International Journal of Multimedia and Ubiquitous Engineering
Vol.15, No.2 (2020), pp.41-48
http://dx.doi.org/10.21742/ijmue.2020.15.2.04

# A Progression Direction for Vehicle License Plate Detectors Based on Performance Evaluations Using Various Real-road Images

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***Abstract***

*Recently, since deep learning technologies have been widely used in developing vehicle license plate detection and recognition schemes, the data set of a large number of vehicle images is highly required. However, vehicle license plate detectors developed with the deficient training data set which does not contain the various conditions of real-roads may have insufficient functionalities for actual usages. Therefore, a training data set reflecting enough various real-road conditions is essential. To construct such a data set, the imitation ways for the various possible situations on real-roads from the actual images taken by CCTVs are defined and the imitated images are augmented to the set. Then, using this data set, performance evaluation was studied with a contemporary vehicle license plate detector proposed by Silva and Jung which is known as good at the detections of vehicle license plates in the unconstrained real environments. And, according to the performance evaluation results, we propose a future progressive direction for the secure functionalities of new vehicle license plate detectors that should be used in real situations in near future.*

***Keywords:*** *Real-road environments, Emulating various real-road conditions, Contemporary vehicle license plate detectors, Future progression directions*

## 1. Introduction

Vehicle license plate recognition is widely used for identifying vehicles in many real applications. For recognizing vehicle license, first, it is necessary to accurately detect the license plate. In the computer vision community, license plate detection schemes have been widely studied for various purposes such as tracking criminal vehicles, vehicle re-identification, and Intelligent Transportation Systems (ITS) [1][2]. Adapting deep neural networks into developing vehicle license plate detectors makes large contributions to improving their detection accuracies in real environments. Therefore, to accurately detect and identify vehicle license plates, the vehicle license plate detection model should be trained with a data set including a lot of vehicle images acquired in various real environments.

However, existing data sets may have images collected in restricted or artificial environments. For example, the OPEN-ALPR data set [2], SSIG data set [3], and AOLP data set [4] that have been frequently used for vehicle license plate detection studies have horizontal license plates with a large proportion. If a vehicle license plate detector is trained using these data sets, it can only detect the license plates in the constrained environments

**Article history:**
Received (August 6, 2020), Review Result (September 9, 2020), Accepted (October 18, 2020)

included in the data set. However, in other unrestricted environments, it may have low detection accuracies [3][4][5]. Therefore, to solve this problem, the previous study [5] considered that, in the images taken with the unrestricted real situations, the license plate area can be of an inclined rectangle shape, as well as a horizontal rectangle shape, due to the viewpoints of cameras in actual environments. So, they proposed a new method to accurately detect the vehicle license plate areas of arbitrary inclined rectangles.

However, vehicle images captured by CCTVs installed on the real-roads may have additional environmental diversities besides having slightly rotated license plate areas. Therefore, it is necessary to construct a vehicle image data set through the transformation from the acquired source data for describing various environmental conditions. For that, we first acquired source images recorded by various CCTVs installed on domestic real-roads and then analyzed the poor image-recording conditions that may occur in real-road environments. Based on these, a vehicle image data set including transformed vehicle images to emulate various poor environmental conditions on real-roads was constructed. And using the vehicle license plate detector model of [6], which was developed for accurate detection on real-road environments, the accuracy of the vehicle license plate detection is analyzed with the constructed data set. Also, based on the performance evaluation results, we confirm the performance level of a contemporary vehicle license plate detection scheme and suggest the progressing direction for future vehicle license plate detectors.

## 2. Related works

### 2.1. Data sets for developing vehicle license plate detection schemes

Among the existing data sets used for developing vehicle license plate detection schemes, data sets [2] and [4] consist of images mostly which were taken in front of vehicles in constrained environments. Especially, in the case of [4], most of the camera viewpoints are composed of the dashcam viewpoints. Therefore, it was confirmed that the shapes of most license plates in [3] and [3] are in horizontal rectangular shapes. And the data set [4] consisted of three subsets, AC (Access Control), Traffic LE (Law Enforcement), RP (Road Patrol), and has front or oblique viewpoints. However, these subsets contain several images taken in restricted cases such as parking or stopping in restricted areas or violation of the law. Therefore, it is necessary to newly construct a data set reflecting various environmental conditions of the real-roads. So, in this study, various environmental conditions are described using source data acquired from domestic real-roads. And based on this, mimic images that are transformed similarly to various poor environmental conditions that can occur in real-roads are generated and included in the data set. OpenCV [6] was used to emulate various poor environmental situations.

