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Detection of Occluded Road Signs on Autonomous Driving Vehicles

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***Abstract*—Autonomous driving vehicle relies heavily on its perception system to sense surrounding environments and make driving decisions. One important task on autonomous driving vehicles is to correctly recognize different traffic signs. However, the traffic signs in the wild can be in various conditions, e.g., occluded, deteriorated, or vandalized, and not all of them are recognizable. In this work, we propose a novel system that leverages the perception system on autonomous vehicle to identify occluded road signs in real time. Based on transfer learning, we propose the occluded sign classification network (OSCN) that is able to achieve a precision of 96.34% on a real-world dataset.**

***Index Terms*—Occluded sign detection, autonomous driving vehicles, transfer learning, deep learning.**

I. INTRODUCTION

Autonomous or driverless vehicle is no longer a technical dream, we are actually entering an era of collaboration among industry, government, and academia to fully introduce autonomous vehicles (AV) into our daily lives. As majority of traffic accidents are caused by human errors, it is expected that the emergence of autonomous vehicles will significantly reduce traffic accidents. However, making autonomous driving vehicles reliable and safe is not an easy task. Among many technical challenges, accurately detecting road signs is a difficult issue, mainly because signs could be in bad conditions and not all of them are distinct to be detected. Since the core of autonomous driving system is the interactions between autonomous vehicles and road infrastructures, there is no doubt that a single mis-detection or mis-classification of road signs can increase the probability of accidents. As a matter of fact, it has been shown in [1] that a stop sign could be mis-recognized as a speed limit sign by putting only a few stickers and graffitis on it.

To keep traffic signs in good conditions, U.S. state departments of transportation (DOTs) periodically evaluate and maintain their road signs. For example, they usually assess the conditions of road signs via visual nighttime inspection, retro-reflectivity measurement, sign age, blanket replacement, and control signs. In most cases, the work relies heavily on manual inspection, which is costly, time-consuming, and sometimes dangerous to the employees of state DOTs. On one hand, because signs in bad conditions are not detected and replaced in a timely manner, it may cause inaccurate detection by the autonomous vehicles. On the other hand, this problem could be potentially addressed by the perception system and deep-learning techniques designed for autonomous vehicles. The paper aims at developing a deep-learning based solution to detect road signs captured by cameras and LiDARs (light detection and ranging), and then to identify occluded road signs. Although we focus only on occluded stop sign and share-the-road sign detection, the proposed method can be extended to detect other types of signs in various (e.g., deteriorated or vandalized) bad conditions.

The current perception system on autonomous vehicle focuses only on road sign detection and classification, however, road sign condition assessment is out of the scope of AV technologies. We argue that AV techniques can be leveraged to assess the road sign conditions in real-time when autonomous vehicles are running on the road. An autonomous vehicle is typically equipped with LiDAR, cameras, and on-board processing unit. The processing unit, e.g., Nvidia PX2, is usually very powerful and is designed to support huge volume of image and LiDAR data processing. With the help of GPUs, many deep learning algorithms, e.g., SSD [2] and YOLO [3], can be executed at a fast speed. These characteristics of an autonomous vehicle make one believe that AV techniques can help with real-time road sign condition assessment.

In fact, a special application (APP) could be developed and deployed on autonomous vehicles which automatically detects road signs in bad conditions and reports the information to DOTs. If enough autonomous vehicles participate in the crowd-sourcing system, similar to what WAZE does on smart phones, it is reasonable to expect a large area of real-time road sign conditions be obtained. If DOTs accessed these information, they could plan their road sign maintenance accordingly, and thus provide a better road infrastructure to autonomous driving vehicles. Although there are not too many autonomous driving vehicles currently on the road, we envision an effective transportation ecosystem in the future. In the system, autonomous vehicles help DOTs assess their road signs; with the assessment results, DOTs maintain and replace signs in a timely manner, thus increase the safety and reliability of autonomous vehicles.

