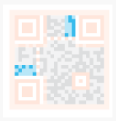
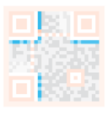
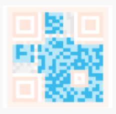
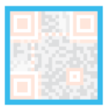
OpenCV is a cross-platform computer vision and machine learning software library released under the BSD license (open source) and can run on Linux, Windows, Android and MacOS operating systems. [1] It is lightweight and efficient - it consists of a series of C functions and a small number of C++ classes. It also provides interfaces in Python, Ruby, MATLAB and other languages, and implements many common algorithms in image processing and computer vision.

5.2, QR code

5.2.1. Introduction to QR code

QR code is a type of two-dimensional barcode. QR comes from the abbreviation of "Quick Response" in English, which means quick response. It comes from the inventor's hope that the content of QR code can be decoded quickly. QR code not only has large information capacity, high reliability, and low cost, but can also represent various text information such as Chinese characters and images. It has strong confidentiality and anti-counterfeiting and is very convenient to use. What's more important is that the QR code technology is open source.

5.2.2. Structure of QR code

Pictures	Analysis
	**Positioning markings** indicate the direction of the QR code.
	**Alignment markings** If the QR code is large, these additional elements help with positioning.
	**Timing pattern** Through these lines, the scanner can identify how big the matrix is.
	**Version information** (Version information) Here you specify the version number of the QR code being used. Currently, there are 40 different version numbers of QR codes. Version numbers used in the sales industry are usually 1-7.
	**Format information** (Format information) Format patterns contain information about fault tolerance and data masking patterns, and make scanning code easier.
	**Data and error correction keys** (Data and error correction keys) These modes save the actual data.
	**Quiet zone** (Quiet zone) This area is very important for the scanner. Its function is to separate itself from the surroundings.

5.2.3. Characteristics of QR code

The data values in the QR code contain repeated information (redundant values). Therefore, even if up to 30% of the QR code structure is destroyed, the readability of the QR code is not affected. The storage space of the QR code is up to 7089 bits or 4296 characters, including punctuation marks and special characters, which can be written into the QR code. In addition to numbers and characters, words and phrases (such as web addresses) can also be encoded. As more data is added to the QR code, the code size increases and the code structure becomes more complex.

5.2.4. QR code creation and recognition

Source code path: ~/transbot_ws/src/transbot_visual/simple_qrcode

Install

The factory image of the car has already been installed, no need to reinstall it.

```
python3 -m pip install qrcode pyzbar
sudo apt-get install libzbar-dev
```

- create

Create qrcode object

```
'''
    Parameter meaning:
```

```
    version: an integer with a value from 1 to 40, controlling the size of the QR code (the minimum value is 1, which is a 12×12 matrix).
              If you want the program to determine this automatically, set the value to None and use the fit argument.
    error_correction: Controls the error correction function of the QR code. Possible values are the following 4 constants.
    ERROR_CORRECT_L: About 7% or less of errors can be corrected.
    ERROR_CORRECT_M (default): About 15% or less of errors can be corrected.
    ROR_CORRECT_H: About 30% or less of errors can be corrected.
    box_size: Controls the number of pixels contained in each small grid in the QR code.
    border: Control the number of cells included in the border (the distance between the QR code and the image border) (the default is 4, which is the minimum value specified by relevant standards)
    '''
    qr = qrcode.QRCode(
        version=1,
        error_correction=qrcode.constants.ERROR_CORRECT_H,
        box_size=5,
        border=4,)
```

Add logo to qrcode QR code

```
    # If the logo address exists, add the logo image
    my_file = Path(logo_path)
    if my_file.is_file(): img = add_logo(img, logo_path)
```

