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TRAFFIC LIGHT DETECTION FOR SELF DRIVING VEHICLES USING MACHINE LEARNING

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Abstract—Due to the unavailability of Vehicle-to-Infrastructure (V2I) communication in current transportation systems, Traffific Light Detection (TLD) is still considered an important module in autonomous vehicles and Driver Assistance Systems (DAS). To overcome low flflexibility and accuracy of vision-based heuristic algorithms and high power consumption of deep learning-based methods, we propose a lightweight and realtime traffific light detector for the autonomous vehicle platform. Our model consists of a heuristic candidate region selection module to identify all possible traffific lights, and a lightweight Convolution Neural Network (CNN) classififier to classify the results obtained. Offlfline simulations on the GPU server with the collected dataset and several public datasets show that our model achieves higher average accuracy and less time consumption. By integrating our detector module on NVidia Jetson TX1/TX2, we conduct on-road tests on two full-scale self-driving vehicle platforms (a car and a bus) in normal traffific conditions. Our model can achieve average detection accuracy of 99.3% (mRttld) and 99.7% (Rttld) at 10Hz on TX1 and TX2, respectively. The on-road tests also show that our traffific light detection module can achieve < $\pm 1.5m$ errors at stop lines when working with other self-driving modules.

I. INTRODUCTION

With the rapid development of sensor techniques (such as LIDAR, millimeter-wave radar, camera, and differentialGPS), HD Map and deep learning models have speeded up research onself-driving vehicles in the past decade. The most reliable solution for the management and dispatch of self-driving vehicles in the near future maybe Vehicle-toInfrastructure (V2I) communication [1]. In a V2I communication system, the self-driving vehicle can interact with the surrounding transport infrastructure and with each other directly through the vehicular networks [2]. However, due to the lack of the V2I system, detectors for recognizing and tracking vision-based traffific lights, signs, lanes and pedestrians still play important roles in current self-driving systems or advanced driving assistant systems.

Traditional computer vision-based solutions [3]–[6] are highly affected by the placement of cameras, change ofenvironmental lighting conditions, distance of objects [7], and processing ability of the vehicular chip. Generally, a single set of manually set parameters based on the heuristic method is not flflexible for complicated real conditions, and identifification of suitable parameters is also time-consuming. Therefore, recent research interests are concentrated on us

ing machine learning [8]–[12] or deep learning techniques [13]–[18] to train the model in a data-driven way

II.LITERATURE SURVEY:

2 RELATED WORK

In this section, we review the recent research progress in the following two aspects: the traffific light detection algorithms in self-driving vehicles, and the development of deep learning based CNN architectures. From the latter one, we can seek a solution to refifine the current TLD algorithm for lowpower and low-performance vehicular environments.

2.1 Vision-based heuristic algorithm

Considering traffific lights are the lighting source in the outdoor environment and the blobs of traffific lights conform to traffific standards [4], early studies try to detect those unified lights according to their colors and shapes. Visionbased heuristic algorithms are the most basic and fundamental methods for traffific light detection, and the relevant procedures can be summarized as follows: 1) Mapping raw images into different color spaces (RGB [21]; Gray [3]; YUV [4], [22]; LUV [12], [23]; CIELab [24]; HSL [25]; HSV [4], [9], [10], [14]; etc.)