In this paper, we propose a novel solution that is able to detect and classify occluded U.S. road signs from the non-occluded signs. Unlike other road sign detection systems, we leverage the perception system on autonomous vehicles to facilitate accurate road sign detection. Specifically, we consider the intensity of point cloud data captured by LiDAR sensors to extract the regions of road signs from their backgrounds in the corresponding images. The cropped-out regions of road signs then serve as the input of our OSCN model. During the training processing, we leverage the pre-trained Inception_V3 [4] model to extract features from images and

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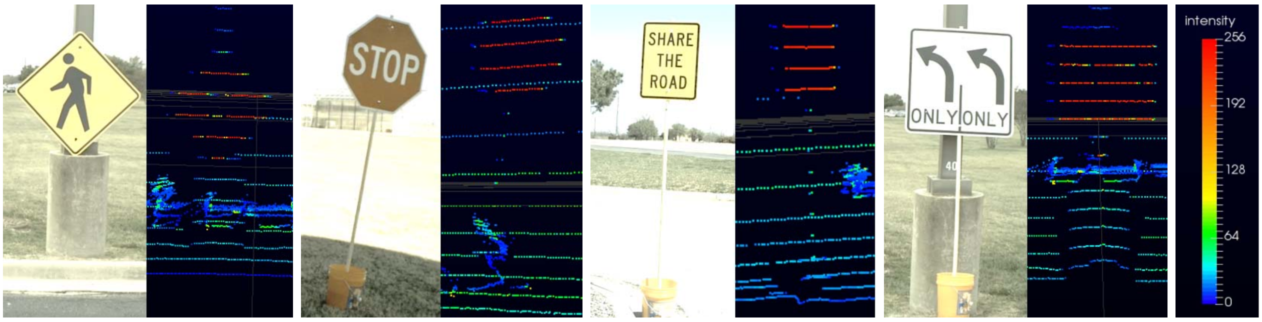


(a) Pedestrian-crossing sign (b) Stop sign (c) Share-the-road sign (d) Left-turn-only sign (e)

Figure 1: LiDAR-assisted road sign detection leveraging the intensity values of point cloud data.

then use the features to train our OSCN model. Experimental results indicate that OSCN can achieve higher precision and recall, using a real-world dataset.

The main contributions of our work can be summarized as follows. First, we collect the first dataset for occluded U.S. stop signs and share-the-road signs detection. In the dataset of 1000 road sign images of either a stop sign or a share-the-road sign, 500 of them are occluded and 500 are non-occluded. Second, leveraging the point cloud data collected by LiDAR sensors, we are able to accurately identify the region in an image that contains road signs. Third, we use transfer learning to overcome the issue of limited amount of training dataset, and achieve an classification precision of 96.34%.

II. OSCN: Occluded Sign Classification Network

To accurately detect occluded road signs, we need to address two fundamental challenges. The first challenge is to recognize signs in the images captured by the cameras on autonomous vehicles. This is a challenge because signs may be occluded partly and/or occluded by obstacles with irregular shapes or colors. Existing solutions, e.g., SSD, have difficulties in determining the existence of a road sign if it is largely occluded. To address this issue, we propose to first crop out the regions in an image that contain road signs. To achieve this goal, we use point cloud data captured by LiDAR sensors to identify the location of road signs in images. As road signs are commonly coated with a layer of high-reflective material, it is easy to distinguish the points corresponding to road signs from others.

The second challenge we need to address is the lack of occluded road sign dataset. As far as we know, there is no existing dataset containing enough occluded road sign images. To deal with this issue, we collect the first occluded road sign (ORS) dataset of two types of road signs, stop sign and share-the-road sign, in which 500 images are occluded and 500 images are non-occluded. With the ORS dataset, we face another technical challenge: the limited amount of images in ORS hinders the application of any deep-learning based solutions. To address this challenge, we adopt the transfer learning technique which leverages the model trained by similar datasets to mitigate the issue of the lack of data. Specifically, we use Inception_V3 [4] as our feature extraction model to obtain the features from the original images. These features are then fed into a single fully connected layer, which will be trained to derive our own model.

