

**DEHAZING ROAD IMAGES FOR DEEP LEARNING BASED TRAFFIC
SIGN RECOGNITION**Jameel Ahmed Khan¹, Hyunchul Shin²^{1,2}Division of Electrical Engineering, Hanyang University ERICA, South Korea

Abstract — Features of traffic signs on road images become dull due to low visibility in hazy weather. In this paper, we propose an algorithm that use image pre-processing before deep learning based traffic sign recognition. We combined reliability guided fusion scheme for image dehazing with Traffic Sign (TS) detector to recognize the traffic signs from hazy day road images. Dehazing is applied on input hazy images and then detection algorithm is applied to detect three classes of traffic signs. Experimental results show that detection accuracy of TS detector is increased by 6.77% owing to the dehazing.

Keywords- Dehazing; Traffic sign detector; reliability guided fusion scheme; YOLOv3; TS detector

I. INTRODUCTION

Traffic sign detection from road images is a very important issue, as this system can alert the driver about road conditions ahead and this system can be used in Advanced Driver Assistance Systems (ADAS). Intelligent Traffic Sign Recognition system (ITSR) [1] used TS detector [2] to detect traffic signs. TS detector, an optimized version of YOLOv3 [3] is designed to detect small size traffic signs accurately. ITSR can detect traffic signs in low illumination condition, and D-patch method [4] can detect occluded traffic signs accurately. Detection of traffic signs in bad weather due to haze and dust is still a challenging task. TS detector fails to detect traffic signs in haze. It is necessary to dehaze the image, so that the features of traffic signs become clear and detector can detect it accurately.

II. PROPOSED METHOD**2.1. Dehazing**

Dust and haze degrade the visibility of an image and thus detection of objects becomes difficult. It is necessary to pre-process the image for enhancing the visibility, so that detection of objects becomes easier. Several image dehazing techniques have been proposed in last few years to enhance the quality of hazy images. Irfan et al [5] proposed reliability guided fusion scheme for dehazing the input image. They calculated reliability map and used upscaling to calculate fine transmission map, and then used transmission map to get haze free image.



Fig1: Low visibility of traffic sign under hazy weather condition

Haze formation model from single image is given by

$$I(x) = J(x) \times t(x) + A \times [1 - t(x)] \quad (1)$$

where $I(x)$ is the input hazy image, $J(x)$ is the unknown haze free image, $t(x)$ is the transmission map, and A is atmospheric light. We used this model for dehazing our hazy dataset and get haze free images before detection. In reliability guided fusion scheme, a high quality fine dark channel is generated with depth edge preserving and texture smoothing properties. The transmission map preserves the depth-edge information and the texture noise has been reduced

through the guided fusion process [5]. In most of the non-sky, haze-free patches, at least one color channel tends to be zero. Air light is estimated by picking up the pixels of the image corresponding to the dark channel.



Fig2: Example of visibility improvement by applying the dehazing algorithm

2.2. Traffic Sign Recognition

Traffic sign detection steps include training and testing. For training the neural network, the input images are annotated to define the position of traffic signs in images. The input data is given to neural network to learn the features. Once the detector is trained, it can detect the position of traffic signs from the given test images. TS detector is trained on Korean traffic signs, and it can detect three super classes of traffic signs [2].

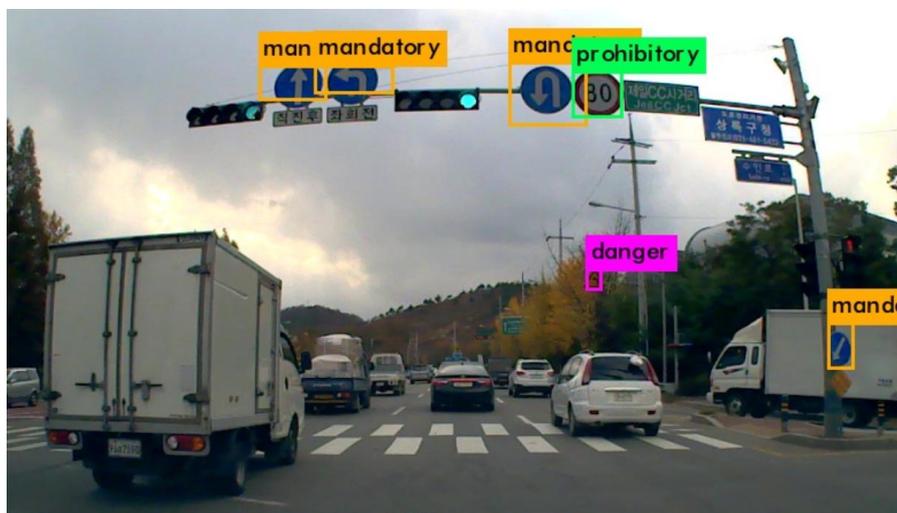


Fig3: Detection of traffic signs using TS detector

We applied dehazing on test data for accurate detection of traffic signs in hazy images. In Figure 4 (a), we can see that the visibility of mandatory class traffic sign is affected by haze in the environment. Input image is dehazed in Figure 4 (b). Deep learning based traffic sign detection is applied and mandatory class traffic sign is detected in Figure 4 (c).



Fig4: dehazing before detection of traffic signs

2.3. Experimental Results

We applied testing on our hazy weather Korean traffic sign dataset to calculate the accuracy of three algorithms. We used Mean Average Precision (MAP) to compare the results. We used the same evaluation method as used in [1]. Table 1 shows that our TS detector with dehazing gives best detection performance, by improving the MAP by 6.77% for our TS detector.

Table 1: MAP comparison of three detection algorithms

Detection method	Mean Average Precision
YOLOv3	73.23%
TS detector without dehazing	82.69%
TS detector with dehazing	89.46%

2.4. Discussion and conclusion

Detection accuracy of traffic signs on hazy dataset can be increased by applying the dehazing algorithm, however if we apply dehazing algorithm on clear day images, the quality of some images degrades, and detection accuracy is reduced. It is necessary to develop an intelligent weather classification algorithm that can classify hazy days. In this paper, the test dataset contains only hazy images and we achieved significant improvement in detection accuracy.

ACKNOWLEDGEMENT

This material is based upon work supported by the Ministry of Trade, Industry & Energy (MOTIE, Korea) under Industrial Technology Innovation Program (10080619).

REFERENCES

- [1] J. A. Khan, D. Yeo, and H. Shin, "New Dark Area Sensitive Tone Mapping for Deep Learning Based Traffic Sign Recognition", *Sensors*, 18(11), p.3776 November 2018.
- [2] P. Manocha, A. Kumar, J. A. Khan, H. Shin, "Korean Traffic Sign Detection Using Deep Learning", *ISOC: Daegu, Korea*, November 2018.
- [3] YOLOv3. Available online: <https://pjreddie.com/yolo/> (accessed on 24 November 2018).
- [4] Y. Rehman, I. Riaz, H. Shin, "Effective traffic sign detection with occlusion handling", *IET computer Vision* 2017, 11, 368-377
- [5] I. Riaz, Y. Teng, H. Shin, "Single image dehazing via reliability guided fusion", *Journal of Visual Communication and Image Representation* 40 (2016): 85-97