### 2.2. Vehicle license plate detection schemes

There are many studies on vehicle license plate detection schemes [1][2][2][3][4]. However, these license plate detectors can detect the license plates only in the rectangular shapes and they are not sufficiently trained to reflect the actual road environments. To overcome these limitations of the previous works, [5] proposed a method that can detect the license plates even in the rotated cases and can finally improve the detection accuracies in real environments. Therefore, we analyzed the detection accuracy of the vehicle license plate detector using WPOD-NET proposed in [5] with our data set of real-road environmental conditions. As shown in [Figure 1], [5] uses a network that predicts the coefficients of the affine transformation matrix that can handle rotations, distortions, and size variations of the vehicle license plates. So, it was possible to detect even if the vehicle license plate is in arbitrary inclined rectangles.

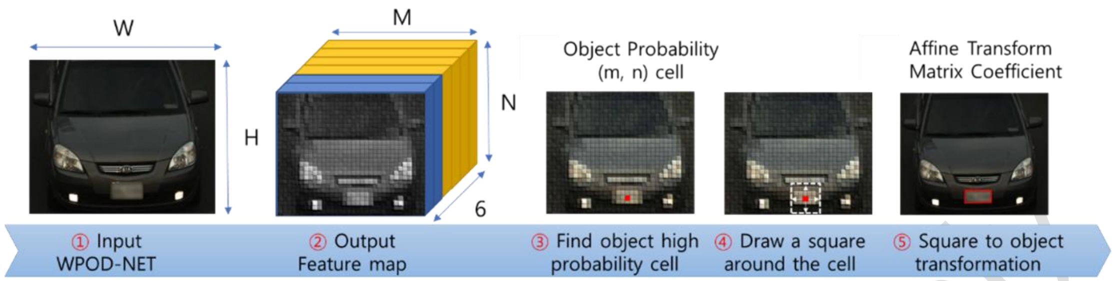


Figure 1. License plate detection steps using WPOD-NET

However, in the actual real-road environments, there are many other poor environmental conditions such as those with low-resolutions, noise-included, low-illuminations, and high-speed vehicles besides rotated viewpoints. Therefore, to develop a license plate detection method that can be operated in actual environments, it is necessary to analyze these various conditions.

## 3. Construction methodology for an emulated data set

In this section, we introduce the construction of an emulated data set for developing license plate detectors that can be used on real-roads. As shown in [Figure 2], it consists of three steps; actual data acquisition, poor condition analysis, and the imitation.


Figure 2. Construction of an emulated data set including various real-road image

### 3.1. Acquiring actual source data from real-roads

To construct a data set of various poor environmental conditions, vehicle images were acquired in various places. As shown in (A), (B), and (C) of [Figure 3], the vehicle images were taken from different viewpoints and the various distances; (A) was taken from the right-front side of a vehicle, (B) was taken at a greater distance than (A), and (C) was taken from the right-rear side of a vehicle. Also, for recording time, images were taken in the morning, noon, evening, and night are included. Through this, various illuming conditions are reflected. As shown in (D), (E), and (F) of [Figure 3], (D) was taken during the bright daytime, (E) was taken during the evening when the sun was setting, and (F) was taken during the night when the sun was completely set. Based on these, the source data set includes various environmental conditions by not being constrained to some viewpoints, distances, and times. After data cleansing, 9,596 vehicle images were finally used as the original data for representing actual real-road conditions. [Table 1] shows the number of source data based on different collection situations.