A. LiDAR-Assisted Road Sign Detection

Most CNN-based traffic sign detection algorithms aim at identifying rectangular areas that contain objects, via the extraction of features from objects' pattern, color and other 2D features. It requires a huge amount of training data for each class to fit the model for satisfying results. With a relatively large dataset (e.g., Imagenet [5]), however, the state-of-art solutions yield a large detection error rate. In our ORS dataset, there are only 1000+ images that share similar features, making the classification even more difficult.

Figure 2: A region cropped out from an image using the LiDAR-assisted sign detection method.

Differing from existing object detection algorithms (e.g., YOLO or SSD), we consider LiDAR point cloud data in the detection process. To show that our approach not only works for the types of signs we collect in our ORS dataset, we collect the intensity of various road signs in wild. As shown in Figure 1, we can clearly observe a significantly higher intensity of points corresponding to road signs than that of other points. The color of a point in Figure 1(e) represents its intensity value. Red color represents high intensity (up to 255) and black color represents low intensity (down to 0). As we can see in Figure 1, the intensity of points on the road sign region can be as high as 255. The intensity of points of the surrounding region, however, is only around 60. In real-world environments, very few objects can generate such high-intensity points except those designed for that purposes, e.g., road signs, reflective pavement markers, etc. The significant difference of intensity in LiDAR data basically offers a simple way to detect the region of road signs in images. We calibrate the LiDAR and camera so that the image and LiDAR data are perfectly aligned. As such, the high-intensity region in LiDAR data is used to crop out the road sign region in an image, which is more precise than the state-of-art CNN-based solutions.

Figure 2 shows an example about the detection result, using the LiDAR-assisted road sign detection method. In the figure, we can see that the cropped-out region is defined by two points $p_1 = (u_1, v_1)$ and $p_2 = (u_2, v_2)$ where p_1 and p_2 are the top-left and bottom-right corners of the figure, respectively, in the original image. To obtain these two points, we simply sort the coordinates (u_i, v_i) of all LiDAR points with high-intensity values, and set $u_1 = \min\{u_i\}$, $u_2 = \max\{u_i\}$, $v_1 = \min\{v_i\}$, and $v_2 = \max\{v_i\}$. This region is cropped out from the original image and then fed into our classification algorithm, which will be introduced in the next section.

B. Necessity of Adopting Transfer Learning

Using the LiDAR-assisted road sign detection method, we are able to determine the regions of road signs in an image. If we use these cropped images to train a traditional deep-learning model, e.g., SSD, the classification results suffer from low precision and recall. Figure 3 shows an example of the classification results, offered by the SSD model trained on our dataset. As we can see, SSD classifies it as a non-occluded sign, with a confidence level of 0.99.

Figure 3: SSD fails to detect an occluded stop sign.

The unacceptable performance is caused mainly because of the limited amount of training data in the ORS dataset. To deal with this issue, we decide to adopt the transfer learning technique. Transfer learning is a technique that can achieve a high precision in the target domain, with a smaller dataset, leveraging the knowledge learned from another domain.

There are several reasons for us to adopt transfer learning in the proposed solution. First, to the best of our knowledge, all existing road sign datasets are built for road sign recognition [6], i.e., and none of them is designed for occluded sign detection. Among the images in these datasets, very few of them are occluded. To overcome limited amount of training data, transfer learning technique is probably the best choice. Second, there are many well-trained models on fairly large datasets, e.g., ImageNet [5], and most of these models are able to detect traffic signs. In other words, we have a variety of choices for our base model, which will be used to extract the key features from images in the ORS dataset. Finally, transfer learning can essentially shorten the training time and make the classification process faster. Considering all the above-mentioned benefits, transfer learning is chosen in our solution.

C. Road Sign Classification

Transfer learning techniques are typically grouped into four categories: instance transfer, feature representation transfer, parameter transfer, and relational knowledge transfer [7]. Finding the best type of transfer learning approach is another technical challenge we face.

