This is a summary for the article titled “Detection of Occluded Road Signs on Autonomous Driving Vehicles”, originally published in ICME, 2019. In this article, the authors propose a new approach to detect and classify road signs that are occluded (have an obstacle between its line of sight).

Autonomous Vehicles (AV) are on the cusp of reality, and it is expected they would reduce traffic accidents caused mostly due to human errors significantly. However, the authors point out, challenges remain for AV. One of them being the accurate detection of road signs. AV heavily depend on road signs, meaning a misclassification or misdetection of road signs could increase the likelihood of accidents.

Misclassification of road signs can occur due to the signs being in bad conditions and not being distinct enough for the AV perception systems to distinguish them. To prevent this outcome, transport authorities need to conduct frequent inspections of the signs, which could be costly and dangerous to the personnel and drivers alike. The authors address this issue and suggest utilizing the perception systems (which may include cameras, LiDAR, processing units) already in place on autonomous vehicles and use the said systems to assess road sign conditions when AV pass by road signs. The authors believe crowd-sourcing the assessment of road sign conditions and sharing that information with the relevant authorities would help with quicker maintenance and thus improve road safety. The authors are quick to point out, though, that because this proposal is dependent on the number of AV on the road, it might be a while for the idea to come to fruition.

The authors present OSCN (Occluded Sign Classification Network) model to tackle the issue of occluded road sign detection. The model has two components: a feature extraction module and a fully connected neural network. The feature extraction module uses a technique called Transfer Learning, which works by training a model on a larger dataset and then using that trained model on one’s own smaller dataset. The method is employed here, and in general, to make up for low-precision predictions resulting from training on small datasets.

To start, the authors collect 1000 images of US road signs, limited to the stop sign and share-the-road signs, of which 500 are occluded and 500 non-occluded, making up the ORS (Occluded Road Sign) dataset. Then they use LiDAR (Light Detection and Ranging, a detection system which works like a radar but uses light from lasers) sensors to collect point cloud data identifying regions with road signs, which are distinguishable from other regions due to the high-reflective materials on the road signs. Afterwards, Transfer Learning is used for feature extraction with the aid of the Inception_V3 model trained on the ImageNet dataset, the extracted features are then fed forward to the fully connected neural network component of the OSCN.

The OSCN then gives predictions on whether a road sign is occluded, including prediction values ranging from 0 to 1. The performance of the model achieves a Mean Average Precision of 96.34%, compared to the 51.26% of the SSD (Single Shot MultiBox Detector) model, which is another real-time object recognition technique based on Convolutional Neural Networks. The authors note, however, that the poor performance by the SSD is due to the limited size of the ORS dataset and feature extraction for the SSD being carried out by a different dataset, LISA, which compared to the ImageNet dataset, has more distinction from ORS.

The detection results are highly polarized, meaning huge confidence in prediction values for occluded and non-occluded sign classifications. Over 93% of occluded signs are detected correctly with a prediction value between 0.9 and 1.0. Some mildly occluded signs were classified as non-occluded, but the authors believe that this will not be a problem since those signs would not be road safety hazards and would thus not need replacement.

Although, the scope of the paper is limited to the occluded “stop” and “share-the-road” signs, the authors conclude with the assertion that the OSCN model can be extended to other types of road signs and road sign conditions, including deteriorated, vandalized, or tilted signs. The authors also suggest OSCN’s levels of prediction and recall can be increased if the model is pre-trained with other deep learning models for feature extraction.