 

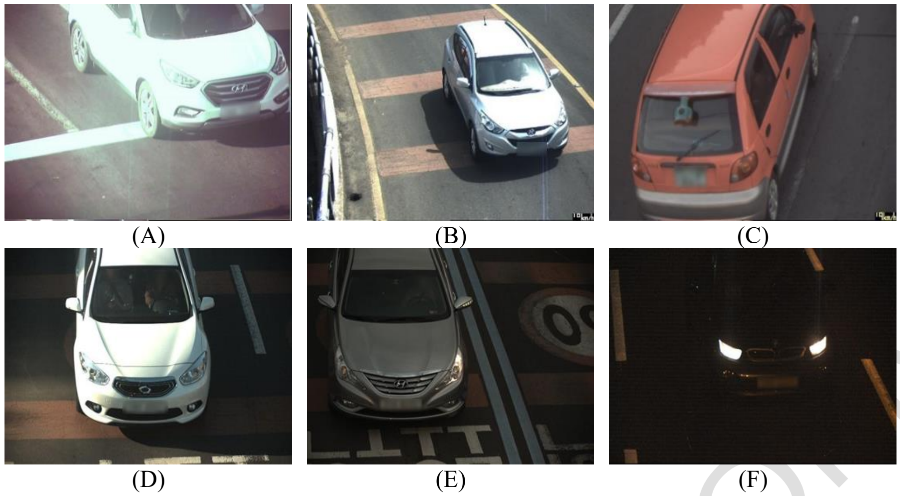


Figure 3. Sample source data taken from real-roads with different locations and times

Table 1. The number of data based on different collection situations

| Collection situations | Detailed condition | Number of images | Total |
|---|---|---|---|
| Recording time (Illumination) | Daytime | 5,504 | 9,596 |
| | Evening | 2,809 | |
| | Night | 1,283 | |
| Recording distance | Near (~5m) | 5,439 | 9,596 |
| | Medium (5~10m) | 2,728 | |
| | Far (10m~) | 1,429 | |
| Recorded directions of the vehicles | Front or Rear | 8,065 | 9,596 |
| | Sides | 1,531 | |

### 3.2. Analyzing various poor environmental conditions

To analyze the poor environmental conditions from the collected source data, images that interfere with the correct detection of the license plate area were selected manually. [Figure 4] shows some selected examples; (A) is a case of strong sunlight while (B) is of the dark night, (C) is of thick foggy, and (D) has an afterimage along the direction as the vehicle runs fast.

### 3.3. Emulating images for various poor real-road conditions

Based on these poor conditions, emulated images were generated using OpenCV. Besides the origin case, 19 degradation cases were defined and generated, and these cases can be divided into 6 subgroups. First, images according to the difference in illuminance were generated by referring to the case taken in the daytime and nighttime. Two cases of degradations are for the daytime and one is for the night. Second, images according to the difference in hazy were generated by referring to the thick fog situations. The images are divided by pixel values to lower the color contrast, and then the hazy effect was given by adding the pixel value. There are two cases of degradations depending on the thickness of the fog. Third, images according to the differences in the resolutions were generated by referring to the cases taken with low-resolution cameras. Source images are transformed into smaller resolution images with 1/N of the origin. Here, N is 2, 4, 6, and 8. Fourth, images were created by referring to the case of an afterimage caused by rapid movements. The images were repeatedly blended while moving every 5 pixels down from the original image. Two cases are depending on the distance between the original image and the last blended image. The distances used in each case are 10 and 20 pixels, respectively. Fifth, images were created by referring to the case taken with the license plate rotated according to the camera's viewpoints. Four cases rotate 10 degrees and 20 degrees counterclockwise and clockwise, respectively. Finally, images of the last group were generated by referring to the case of motion blur. There are four cases, depending on the blurring kernel containing two diagonals, top-bottom, and left-right.