2.2 Machine learning-based algorithm

2.2.1 Traditional machine learning-based model To automatically select and optimize the parameters from a large amount of traffific light data set, researchers try to build machine learning-based models for traffific light detection/recognition in a data-driven way. The supervised learning often uses a simple sliding window to scan each image and extract the HOG feature from each window to feed into the machine learning models (such as SVM [8], [10]; boosting [22], and tree-based model [23]). Considering the global scan and the predefifined window size of sliding window-based detection approaches usually suffer from large computation and multi-scale problems, later solutions for ROI selection, such as Adaptive Background Suppression Filter (AdaBSF) [11], template matching algorithm [9], and integrating Visual Selective Attention (VSA) [8], try to replace scanning of the global sliding window with a heuristic algorithm and to fifind a subset of the candidate region of traffific lights. Other improvements include using well-trained ensemble learning [10], [25] and inter-frame information for tracking [26]. The size and effificiency of traditional machine learning based TLD methods are suitable for the vehicular environment; however, the main problem is that the learning ability is still too poor to cover rich features in image processing. Moreover, valuable information may get lost in extraction of HOG features from RGB or other color spaces. The two above problems can lead to low detection accuracy in outdoor and high-speed environments.

2.2.2 Deep learning-based model

In [14], the authors combine the HOG-based SVM for traffific light region detection and CNN for light state recognition. DeepTLR [18] also analyzed different confifigurations modified from the AlexNet [27] in dealing with traffific light data set. John *et al.* [13] also proposed a CNN-based TLD for saliency map generation. To deal with high-resolution images, the authors [17] deploy the YOLO [28] detecting model and stereo vision images for TL tracking. Recent rapid development of deep learning-based TLD benefifits from the following two aspects: 1) more features can be extracted from the convolution layer than HOG, and 2) the multi-layer structure of the CNN model can learn hundreds or thousands of times more feature combinations than simple machine learning models. This makes it possible to learn as many potential patterns as possible from mass data, and to achieve better detection performance according to the data collected from real road conditions.

3 REAL-TIME TLD MODEL

In this section, we introduce our TLD model that combines the heuristic algorithm and deep learning models. We also analyze current traffific light datasets and bias of samples. We then propose a new dataset collected with HD driving map and DGPS from real road conditions.

3.1 TLD model

For traffific light detection in the self-driving vehicular environment, there are mainly two challenges. 1) Wide angle lens are often used on self-driving vehicles to capture wide images in front of the car, and this can lead to highresolution raw images (such as 1292 × 964) but larger

consumption of computer resources. 2) Considering power supply and stability of both software and hardware, the traditional PC is not suitable for the self-driving vehicular environment. We design a vehicular platform–'Driving Brain'–with four NVidia Jetson TX1 and two FPGA chips.

The power consumption of a single chip of the platform is lower than 10 watts (about 4% of the Titan X, and 11% of the Intel i7-7700k), and the whole device consumes less than 100 watts.

Considering that the global scan of the CNN model is ineffificient, we develop a vision-based heuristic algorithm to select the candidate traffific light area, and then distinguish all possible lights and invalid regions with the CNN classififier. The whole pipeline of our detector is shown in Fig. 1.

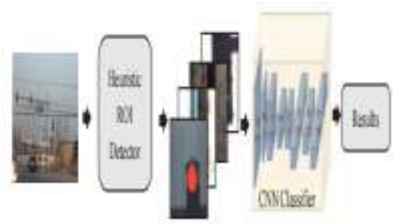

Fig. 1. Pipeline of our real-time traffific light detector: 1) a heuristic ROI detector fifirst tries to fifind all possible traffific lights (including some error background); 2) a small size CNN classififier tries to identify the right class of each ROI and then gives the result.

3.1.1 Heuristic ROI detector

The SSD [41] and other region proposal-based detection model will generate large amount of proposals according to pre-settings (such as the number of anchors and sizes of proposals) [42]–[44]. Therefore, when the resolution increases, more proposals need to be dealt with during training and testing. This is the main cause for huge GPU memory consumption, besides the complex model architecture. Most deployments resize the input to fulfifill the memory requirement, but the method is not suitable for our task of traffific light detection. *Unlike moving objects of vehicles or pedestrians, the distance of traffific lights may be far away from the current vehicle, which makes the targets contain less pixels in each image. Therefore, resizing the raw images may lead to further reduction of pixels for each traffific light, and make it harder to deal with less convolution features from those pixels in the later model training and detection.* We replace the region proposal with a heuristic detector, which can fifind about 30 candidate

regions with fifixed size. This helps us solve the problems regarding both memory consumption and processing time•

