2023 International Conference on Consumer Electronics - Taiwan (ICCE-Taiwan) | 979-8-3503-2417-4/23/$31.00 ©2023 IEEE | DOI: 10.1109/ICCE-Taiwan58799.2023.10226883

License Plate Restoration System

Meng-Chen Luo*, and Chia-Yu Lin†
* *Department of Computer Science and Engineering, Yuan Ze University, Taoyuan, Taiwan*
† *Department of Computer Science and Information Engineering, National Central University, Taoyuan, Taiwan*
Corresponding Author: Chia-Yu Lin (sallylin0121@ncu.edu.tw)

***Abstract*—The advent of intelligent transportation systems has led to the direct recognition of license plates by license plate recognition systems. However, the system is affected by environmental factors, such as underexposure, resulting in over-dark images. In this paper, we propose a two-stage restoration system to address these issues. In the first stage, we use image processing to enhance the license plate, and in the second stage, we employ a deep learning model to further repair the license plate. Our approach has greatly improved the Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity (SSIM) metrics, increasing by 3.8094 and 0.0137.**

I. Introduction

License plate recognition systems have many applications, including parking lots. However, license plates captured in different scenes may have various issues, such as shadows.

To recover these images, we use Histogram Equalization (HE), commonly used but can result in color separation and amplified noise. Adaptive Histogram Equalization (AHE) solves the problem of color separation but not noise, while Contrast Limited Adaptive Histogram Equalization (CLAHE) [1] proposed by Zuiderveld *et al.* solves both problems. The pix2pix model [2] proposed by Isola *et al.* uses cGAN with the U-Net generator and patchGAN discriminator.

To address the issues with license plates, we propose a License Plate Restoration System (LPRS). The first stage of our system has two steps. Firstly, we use CLAHE to enhance the clarity of blurry and overexposed images. Gamma correction is used to adjust the brightness of over-dark images. Finally, Unsharpen Mask is applied to sharpen the target contours and obtain a clear license plate. In the second stage, we use Otsu to divide license plates into black or white backgrounds, and then train the pix2pix models for restoration.

Our paper contributes to restoring blurry, overexposed, and over-dark license plates, vastly improving PSNR and SSIM metrics, which increased by 3.8094 and 0.0137.

II. License Plate Restoration System

The system architecture of LPRS is depicted in Fig. 1. In the initial stage, LPRS employs image preprocessing techniques to restore license plates. If the restored license plate can be directly recognized, it is immediately outputted. Subsequently, LPRS determines whether the license plate is black or white and applies an appropriate inpainting model to restore it.

A. Image Preprocessing

During this stage, we employ Contrast Limited Adaptive Histogram Equalization (CLAHE), Gamma Correction, and Unsharp Mask techniques to process images.

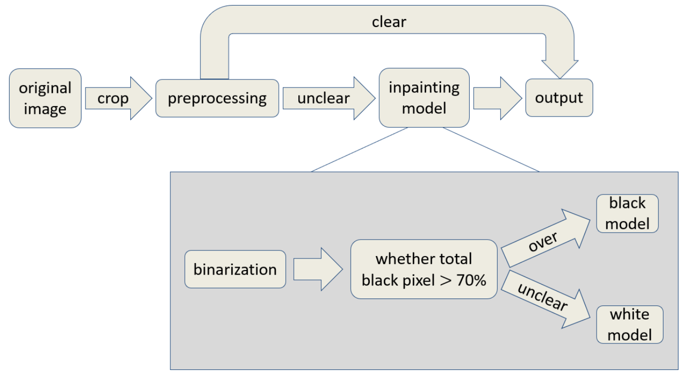

Fig. 1: The overview of the restoration system architecture

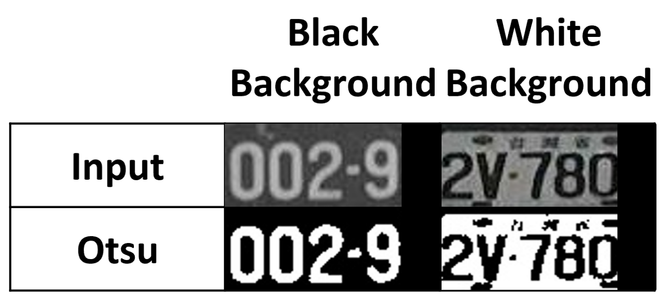

Fig. 2: license plate of otsu

Firstly, Gamma Correction is used to adjust the brightness of the over-dark license plates by utilizing the following formula

$$y(m,n) = x(m,n)^{\gamma} \times 255$$

Where $x(m,n)$ is the individual pixel value of the input image, $y(m,n)$ is the output image, γ represents the adjustment range, $\gamma = 1$ represents brightness unchanged, $\gamma < 1$ will brighten the image and $\gamma > 1$ will darken the image.