Note: When using Chinese, Chinese characters need to be added

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```
cd ~/transbot_ws/src/transbot_visual/simple_qrcode
python3 QRcode_Create.py
```

Raspberry Pi 5

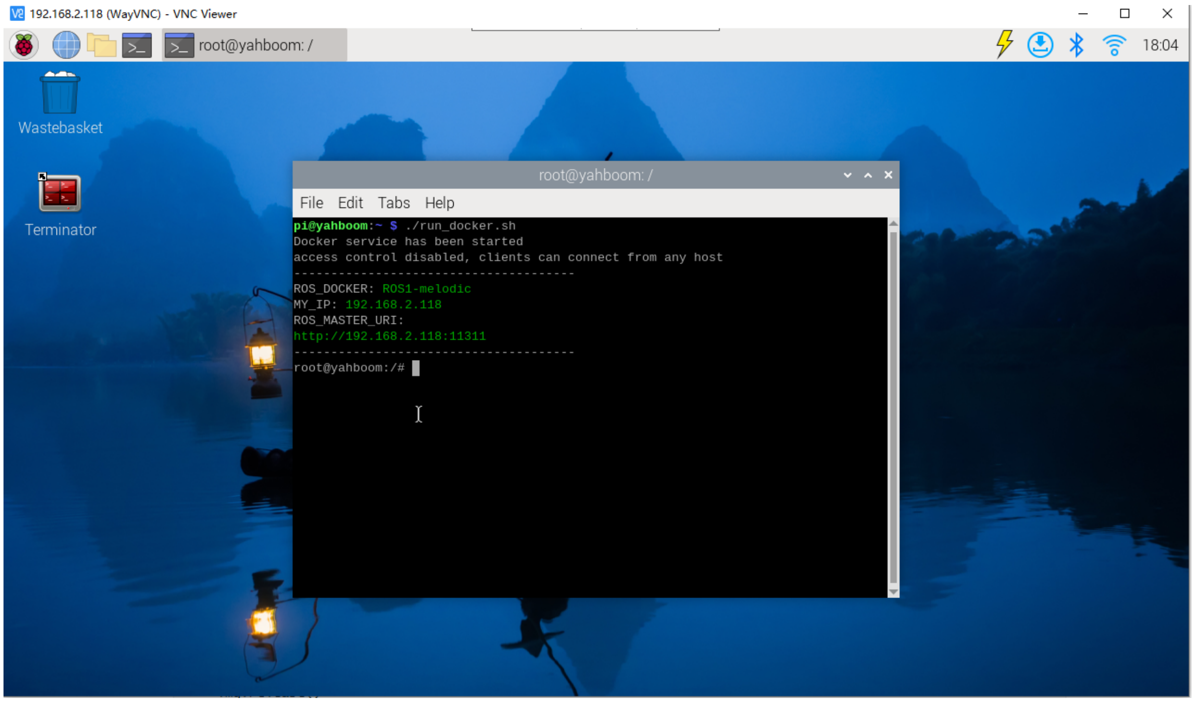
Before running, please confirm that the large program has been permanently closed

Enter docker

Note: If there is a terminal that automatically starts docker, or there is already an open docker terminal, you can directly enter the docker terminal to run the command, and there is no need to manually start docker

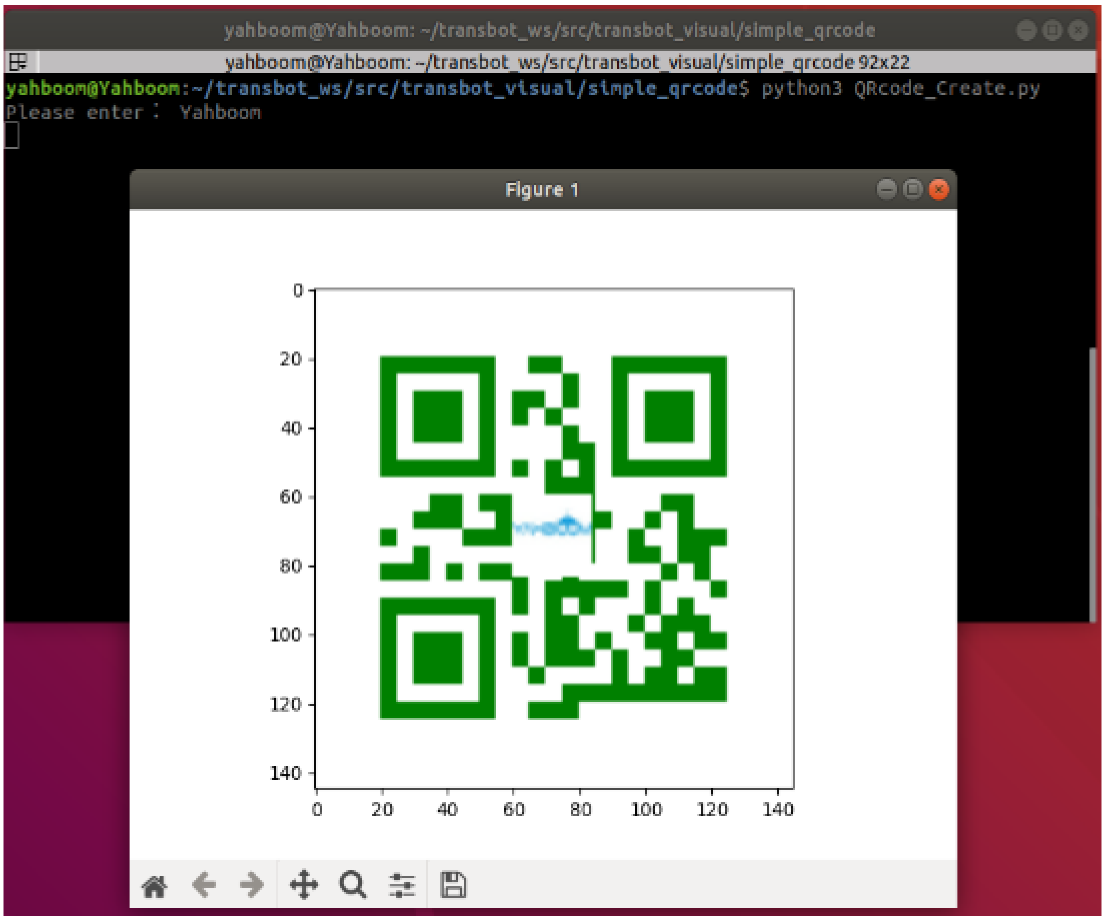
Start docker manually

