Recent Tesla Model X AutoPilot Accident Analysis and Possible Solution via Traffic Sign and Lane Detection

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Abstract

Tesla Autopilot is an advanced driver-assistance system feature offered by Tesla that has lane centering, adaptive cruise control, self-parking, ability to auto change lanes without requiring driver steering. Recent report shows a Tesla Model X was involved into a fatal crash while the autopilot mode was on.

In this paper, we analysis the car accident and come up with a possible solution to avoid car crash by combining traffic sign detection with lane detection. To detect traffic sign, we implement Faster R-CNN [1] and trained on GTSDB Dataset. To detect lane segmentation, we leverage VPGNet [3], trained and tested on Caltech Lanes Dataset.

1. Introduction

1.1. Problem Statement

One tesla model x was involved into a crash in California which the car hit concrete barrier while its Autopilot feature was on. Few days later, another Tesla Model X owner reproduced the same hitting scenario at the place where the accident happened. The car driver turned on Autopilot feature while driving on the freeway, while the car was getting closed to the road bifurcation, it didn't follow the correct pavement markings and direct driving toward the concrete barrier showed on Figure 1. There is a clear divider sign on Figure 1, but the car did not capture it and make the stop or slow down decision. Based on the posted experiment video on YouTube, the Tesla driver has to push the brake to stop the car manually.

Therefore our problem will be divided into two steps, the first step will mainly focus on detection, which means the system should be able to recognize traffic signs, localize it and draw the bounding box around it. The second part is lane detection, which means the system should be able to detect the right lanes based on the pavement markings, draw lines on top of the input image.

1.2. Plan

Based on the steps mentioned above, we split the whole project into two sections. The first part would be traffic sign detection. There are a lot of methods doing this job but we will stick on leveraging Faster R-CNN, implement the code from sketch, train and fine-tuning the model on GTSDB dataset. The second part would be lane detection. We will try to implement the VPGNet code, train and evaluate the model on Caltech Lanes Dataset.

1.3. Expected Results and Evaluation

The traffic sign detection task should meet an average overlap > 80% on GTSDB test dataset

The lane detection task should meet an test accuracy > 0.80

Figure 1: Divider sign on top of the concrete barrier

2. Methods

2.1. Traffic Sign Detection Algorithm

State-of-the-art object detection methods are in two major groups: region proposal based methods like Faster R-CNN [1], and regression based methods like YOLO [2]. In this work, we will focus on use Faster R-CNN to detect traffic signs. Faster R-CNN is composed of two modules. The first module is a Region Proposal Network (RPN), which proposes regions for the second module, Fast R-CNN detector, to inspect. In RPN module, a small network slides over convolution feature map with multiple anchors at each sliding window location. The RPN outputs a bounding boxes (region proposals) and predicted class as a Fast R-CNN module does. A four-step alternating training is adopted to share features for both modules.

2.2. Lane Detection Algorithm

We explored bunch of lane detection methodologies, of which deep learning methods have shown great success comparing with traditional computer vision method. We went through multiple different Convolutional Neural Net based lane detection, [4, 5] proposes a lane detection algorithm based on a CNN. Jun Li *et al*. [6] uses both a CNN and a Recurrent Neural Network (RNN) to detect lane boundaries. Bei He *et al*. [7] proposes using a Dual-View Convolutional Neural Network (DVCNN) framework for lane detection. Bailo *et al*. [8] propose a method that extracts multiple regions of interest as MSERs [9], merges regions that could possibly belong to the same class, and classify region proposals by PCANet [10] and a neural network. Finally, when we are exploring VPGNet [3], we found it is currently the most robust lane detection model comparing with any models mentioned upon. It could keep good performance even under poor weather conditions. In this application, we will leverage VPGNet due to it performs well in any situation including bad weather and low illumination conditions.

3. State and evaluate of the results.

3.1. Environment Setup

All experiments are running on an Amazon Web Service P2.8xLarge instance with 8 NVIDIA Tesla K80 GPUs. All necessary software was installed including CUDA9.0, CuDNN7.0, Tensorflow and Keras.

3.2. Implementation of Faster R-CNN via Keras

Referring to origin paper of Faster R-CNN and few open sourced repositories on github, we are able to implement the Faster R-CNN via Keras framework and trained on GTSDB Dataset. Figure 2 shows an evaluation result on the GTSDB test dataset. The code will be open sourced later during the final report.

Figure 2: Evaluation on GTSDB test dataset

3.3. Implementation of VPGNet via Keras

In progress.

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