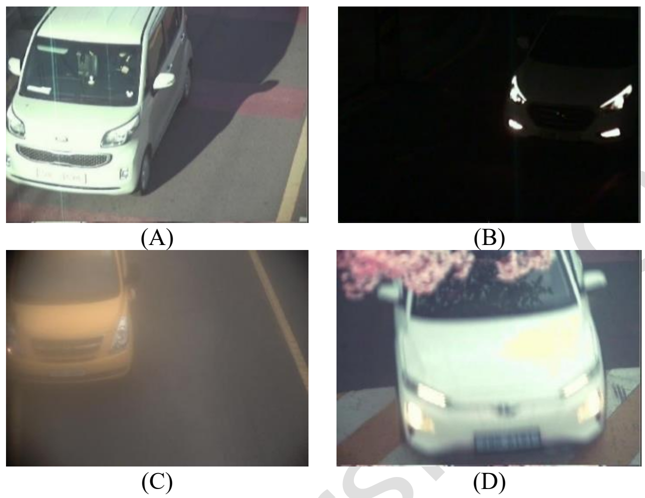


Figure 4. Sample source data taken from real-roads with different locations and times

## 4. Performance evaluation of WPOD-NET using the emulated data set

In this section, we analyzed the detection performance of a contemporary plate detection scheme named WPOD-NET which was proposed recently to improve detection accuracy in the actual environments. The network model and the trained weights provided by the author of [5] through Github were used. After that, based on the results of the accuracy, we suggest future directions for the vehicle license plate detectors. In the process, first, vehicle detection was performed using Yolo-v2 [7]. In [5], Yolo-v2 was used for vehicle detection in the first step since it is likely fast and of high recall and precision. As a result, only one vehicle was detected and cropped from 147,115 (77.68%) of 189,380 images.

And then, for each cropped vehicle image, license plate detection was performed using WPOD-NET. When the vehicle was not detected in the previous step by Yolo-v2, the whole image is used instead of the cropped vehicle image. Based on results obtained through this process, the results were compared with the ground truth data that are manually tagged. And detection results that have IOU greater than 0.5 were considered as the correct ones in very similar way to the previous studies [2][2][3][4][5]. As the results, [Figure 5] shows the detection accuracies of WPOD-NET against the emulated data set which includes several bad conditions such as bad-illuminations, foggy, low-resolution, fast-moving cars, rotated vehicle images, and blurred images. According to the experimental results, WPOD-NET provides better detection accuracy than the origin for rotated cases as the claims of [5]. The average detection accuracy of 81.53 is little bit higher scores than 76.47 of the original case. And for the illumination and foggy cases, WPOD-NET shows slightly low accuracies (≤10%) than the original case. Therefore, some performance improvements are needed for these cases. On the other hand, it shows quite differences (>10%) from the original case against low-resolution, moving fast, and blurred image cases. Hence, for these cases, we need big performance improvements essentially.

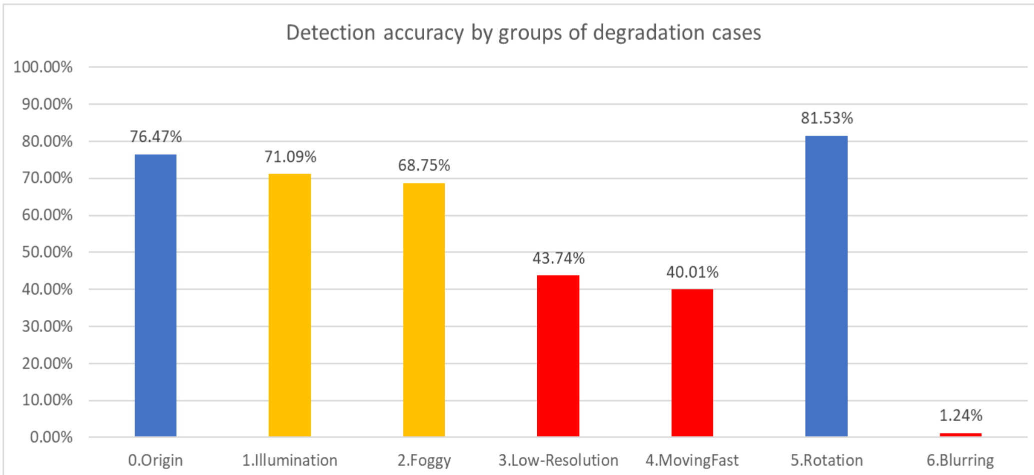


Figure 5. Detection accuracies of WPOD-NET according to the real environment conditions

