Improving License Plate Recognition Accuracy in Motion and Out-of-Focus Blur Environments

JAE SEOK LEE
Dept. of AI Techno Convergence
Soongsil University
Seoul, Korea
koreathomas@ soongsil.ac.kr

MYUNGAHN KIM
Dept. of AI Techno Convergence
Soongsil University
Seoul, Korea
kimma0924@soongsil.ac.kr

KWANG YOUNG PARK
Dept. of AI Techno Convergence
Soongsil University
Seoul, Korea
1004pky@ssu.ac.kr

HA JI HYEON
AI Convergence Research Institute,
Soong-Sil University
Seoul, Korea
ilmarejh@ssu.ac.kr

GYE YOUNG KIM
Dept. of AI Technology Convergence,
Soong-Sil University
Seoul, Korea
gykim11@ssu.ac.kr

***Abstract*— This report aims to enhance the recognition accuracy of vehicle license plate characters by restoring motion blur and out-of-focus blur caused by high-speed motion or lens focus errors using deep learning techniques. The primary factors contributing to recognition accuracy degradation in deep learning-based vehicle license plate recognition are image blurring caused by rapid vehicle movement or camera shake (e.g., due to wind or vibrations). This issue is particularly prominent in rolling shutter cameras, where motion blur becomes more severe depending on the speed of motion and exposure time. Therefore, preprocessing techniques capable of addressing motion blur from high-speed vehicles and focus blur caused by lens setting changes are essential. To solve this issue, a deblurring process was added to the conventional license plate recognition workflow, generating deblurred license plate images for recognition. A comparative analysis was then conducted to evaluate the difference in recognition accuracy between the conventional method and the deblurring-enhanced approach. A total of 219,756 license plate images from 8 classes were collected, and two types of artificial blurring, Gaussian blur and motion blur, were applied to simulate degraded images. The effectiveness of deblurring preprocessing on recognition performance was analyzed using four deep learning models. The evaluation results confirmed that applying preprocessing models capable of effectively removing motion and focus blur reduced false negatives and false positives, leading to a significant overall improvement in recognition accuracy.**

I. INTRODUCTION

Recently, CCTV cameras have been providing clear, high-resolution (FHD, 4K) color footage both day and night. Thanks to these technological advancements, it has become possible to recognize vehicle license plates even with general surveillance CCTV cameras. Just a few years ago, vehicle license plate recognition was typically performed using images obtained from road surveillance cameras (Global Shutter) dedicated to license plate recognition. This was mainly because general surveillance CCTV cameras commonly used rolling shutter sensors, and due to the characteristics of these sensors, images extracted from still frames of fast-moving objects often had blur, making it difficult to recognize characters or numbers.

The main factors that hinder license plate recognition with surveillance CCTV cameras can be categorized into two: First, when the image is blurred due to the lens being out of focus; second, when the focus is correct, but motion blur occurs because of slow shutter speed when capturing fast-moving objects. Even dedicated global shutter cameras installed for vehicle license plate recognition are not without issues. Over time, the manually configured focus settings can shift slightly, causing focus blur, which can hinder license plate recognition.

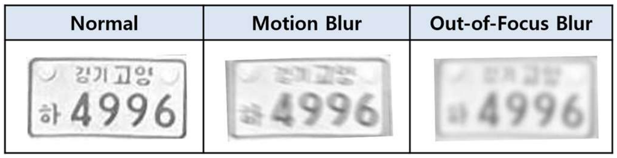
This study aims to improve recognition accuracy to the maximum possible range by applying deblurring techniques to remove motion blur and focus blur from preprocessed vehicle license plate images. To achieve this, the study proposes a method for improving vehicle license plate recognition performance by collecting vehicle license plate images, extracting the license plate area, generating a training dataset by mapping input and target images, and restoring blurred vehicle license plates.