```
./run_docker.sh
```



```
pi@yahboom:~ $ ./run_docker.sh
Docker service has been started
access control disabled, clients can connect from any host
-------------------------------------
ROS_DOCKER: ROS1-melodic
MY_IP: 192.168.2.118
ROS_MASTER_URI:
http://192.168.2.118:11311
-------------------------------------
root@yahboom:/#
```

```
cd ~/transbot_ws/src/transbot_visual/simple_qrcode
python3 QRcode_Create.py
```


yahboom@Yahboom: ~/transbot_ws/src/transbot_visual/simple_qrcode
yahboom@Yahboom: ~/transbot_ws/src/transbot_visual/simple_qrcode 92x22
Figure 1
0
20
40
60
80
100
120
140

```
yahboom@Yahboom:~/transbot_ws/src/transbot_visual/simple_qrcode$ python3 QRcode_Create.py
Please enter： Yahboom
```

- Identify

```
def decodeDisplay(image, font_path):
    gray = cv.cvtColor(image, cv.COLOR_BGR2GRAY)
    #You need to convert the output Chinese characters into Unicode encoding
form first.
```

```
    barcodes = pyzbar.decode(gray)
    for barcode in barcodes:
        #Extract the position of the bounding box of the QR code
        (x, y, w, h) = barcode.rect
        # Draw the bounding box of the barcode in the image
        cv.rectangle(image, (x, y), (x + w, y + h), (225, 0, 0), 5)
        encoding = 'UTF-8'
        # To draw it, you need to convert it into a string first
        barcodeData = barcode.data.decode(encoding)
        barcodeType = barcode.type
        # Draw the data and types on the image
        pilimg = Image.fromarray(image)
        #Create brush
        draw = ImageDraw.Draw(pilimg)
        # Parameter 1: font file path, parameter 2: font size
        fontStyle = ImageFont.truetype(font_path, size=12, encoding=encoding)
        # Parameter 1: Print coordinates, Parameter 2: Text, Parameter 3: Font
color, Parameter 4: Font
        draw.text((x, y - 25), str(barcode.data, encoding), fill=(255, 0, 0),
font=fontStyle)
        # PIL image to cv2 image
        image = cv.cvtColor(np.array(pilimg), cv.COLOR_RGB2BGR)
        # Print barcode data and barcode type to the terminal
        print("[INFO] Found {} barcode: {}".format(barcodeType, barcodeData))
    return image
```

- Effect demonstration

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```
cd ~/transbot_ws/src/transbot_visual/simple_qrcode
python3 QRcode_Parsing.py
```