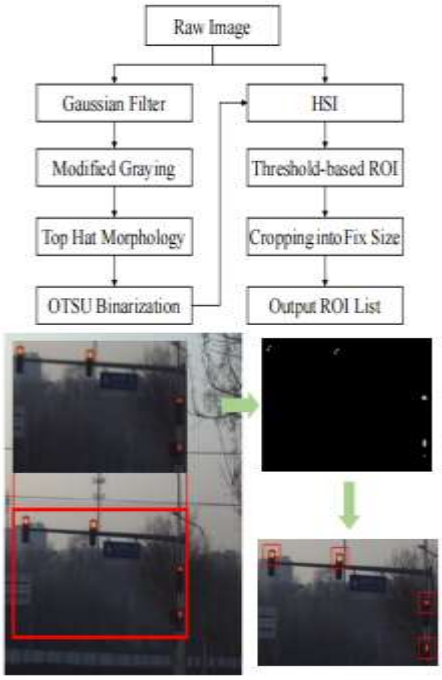

Fig.
2. Flowchart of the heuristic ROI detection algorithm using traditional vision-based modules. At the bottom is an example: through a series of processing, we get all possible pixels from the binary image; by transforming these pixels into the HSI color space, we get all possible ROIs and crop them into predefined sizes.

3.2 Collection of traffific light dataset

3.2.1 Biased sampling in traffific light dataset

The problem of the imbalanced dataset has long been studied in data mining. Recently, Zhao *et al*. [47] also found that the models trained on those datasets will further amplify the existing bias. Without properly quantifying and reducing the reliance on such correlations, we may get incompletely trained models, and broad wide adoption of these models may lead to serious problems in real-world applications, especially in self-driving. However, the imbalance of traffific light dataset has never been studied before. In our investigation of several public traffific light datasets (VIVA [48], Bosch [31], WPI [30] and
LaRA [29]) and data collected on our own self-driving vehicles, we fifind a series of implicitly biased sampling that may lead to an imbalanced dataset, and summarize the biases as follows:

• Bias is caused by traffific rules: during data collection, vehicles have to stop during the red light, and pass the intersection when the light is green; this may lead to more red light samples.

• The intersection types of a collecting route have different kinds of traffific light, for example, a T-junction may not have a left-turn light; this may inflfluence the distribution of the light types we collected.

• The pre-set duration of each light of different intersections maybe not the same. For example, the duration of red light is often longer than green light in most crossroads in China.

• During manual annotation, inter-observer variations may lead to different labeling results, such as the color, the arrow type, and the effective size of a light.

• For semi-automatic annotation, the setting of the thresholds (such as the values of the color space, the size of the bounding box, etc.) may lead to different outputs.

4.CONCLUSION

We have presented a practical traffic light detection system that combines the popular CNN classifier model and the heuristic ROI candidate detection algorithm to satisfy the requirement of self-driving hardware platform (NVidia Jetpack Tx1/2 on the Driving Brain). In this way, we develop a high-performance traffic light detection module which can handle high-resolution images to guarantee wide view and fulfill low weak computational vehicular hardware.

We compare our model with several existing CNN models on different hardware platforms to show the performance of our model from different perspectives. In addition, we also conduct real on-road testing on different full-scale selfdriving vehicles, the RAETON and Yutong Ibus, to evaluate our real-time traffic light detection module along with the whole self-driving system. Both simulation and real testing show acceptable performances of our hardware platform and self-driving system at low vehicle speed. However, the current module still needs to be improved

from the following aspects in the future.

1) The heuristic ROI detector can be improved by simple machine learning models.

2) To train and test the current module, the current dataset needs to be extended with more traffic light classes and images from worse light conditions.

3) The current model architecture can be improved with newly developed techniques in deep learning

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