Traffic Sign Detection and Recognition for Autonomous Driving in Virtual Simulation Environment

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Abstract: This study developed a traffic sign detection and recognition algorithm based on the RetinaNet. Two main aspects were revised to improve the detection of traffic signs: image cropping to address the issue of large image and small traffic signs; and using more anchors with various scales to detect traffic signs with different sizes and shapes. The proposed algorithm was trained and tested in a series of autonomous driving front-view images in a virtual simulation environment. Results show that the algorithm performed extremely well under good illumination and weather conditions. Its drawbacks are that it sometimes failed to detect objects under bad weather conditions like snow and failed to distinguish speed limits signs with different limit values.

1 Introduction

Traffic sign recognition systems form an important component of Advanced Driver-Assistance Systems (ADAS) and are essential in many real-world applications, such as autonomous driving, traffic surveillance, driver safety and assistance, road network maintenance, and analysis of traffic scenes. In this study, we are required to identify the traffic signs that appear randomly in a virtual driving environment and return the corresponding recognition results in the order in which they appear. The virtual simulation environment is accompanied by interference factors such as pedestrians and non-motor vehicles, and has diverse weather conditions (including illumination).

2 Related Work

Arcos-Garcia et al. (2018) did a excellent review of traffic sign detection methods. The concluded that the state-of-the-art methods include detection modules (Faster R-CNN (Ren et al., 2015), R-FCN (Dai et al., 2016), SSD (Liu et al., 2016), and YOLO (Redmon, Farhadi, 2018)) combined with various feature extractors (Resnet V1 50 (He et al., 2016), Resnet V1 101, Inception V2 (Szegedy et al., 2017), Inception Resnet V2, Mobilenet V1 (Howard et al., 2017), and Darknet-19). Below is a summary of several frequently used detection methods.
• Faster R-CNN: Faster R-CNN has two networks: region proposal network (RPN) for generating region proposals and a network using these proposals to detect objects. The main difference here with Fast R-CNN is that the later uses selective search to generate region proposals. The time cost of generating region proposals is much smaller in RPN than selective search, when RPN shares the most computation with the object detection network. Briefly, RPN ranks region boxes (called anchors) and proposes the ones most likely containing objects.

• YOLO: The input image is divided into an S x S grid of cells. For each object that is present on the image, one grid cell is said to be “responsible” for predicting it. That is the cell where the center of the object falls into. Each grid cell predicts B bounding boxes as well as C class probabilities. The bounding box prediction has 5 components: (x, y, w, h, confidence). Adding the class predictions to the output vector, we get a S x S x (B * 5 +C) tensor as output.

• SSD: The deep layers cover larger receptive fields and construct more abstract representation, while the shallow layers cover smaller receptive fields. In SSD, multiple boxes for every feature point are called priors, while in Faster R-CNN they are called anchors.

3 Data Description and Evaluation Metric

Data come from a competition called [Traffic Sign Recognition for Autonomous Driving in Virtual Simulation Environment](http://example.com). The competition provides a series of autonomous driving front-view images in a virtual simulation environment, where the traffic signs are marked.

**Training data:** RGB images with a total size of around 14 GB, and the corresponding labels with the format as shown in Table 1.

| Field     | Type | Description                                                                 |
|-----------|------|-----------------------------------------------------------------------------|
| Filename  | String | Image filename                                                             |
| x1, y1   | int  | Upper left corner x and y coordinate                                      |
| x2, y2   | int  | Upper right corner x and y coordinate                                     |
| x3, y3   | int  | Bottom left corner x and y coordinate                                      |
| x4, y4   | int  | Bottom right corner x and y coordinate                                     |

- 1: parking lot; 2: yield to parking; 3: driving on the right;
- 4: left or right turn; 5: Bus passage; 6: driving on the left; 7: slow down;
- 8: driving through or right turn for motorized vehicles; 9: yield to pedestrians;
- 10: roundabout; 11: driving through or right turn; 12: no bus access;
- 13: motorcycles are prohibited; 14: Prohibition of motor vehicles;
- 15: Prohibition of non-motor vehicles; 16: no honking;
- 17: Driving through or turning on bypass; 18: 40 km/h speed limit;
- 19: 30 km/h speed limit; 20: honking; 0: others

A few examples of the training images are shown below.
Testing data: RGB images with a total size of around 16 GB.

Expected output on testing data: traffic sign locations \((x_1,y_1,x_2,y_2,x_3,y_3,x_4,y_4)\) and the classes of the detected traffic signs \((0,20)\).