There are two factors in determining our choice: (1) the size of dataset (of the target domain), and (2) the similarity between the datasets of the source and target domains. Although the ORS dataset is fairly small, it is very similar to the dataset used to train the Inception_V3 model [4]. As such, the feature representation transfer learning becomes the best choice [8]. The feature representation transfer learning is an approach that uses features to represent the original images. In other words, we could use a pre-trained model, e.g., Inception_V3 model [4], to extract the key features from a training image dataset, and then use these features to represent these images.

The proposed occluded sign classification network (OSCN) consists of two components: a feature extraction module and a fully connected neural network layer. Specifically, as shown in Figure 4, we leverage the pre-trained Inception_V3 [4] model to extract the feature vectors from the ORS dataset. The Inception_V3 model was trained on ImageNet, achieving a very high precision for image recognition. By removing the last layer from the Inception_V3 model, we obtain the feature extraction module that outputs a set of features from each input image. As such, an image in the training dataset will be represented by a feature vector generated from the partial Inception_V3 model. The length of the feature vector is 2048. The generated feature vectors are fed into one fully connected layer, thus only 2049 weights need to be trained. After training, the OSCN model is able to provide a prediction value representing the occluded condition for each testing image. As the prediction value ranges from 0 to 1, we pre-define a threshold to distinguish occluded and non-occluded classification results. The original value of the threshold is 0.5. This threshold can be adjusted based on application requirements, e.g., a higher threshold implies a higher recall rate, which might be more appropriate in practice as DOTs may not want to miss the detection of any occluded signs but can tolerate false alarms on non-occluded signs.

III. EXPERIMENTS

In this section, we introduce how the ORS dataset is collected and how the proposed OSCN performs on the dataset, in regards to accurately detecting occluded stop signs.

A. Dataset Collection

There are several public road sign datasets available on-line [9], [6]. However, none of them is collected or designed for occluded signs recognition. The German Traffic Sign Benchmarks (GTSRB) [9] is a well-known dataset for traffic sign recognition, however, the signs in it are different from

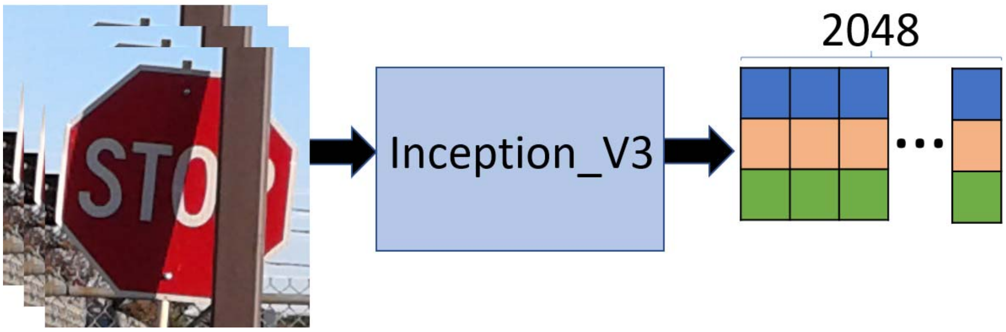


Figure 4: Feature vector extraction based on the pre-trained Inception_V3 model.

the U.S. road signs. Moreover, very few of road signs in GTSRB are occluded. The Laboratory for Intelligent and Safe Automobiles (LISA) traffic sign dataset [6] provides images containing U.S. traffic signs. Unfortunately, we are not able to identify enough occluded signs in the dataset.

1) ORS Dataset: To facilitate occluded road sign detection and recognition, we collect the first dataset for occluded road signs. The ORS dataset contains two types of road sign: stop sign and share-the-road sign. We place these two types of signs in various locations under different lighting conditions. Figure 5 shows an example scene where we take a picture of a stop sign occluded by a tree.

Figure 5: A stop sign is occluded by a tree in a parking lot.

The entire ORS dataset contains 1000+ images of occluded and non-occluded road signs. To prove that our OSCN model works on different kinds of road signs, we collect two types of road signs in our dataset: stop sign (hexagon, red background) and share-the-road sign (rectangle, yellow background). To emulate various conditions in wild, we collect data/images under various light conditions and/or backgrounds. For a particular setting, we take a few images from different angles and/or distances.