Raspberry Pi 5

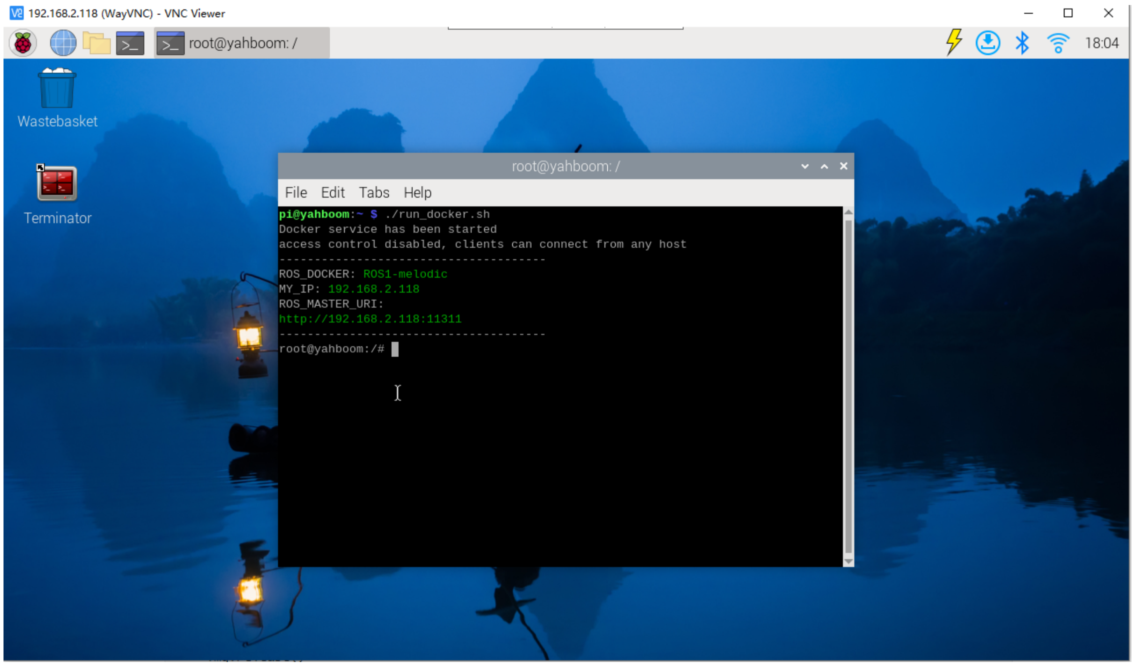
Before running, please confirm that the large program has been permanently closed

Enter docker

Note: If there is a terminal that automatically starts docker, or there is already an open docker terminal, you can directly enter the docker terminal to run the command, and there is no need to manually start docker

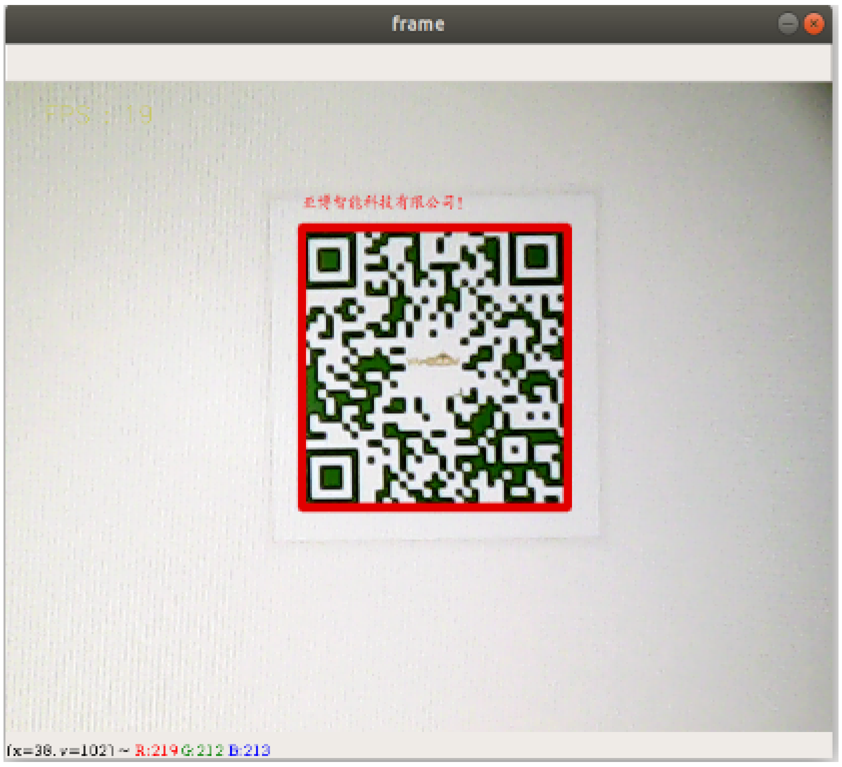
Start docker manually

```
./run_docker.sh
```



```
pi@yahboom:~ $ ./run_docker.sh
Docker service has been started
access control disabled, clients can connect from any host
----------------------------------------
ROS_DOCKER: ROS1-melodic
MY_IP: 192.168.2.118
ROS_MASTER_URI:
http://192.168.2.118:11311
----------------------------------------
root@yahboom:/# 
```

```
cd ~/transbot_ws/src/transbot_visual/simple_qrcode
python3 QRcode_Parsing.py
```