II. RELATED RESEARCH

In this study, the conditions under which vehicle license plates are not recognized are defined as follows:

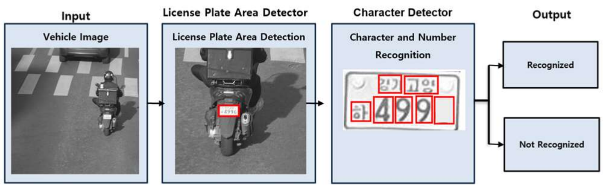
1) The recognition rate of the vehicle license plate is low due to focus blur on the license plate.
2) The recognition rate of the vehicle license plate is low due to motion blur on the license plate.

The characteristic of objects that are not detected under these conditions is that the numbers and characters are blurred to the point that they are difficult to recognize. A representative example is shown in <Figure 1>.



<Figure 1> Examples of Different Types of Blur

Generally, the process of license plate recognition involves the following steps: inputting the vehicle image, detecting the license plate area from the image, and detecting the numbers and characters, as shown in <Figure 2>.

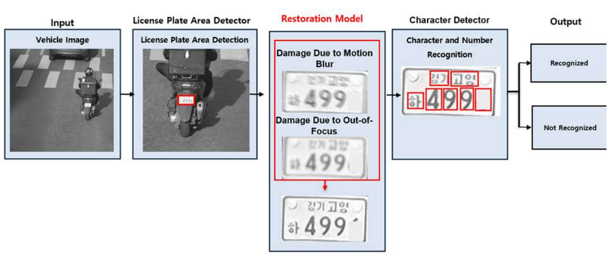


<Figure 2> General License Plate Recognition Process

In typical enforcement or license plate recognition systems, the vehicle images obtained often contain blur, causing characters or numbers to become unclear. This, combined with the fact that the number detector attempts to recognize the characters and numbers without any preprocessing, becomes a major factor in degrading the recognition performance.

III. Proposed Image Preprocessing Techniqueused

In this section, we propose a preprocessing structure and method to determine the most effective way to preprocess the image. <Figure 3> shows the structure of the image preprocessing system.



<Figure 3> License Plate Recognition Process with Enhanced Plate Restoration

In <Figure 3>, the image preprocessing solution differs from conventional vehicle license plate recognition systems by using a single deep learning model to improve both motion blur and out-of-focus blur, without the need to determine whether the image contains blur or to distinguish between the types of blur.

The process consists of the following steps: inputting the vehicle image, detecting the license plate area, removing and restoring blur from the license plate, recognizing the numbers and characters, and outputting the results of whether the license plate was recognized or not.

The method for building the training dataset for the license plate restoration deep learning model in this system is carried out in the following order.

1) Collect vehicle images for training.
2) Crop only the license plate area from the collected vehicle images.
3) Create the training dataset by mapping the input images to the target images.
4) Use clean original license plate images as the target images for restoration.
5) Use damaged images caused by blur as the input images, artificially generating blur-damaged images by applying two types of blur to the original license plate images.
6) Two methods are used to create the damaged images by applying blur:

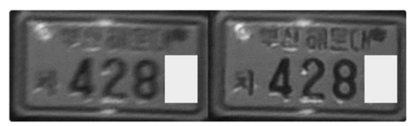
$$h(x,\sigma) = \frac{1}{\sqrt{2\pi\sigma}} \exp\left(-\frac{x^2+y^2}{2\sigma^2}\right), \quad x \in \mathbb{R}$$

(Generating out-of-focus blur using Gaussian blur)

$$h(x,y) = \begin{cases} \frac{1}{M} & \text{if } x\sin(\omega) + y\cos(\omega) = 0,\ x^2+y^2 \le \frac{M^2}{4} \\ 0 & \text{elsewhere} \end{cases}$$

(Generating motion blur using motion blur modeling)

7) Below, <Figure 4,5> shows the result of restoring the blur-damaged image using the license plate restoration model.



<Figure 4> Image with Motion Blur Removed

<Figure 5> Image with Out-of-focus Blur Removed

IV. Data Construction Environment

The evaluation dataset consists of 1,564 images, where blur damage was applied using the method for generating training data. The blur-damaged images were input into the restoration models U-Net, U-Net-Res, FFDNet, and Uformer for restoration. Then, the restored and pre-restored images were input into the same license plate recognition model to compare the recognition performance before and after restoration.