To analyze the performance of WPOD-NET in more detail according to the levels of bad conditions of each case, [Table 2] shows the detection accuracies based on the transformation levels from the original images. Among them, WPOD-NET shows the results of good accuracy about daytimes, night, and foggy cases and low-resolution images with the change in size except smaller than 1/4. This is because WPOD-NET performed data augmentation by applying various techniques such as brightness change, size change, centering, etc. for training. However, we can observe that the more severe change, the lower performance. And, since WPOD-NET was proposed to be able to detect the vehicle license plate area of the inclined rectangles, it was confirmed that detections of WPOD-NET are robust in the rotational degradation cases. Finally, it can be seen that the performances of vehicle license plate detection are very poor for the degradation cases with size reduction of smaller than 1/4, the degradation case in which afterimages are combined in the direction of progression up to 20 pixels, and the motion-blurring degradation cases. If we compared images of these poor cases and images of origin case, the images of these cases have a large difference visible to the naked eye. Based on this result, we can confirm that the environmental conditions to be considered when training the vehicle license plate detection models. Also, although the rotation degradation cases show robust performance that is similar or slightly higher than the accuracy of the original case, the accuracy of the original case is only about 76%. Therefore, we can confirm that these cases also require further improvement.

## 5. Conclusions

In this study, the source data set was acquired from CCTVs that are operated on domestic real-roads, and degradation conditions that may occur in various real-road environments were analyzed. Then, according to the degradation conditions, variously emulated real-road images are generated and augmented into the vehicle data set constructed in our study and, using the data set, we studied the detection performance of the contemporary license plate detection scheme WPOD-NET which was recently proposed to improve detection accuracy in actual environments. As a result, it was confirmed that the detection performance for rotational degradation cases was slightly higher than the original case. However, the detection performance for the original case is about 76% which is considered to need more performance improvement. Also, we can observe that some degradation cases such as the night, foggy, slightly small resolution reductions have a little bit lower than that of the original case. And the performances of other degradation cases such as severely resolution reduction of smaller than 1/4, motion-blurring, high-speed moving cars have much lower performance than the origin case. Through these analyzed results, to detect vehicle license plates correctly even in the bad conditions in real-road environments, the detection functionality of the future vehicle license plate detectors should be improved than even in the aforementioned bad situation cases in addition to the origin, rotation cases.

As further studies, we are developing a vehicle license plate detection scheme using deep learning technologies which can detect better than the previous schemes even in the bad environmental conditions of real-roads.

Table 2. Detailed comparison of detection accuracies based on the transformation levels

| No | Group | Case | Accuracy | Average |
|---|---|---|---|---|
| 0 | Origin | Origin | 76.47% | 76.47% |
| 1 | Illumination | IlluminationDay1 | 76.44% | 71.09% |
| | | IlluminationDay2 | 73.76% | |
| | | IlluminationNight1 | 63.07% | |
| 2 | Foggy | Foggy1 | 74.71% | 68.75% |
| | | Foggy2 | 62.80% | |
| 3 | Low-Resolution | Resolution 1/2 | 76.59% | 43.74% |
| | | Resolution 1/4 | 64.61% | |
| | | Resolution 1/6 | 27.21% | |
| | | Resolution 1/8 | 6.57% | |
| 4 | Moving Fast | MovingFast10px | 72.25% | 40.01% |
| | | MovingFast20px | 7.77% | |
| 5 | Rotation | CntClockwiseRot10 | 86.75% | 81.53% |
| | | CntClockwiseRot20 | 80.33% | |
| | | ClockwiseRot10 | 83.82% | |
| | | ClockwiseRot20 | 75.23% | |
| 6 | Blurring | BlurringTopBottom | 2.44% | 1.24% |
| | | BlurringLeftRight | 2.46% | |
| | | BlurringDiagonal1 | 0.01% | |
| | | BlurringDiagonal2 | 0.04% | |

## Acknowledgments

This work was supported by Institute for Information & communications Technology Promotion (IITP) grant funded by the Korea government (MSIT) (No.2020-0-00237, Development of Video Security Edge Technology with General Intelligence supporting 5G-based Mobility).

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