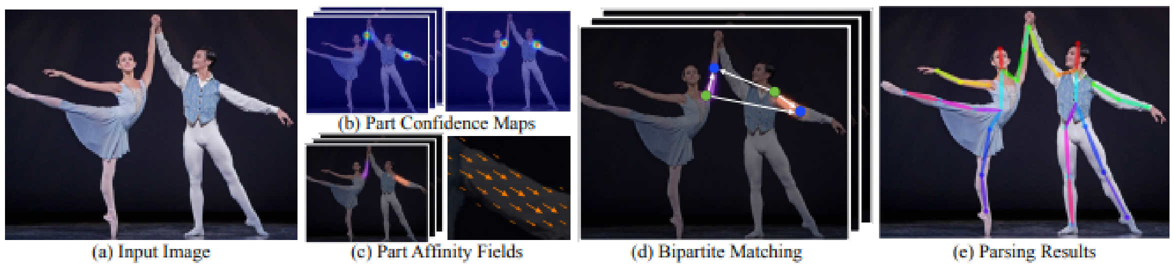
5.3. Human posture estimation

Source code path: ~/transbot_ws/src/transbot_visual/detection

5.3.1. Overview

Human Posture Estimation estimates human posture by correctly connecting the detected key points of the human body in the picture. Key points of the human body usually correspond to joints with a certain degree of freedom on the human body, such as the neck, shoulders, elbows, wrists, waist, knees, ankles, etc., as shown in the figure below.

5.3.2. Principle



Input an image, extract features through the convolutional network, and obtain a set of feature maps, which are then divided into two branches, and the CNN network is used to extract Part Confidence Maps and Part Affinity Fields respectively;
After obtaining these two pieces of information, we use Bipartite Matching in graph theory to find the Part Association and connect the joint points of the same person. Due to the vector nature of PAF itself, the generated even matching is very correct and is finally merged. For the overall skeleton of a person;
Finally, find Multi-Person Parsing based on PAFs—>convert the Multi-person parsing problem into a graphs problem—>Hungarian Algorithm (Hungarian algorithm)
(The Hungarian algorithm is the most common algorithm for partial graph matching. The core of the algorithm is to find the augmenting path. It is an algorithm that uses the augmenting path to find the maximum matching of a bipartite graph.)