Evaluation metric: Intersection over Union (IOU) between ground truth and predicted bounding box will be used to evaluate detection accuracy. Detections’ IOU should be larger than 0.9 to be eligible for recognition evaluation.

\[
IOU = \frac{\text{area of overlap}}{\text{area of union}}
\]  

(1)

The F1 score will be used as the evaluation metric for traffic sign recognition. The F1 score is defined as

\[
F_1 = \frac{2\text{precision} \times \text{recall}}{\text{precision} + \text{recall}}
\]  

(2)

4 Method: RetinaNet

A method based on RetinaNet \cite{lin2017feature} was developed to detect and recognize traffic signs in this study. RetinaNet is a single, unified network composed of a backbone network and two task-specific subnetworks, as shown in Figure \ref{fig:retinanet}. The backbone is responsible for computing a convolution feature map over an entire input image and is an off-the-self convolution network. The first subnet performs classification on the backbone’s output; the second subnet performs convolution bounding box regression \cite{jay2018}. We will describe each important component of this method below.
Image Preprocessing: Cropping
The original sizes of the images in this study are $3200 \times 1800$, with traffic sign being about $50 \times 50$ large. Directly using the large images as training inputs has two downsides: 1) the training speed is slow because we had to use small batch sizes (like 4) to avoid out-of-memory issues; 2) relative to the whole big image, the traffic sign are rather small and hard to detect (we have failed to detect anything due to this).

To overcome this issue, we used cropping technique to let the training network focus on small regions of the whole image. Specifically, for training and validation data, we take the target center (derived from data labels) as the origin, then extend 200 pixels to the left, right, top, and bottom, resulting in an area with $400 \times 400$ size. The extended area is cropped and selected as training and validation images, as shown in Figure 3. For testing data, we first randomly crop the images into $400 \times 400$ sub images. Then detect and recognize traffic signs based on these randomly cropped sub images. Finally, we combine the results from multiple sub images and generate a overall prediction result.

It should be noted that when doing image cropping for train and validation images, we also need to update the bounding box coordinates accordingly to make sure they use the cropped images as references. Besides image cropping, regular image augmentation skills like scaling and flip were also applied to the sub images to avoid over-fitting.

Feature Pyramid Network Backbone
Feature Pyramid Network (FPN) augments a standard convolutional network with a top-down pathway and lateral connections so the network efficiently constructs a rich, multi-scale feature pyramid from a single resolution input image. Each level of the pyramid can be used for detecting objects at a different scale (Lin et al., 2017). In this study, we used ResNet 101 (He et al., 2016) as a backbone network for feature extraction. The residual block of the ResNet 101 is shown in Figure 4.
Anchors
As the original RetinaNet paper, we used anchors with areas of $32^2$ to $512^2$ on pyramid levels P3 to P7, respectively. At each pyramid level we use anchors at three aspect ratios 1:2, 1:1, 2:1. At each level we add anchors of sizes $\{0.1, 0.2, 0.5, 0.8, 1.0, 1.5\}$ of the original set of 3 aspect ratio anchors, rather than anchors of sizes $\{2^0, 2^{\frac{1}{2}}, 2^2\}$ used in the original RetinaNet paper, with the purpose of detect more potential traffic signs with different sizes and shapes.

Classification and Box Regression Subnet
For classification and box regression subnets, we used the same setting as the original RetinaNet paper (Lin et al., 2017). Basically, the classification subnet predicts the probability of object presence at each spatial position for each of the $A$ anchors and $K$ object classes. For each of the $A$ anchors per spatial location, these 4 outputs predict the relative offset between the anchor and the groundtruth box.

Network Training
We created a n1-standard-8 (8 vCPUs, 30 GB memory) Virtual Machine on Google Cloud Platform equipped with 2× NVIDIA Tesla P100 GPUs. Over the total of around 20,000 images, 70% were used as training data, 15% were used as validation data, and the remaining 15% were used as testing data. The hyper parameters were set as follows: learning rate = 0.0001, batch size = 36 (multiple GPUs), number of steps per epoch = 2000, and number of epochs to train = 30. The final weight of our best model trained on the traffic sign dataset can be accessed at https://drive.google.com/file/d/1lzpNg9XVYLFMKZBE5gizEDYkJJS9wkmT6/view?usp=sharing.

5 Results

The final F1 score of our model on the testing data are 0.923. The average processing time for every picture is around 0.15 seconds. Some true and false detection and recognition results are shown below.
6 Discussion

The study developed a traffic sign detection and recognition algorithm based on RetinaNet. Specifically, two main aspects were revised to improve the detection of traffic signs: image cropping to address the issue of large image and small traffic signs; and using more anchors with various scales to detect traffic signs with different sizes and shapes. The algorithm’s strength is it performs extremely well under good illumination and weather condition, with reasonable speed. And the weakness is that it sometimes fails to detect object under bad weather conditions like snow. And it fails to distinguish between speed limits signs with different limit values. Some general discussion:

- Image cropping is important for this problem. Without it, we can not detect anything.
- We have also tried Yolo v3. It can detect objects well but fail to recognize well.
- Setting an proper anchor size and shape is vital for object detection.

7 Future Work

The work can be further improved in the following aspects:

- Do random cropping for training and validation data to improve the model’s performance.
- Deal with class imbalance so that the minority class can also be well detected and recognized.
- Do shape detection (like circle detection) first to localize the traffic signs.
- Play with the anchor size and shapes so that we do not need to do image cropping.
- Try methods in the field of small objects detection, like.
- Try more detection algorithms.
- Try detection by segmentation, like Mask-RCNN (He et al. [2017]).
- Try recently emerging anchor-free detection methods so that we can better deal with scales, like Chen et al. (2019).

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