2) Synthetic Dataset: Because we are not able to simulate all possible cases where road signs are occluded, we construct a synthetic testing dataset that contains 500 occluded images. Our hope is to simulate other types of occluded road signs which are not covered in our dataset. The synthetic dataset is generated by randomly placing obstacles, e.g., leaves, light poles, other signs, on top of non-occluded road sign images.

B. Experiments and Result Analysis

1) Computer Setup: To evaluate the performance of the proposed OSCN, we train and test it on a regular desktop. The processor of our desktop is Intel(R) Xeon(R) E3-1270 v6 and the graphic processing unit (GPU) is NVIDIA Quadro P1000. We implement the OSCN solution on Keras 2.1.4 with tensorflow 1.8.0.

(a) (b)

Figure 6: Examples of occluded road signs that are correctly classified by the OSCN model.

2) Precision and Recall: After the feature is extracted from the pre-trained Inception_V3 model, we use its output to train our model, which contains only one fully connected layer. During this step, we separate our ORS dataset into two parts: training set (70%) and testing set (30%). The proposed OSCN is able to achieve a testing precision of 96.34%, only after 15 epochs of training.

We compare our approach with SSD in Table I. To make a fair comparison, the SSD model is pre-trained on the LISA traffic sign dataset. The mean average precision (mAP) of SSD is only 51.26%, yet our OSCN can achieve an mAP of 96.34%. The poor performance provided by SSD is largely due to the limited size of the ORS dataset and the relatively large difference between LISA and ORS datasets. Figure 6 shows an example of an occluded stop sign and an occluded share-the-road sign that are successfully detected by the OSCN model.

Table I: Mean Average Precision Comparison

Approaches	SSD	OSCN
mAP	51.26%	96.34%

The OSCN model will provide a prediction value between 0 and 1 to represent how likely the testing image contains an occluded road sign. When the prediction value is close to 1, it is more likely that the image contains an occluded road sign. Figure 7 shows the probability density function (PDF) of the testing results, based on 300 testing images in the ORS dataset. Blue bars indicate how many occluded signs are detected with a certain prediction value. For example, more than 93% of occluded stop signs are detected with a prediction value between 0.9 and 1.0. Similarly, the orange bars show how many non-occluded signs are detected, grouped by their detection prediction values. We also conduct the same experiments on our synthetic testing dataset, fortunately, we are able to obtain very similar precision results. Due to limited space, the data is not included in this paper.

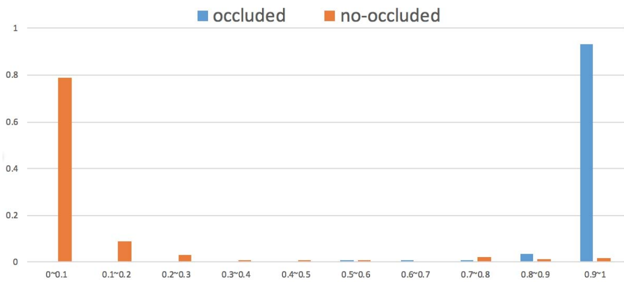


Figure 7: Distribution of detection results of prediction values.

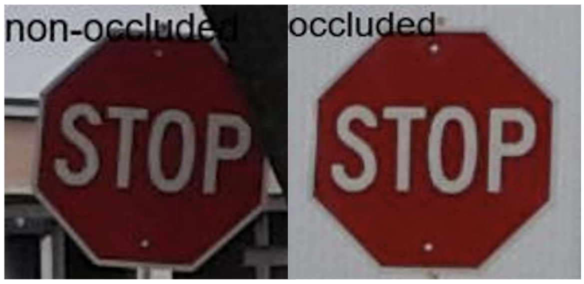
As we can see from Figure 7, the detection results are highly polarized. Most occluded signs are detected with a very large prediction value, i.e., almost all of occluded signs are detected with a prediction value over 0.9. As we aim at providing road sign maintenance suggestion to DOTs, the final decisions still rely on human inspection, implying a higher recall would be expected. As such, we set the detection threshold to be 0.4 (instead of 0.5). That means any image with a prediction value higher than 0.4 is classified as including occluded road signs. In this way, we can achieve a higher recall with a relatively-low accuracy loss. In practice, the threshold can be adjusted based on real-world requirements.