5.3.3. Start

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```
cd ~/transbot_ws/src/transbot_visual/detection
python target_detection.py
```

Raspberry Pi 5

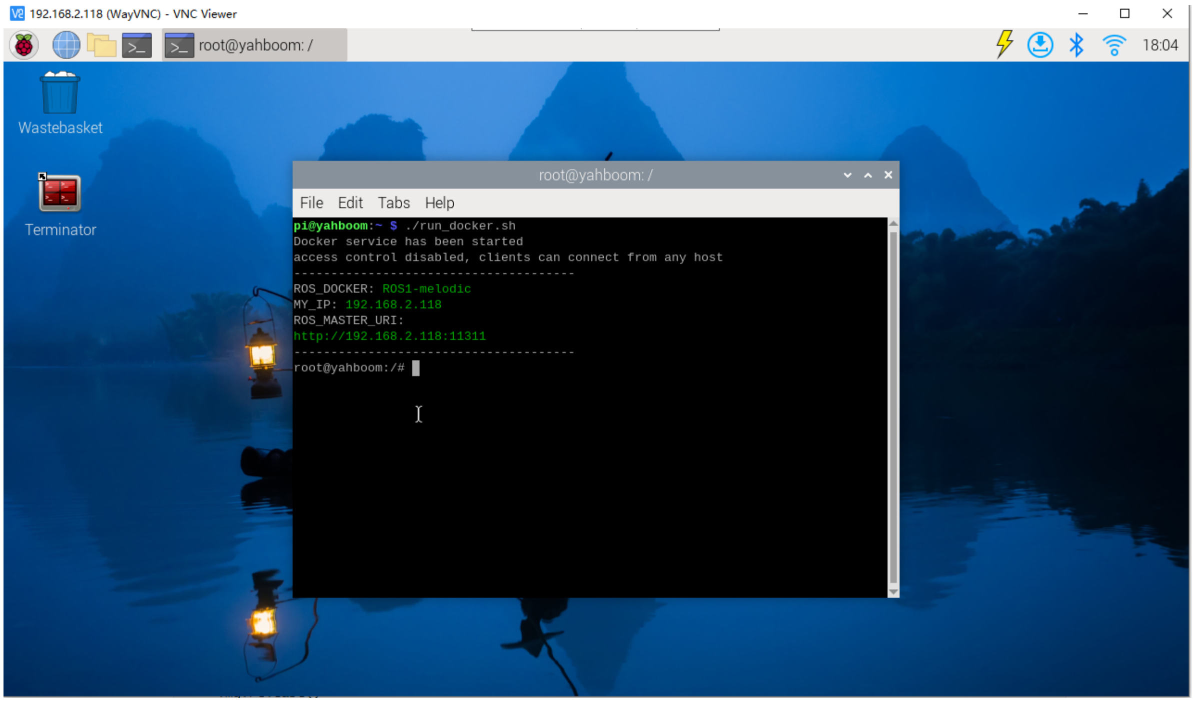
Before running, please confirm that the large program has been permanently closed

Enter docker

Note: If there is a terminal that automatically starts docker, or there is already an open docker terminal, you can directly enter the docker terminal to run the command, and there is no need to manually start docker

Start docker manually

```
./run_docker.sh
```



```
pi@yahboom:~ $ ./run_docker.sh
Docker service has been started
access control disabled, clients can connect from any host
-------------------------------------
ROS_DOCKER: ROS1-melodic
MY_IP: 192.168.2.118
ROS_MASTER_URI:
http://192.168.2.118:11311
-------------------------------------
root@yahboom:/#
```

```
cd ~/transbot_ws/src/transbot_visual/detection
python target_detection.py
```

After clicking on the image box, use the keyboard [f] key to switch target detection.