To measure the FPS (Frames Per Second) and the frame rate, which is the speed of processing a single frame, inference for each license plate restoration model was performed in an Intel Core i7-12700 environment, using input images with a resolution of 256×140.

V. RESULTS

In this paper, it was confirmed that when restoration models were applied to blurred, damaged images through image preprocessing, all restoration models improved recognition performance by suppressing Gaussian blur and motion blur.

Input image	Recognition			Misrecognition			Non-recognition			Quantity
	Quantity	Percentage	Difference	Quantity	Percentage	Difference	Quantity	Percentage	Difference 차	
Damaged Image	1454	92.97	-	56	3.58	-	54	3.45	-	1564
Unet (Restored Image)	1465	93.67	0.70	47	3.01	-0.58	52	3.32	-0.13	
UNetRes (Restored Image)	1462	93.48	0.51	51	3.26	-0.32	51	3.26	-0.19	
FFDNet (Restored Image)	1469	93.93	0.96	51	3.26	-0.32	44	2.81	-0.64	
Uformer (Restored Image)	1499	95.84	2.88	35	2.24	-1.34	30	1.92	-1.53	

<Figure 6> Comparison of License Plate Recognition Rates According to the Application of Each Restoration Model

As shown in <Figure 6>, the Uformer restoration model showed the greatest improvement in recognition rates, with a 2.88% increase in recognition rate, a 1.34% decrease in misrecognition, and a 1.53% decrease in non-recognition, confirming the improvement in performance.

Model	Frame Rate(ms)	FPS
Unet	83	12
UnetRes	56	18
FFDNet	33	30
Uformer	1306	0.8

<Figure 7> Inference Speed by Model

In the case of FFDNet, which showed the fastest speed, it was capable of processing 30 frames per second. However, for Uformer, which had the highest recognition rate, it was unable to process 30 frames per second, leading to the conclusion that applying this model to actual products would be difficult.

The results of this experiment indicate that the Uformer model outperforms the U-Net model for the following reasons:
Uformer, with its Transformer-based architecture, demonstrates superior performance, particularly in handling complex blur patterns. U-Net, built on a Convolutional Neural Network (CNN) framework, excels in extracting local features and utilizes simple skip connections, allowing for relatively lightweight computations and faster processing speeds. However, U-Net has limitations when dealing with global blur patterns or adapting to diverse types of blur.
The Uformer model, however, faces challenges in practical applications:
Its larger model size and complex architecture enable Uformer to provide better generalization performance and higher recognition accuracy in challenging scenarios, such as restoring complex blur patterns. Specifically, in cases like rolling shutter blur, where non-uniform blur occurs across the entire image, Uformer captures long-range dependencies that U-Net often fails to address, delivering superior results.
In conclusion, while Uformer requires more computational resources and longer processing times, it is better suited for applications that demand high recognition accuracy and the restoration of complex blur patterns. On the other hand, U-Net is a more efficient choice for environments where real-time processing and speed are critical. Additionally, Uformer leverages Swin Transformer blocks to simultaneously learn both local and global information, effectively restoring blur over large and complex areas, such as motion blur and focus blur. Its self-attention mechanism further enables precise recovery by learning structural relationships across the entire image, regardless of the blur's location or type. However, this sophisticated architecture increases the number of parameters and computational overhead, contributing to slower processing speeds compared to U-Net.

VI. CONCLUSION

This study presented a method to improve recognition accuracy in vehicle license plate recognition by applying preprocessing techniques to handle blur phenomena using deep learning. To eliminate motion blur caused by high vehicle speed and focus blur due to camera shake, deblurring techniques were introduced, and it was confirmed that these techniques could enhance license plate recognition accuracy. The results demonstrated that applying deblurring techniques reduced missed and false detections and improved recognition rates compared to conventional methods.

VII. ACKNOWLEDGMENT

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