Table II: Running Time Comparison

Size \ Approaches	SSD	OSCN
100	7.78s	6.38s
200	14.66s	8.27s
300	19.74s	9.57s

3) Running Time: In this section, we compare the running times of OSCN and SSD. Considering that the comparison of training time for deep learning based solutions is not useful, we only focus on the time consumption of OSCN and SSD for testing. The testing dataset contains 300 road sign images, which implies that the running time would be very small. Table II shows the running times of OSCN and SSD approaches. As we can see, OSCN outperforms SSD, and the running time of OSCN is only half of SSD's.

4) Discussion on Detection Errors: In the evaluation, we found several images difficult to correctly classify. Examples of these are shown in Figure 8. Figure 8(a) shows a case where only a small portion of the stop sign is occluded. We believe it is not only difficult for OSCN but also challenging for other approaches. In fact, this sign does not need to be replaced as it would not bother drivers too much. While cropping out the regions of road signs in the images, a small portion of the background surrounding the sign is also cropped out. For example, Figure 8(b) shows a classification error. The error is probably caused by the background, which is not a major issue but is inevitable.



(a) (b)

Figure 8: Examples of stop signs that are mistakenly classified by the OSCN model.

IV. RELATED WORK

Road sign plays a important role for both intelligent driving and human driving, they provide essential information to drivers for safety and efficient navigation. Object detection and classification are two important parts in road sign recognition. Many CNN-based solutions are proposed during past years. For example, the Single Shot MultiBox Detector (SSD) [2] is proposed to realize a real-time one-stage recognition technique, using multi-scale feature maps to predict objects. You Only Look Once (YOLO) [3] can also achieve a real-time performance for object detection; it does so by dividing images into numbers of boxes and predicts corresponding classes and confidence for each box.

Methods based on color have good performance for deformed objects, but they are affected by the lighting conditions. Hence, color information is usually used to pre-process raw data for identifying the regions of interest [10] with a shape-based detection method followed. Hue-Intensity-Saturation (HIS) is a method used to avoid the impact of light. A simple normalization over RGB space can achieve similar results as HIS space [11]. Recently, [12] employed visual attention mechanisms to find possible sign regions, with the consideration of colors on road signs. A graph-based algorithm combined with the information of color, salience, spatial and contextual was designed in [13], which is more robust.

Some works can achieve object detection by only using the information of shape from gray-scale images without the color information. The Hough transform method [14] is proposed for lines and circles detection. The fast radial symmetry transformation [15] detects circles with local radial symmetry and has a higher efficiency than the Hough transform. The fast radial symmetry transformation was utilized to detect triangular, diamond (square) and octagonal road signs [16]. However, a serious occluded road sign may be missed due to the missing of edges in the images.

In the domain of road sign detection and recognition, a structure combined feature extraction with a proper classifier has been widely used. A method based on color is used to shorten the computation time in this structure [17]. In [18] [19], the LiDAR was used to detect road sign. For occluded road signs, [20] can detect the occlusion of road signs with a mobile laser scanning system, by detecting the traffic signs' reflectance and geometric features.

V. Conclusion and Future Work

Keeping road signs in good conditions is critical for driving safety, including both conventional driving and autonomous driving. Occluded road signs increase the difficulty of recognizing the corresponding driving rules, therefore, they increase driving risks. We address this issue by proposing the OSCN model to assess whether a road sign is occluded and providing a timely road sign maintenance recommendation to DOTs. Our approach leverages the high intensity of point cloud data corresponding to road signs and the transfer learning technique to achieve a better classification performance. We believe that our proposed OSCN model can be extended to detect road signs in other conditions, e.g., deteriorated, vandalized or tilted, with additional or all types of U.S. road signs included. Moreover, different pre-trained deep learning models can be used to extract the features of images and further increase the precision and recall of the occluded road sign classification.

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