```
if action == ord('f'):state = not state # Function switching
```

Enter image

Output picture

5.4. 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 approach is technically difficult to understand (especially for deep learning newbies), difficult to implement, and difficult to train.

In addition, even if the "Faster" method is used to implement R-CNNs (where R represents the 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.

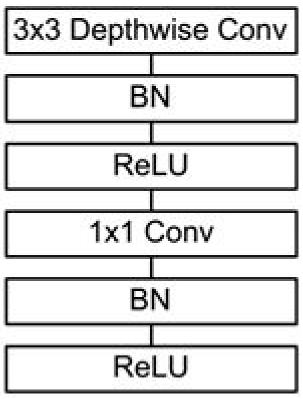
SSDs were originally developed by Google and can be said to be a balance between the above two. Compared with Faster R-CNNs, its algorithm is more straightforward. Compared with YOLO, it is more accurate.

5.4.1. Model structure

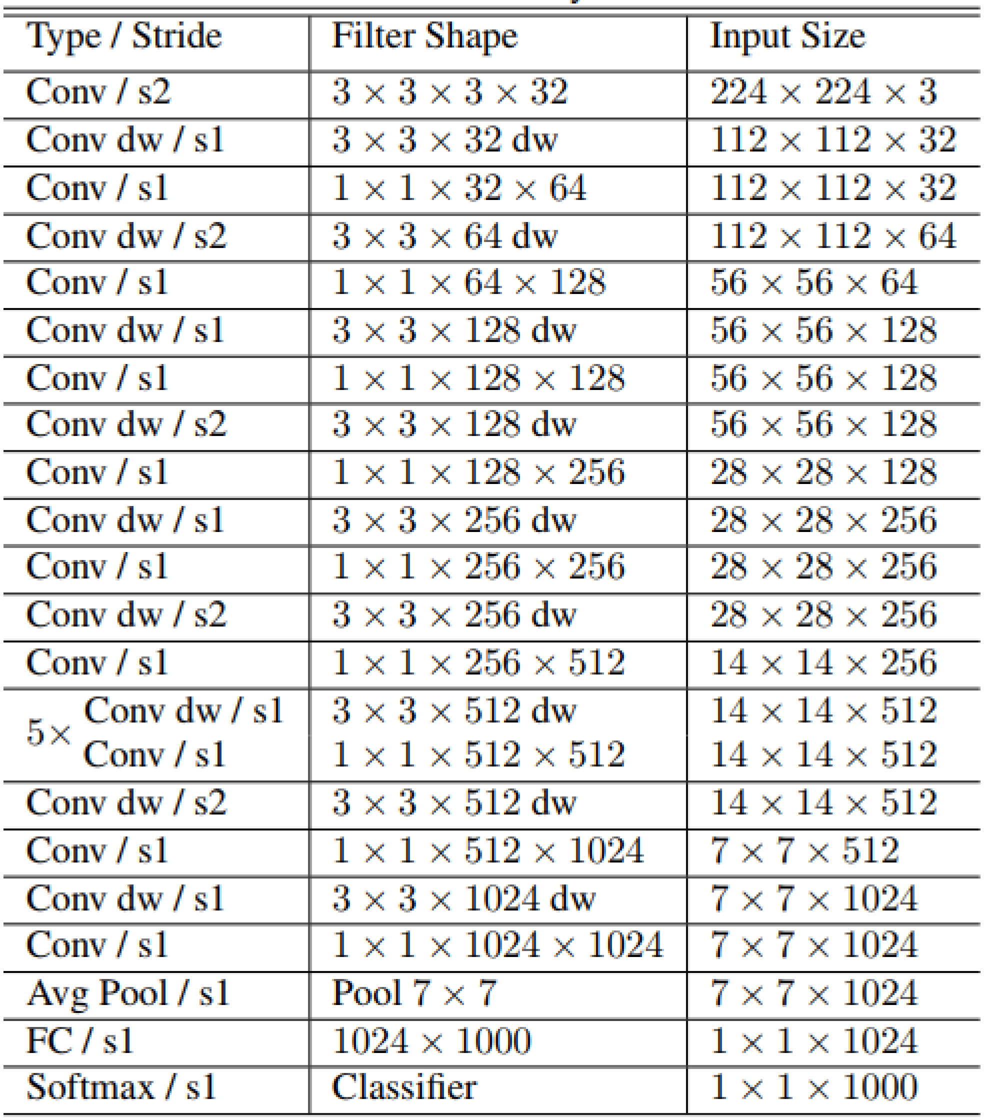
The main work of MobileNet is to use depthwise sparable convolutions (depth-level separable convolutions) to replace the past standard convolutions (standard convolutions) to solve the problems of computational efficiency and parameter quantity of convolutional networks. The MobileNets model is based 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 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 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	$1 \times 1 \times 1000$

5.4.2. Code analysis

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 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 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()
     # Iterate through each test
     for detection in output[0, 0, :, :]:
         # Extract the confidence of the detection
         confidence = detection[2]
         # Only draw bounding boxes when the detection confidence is higher than
a certain threshold, otherwise skip
         if confidence > .4:
             # Get the ID of the class
             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
```

5.4.3. Start

jetson motherboard/Raspberry Pi 4B

```
cd ~/transbot_ws/src/transbot_visual/detection
python target_detection.py
```

Raspberry Pi 5

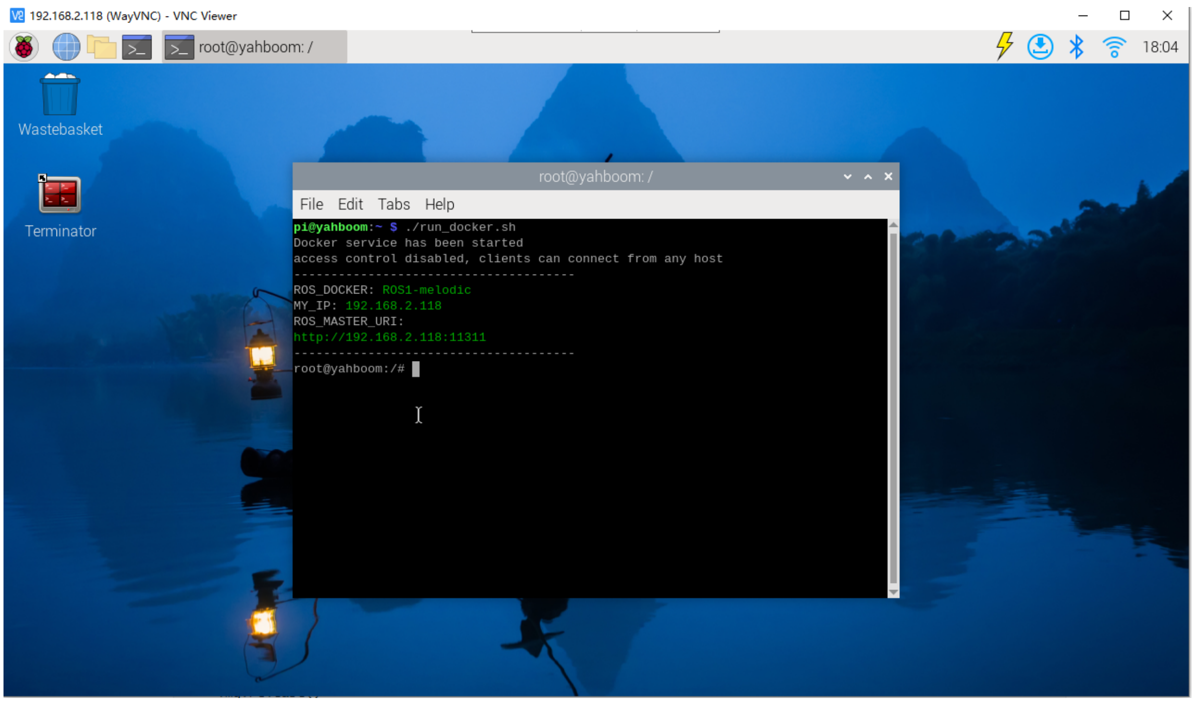
Before running, please confirm that the large program has been permanently closed

Enter docker

Note: If there is a terminal that automatically starts docker, or there is already an open docker terminal, you can directly enter the docker terminal to run the command, and there is no need to manually start docker

Start docker manually

```
./run_docker.sh
```

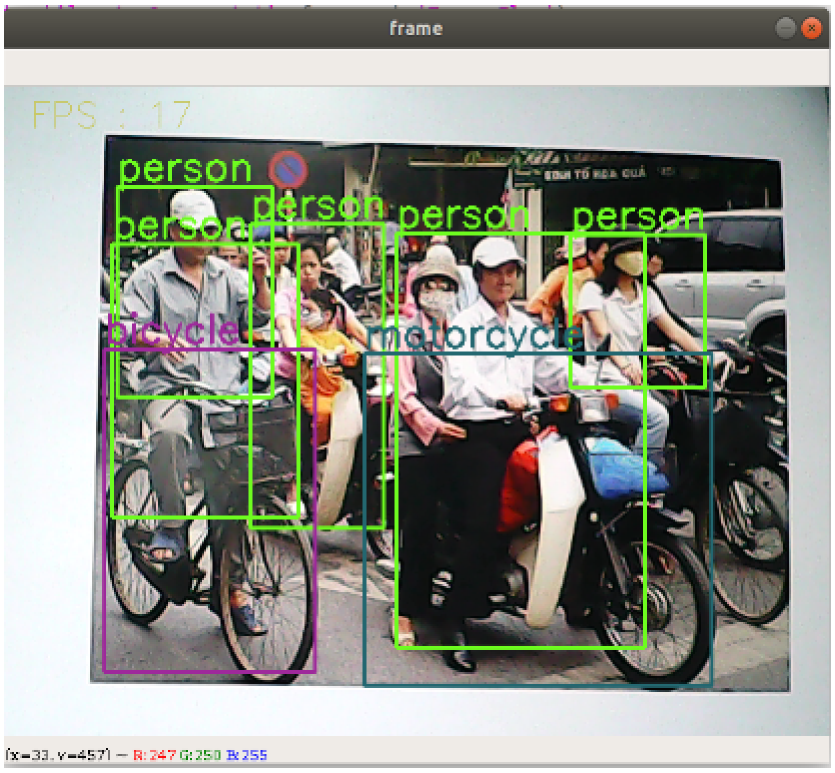


```
pi@yahboom:~ $ ./run_docker.sh
Docker service has been started
access control disabled, clients can connect from any host
--------------------------------------
ROS_DOCKER: ROS1-melodic
MY_IP: 192.168.2.118
ROS_MASTER_URI:
http://192.168.2.118:11311
--------------------------------------
root@yahboom:/#
```

```
cd ~/transbot_ws/src/transbot_visual/detection
python target_detection.py
```

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

```
if action == ord('f'):state = not state # Function switching
```


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