and then use CLAHE to clarify the contour of all types of license plates.

After implementing Gamma Correction, we proceed with Unsharp Mask [3], a technique proposed by Malin, to enhance the edges of the license plate. The formula is as follows:

$$y(m,n) = x(m,n) + (x(m,n) - G(x(m,n))) \times \lambda$$

Where $x(m,n)$ and $y(m,n)$ are the input and output image, $G()$ is the Gaussian blurred image, and L is the scaling factor.

Prior to entering the second stage, we utilize Otsu to detect whether the input is a black or white background. The criterion

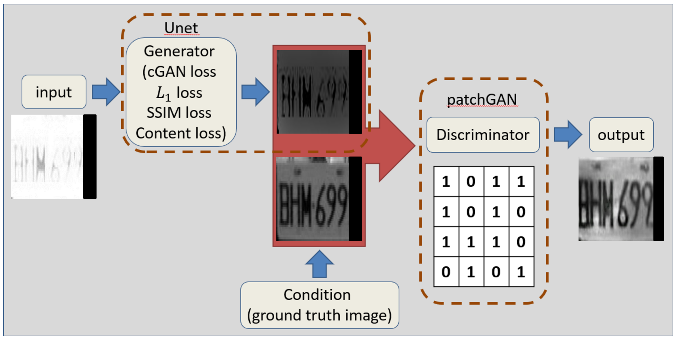

Fig. 3: The architecture of the pix2pix model.

dataset	Original		Inpainted	
	PSNR	SSIM	PSNR	SSIM
blur white	14.3081	0.4489	14.2318	0.3254
blur black	16.1121	0.4748	15.6357	0.3740
exposure white	7.7101	0.4245	13.3329	0.3786
exposure black	5.6640	0.2767	15.0709	0.3607
overdark white	8.4512	0.1839	13.3665	0.3740
overdark black	10.8549	0.2299	14.3190	0.3080

Table. I: PSNR and SSIM of three types of image

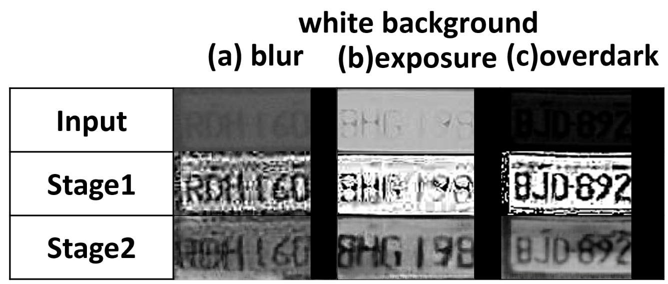

Fig. 4: (a) RDH-160* (b) BHG-198* (c) BJD-892*

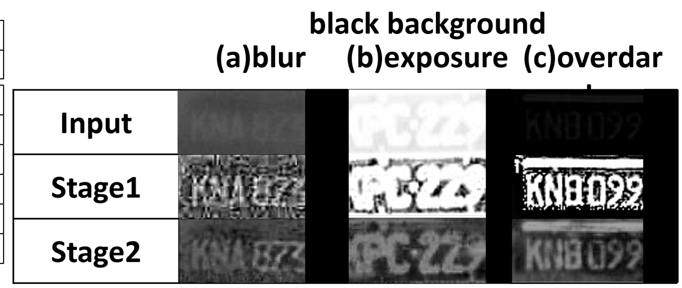

Fig. 5: (a) KNA-823* (b) KPC-229* (c) KNB-099*

for decision is based on the proportion of white pixels in the image. If the proportion of overexposed license plates is greater than 70% or if blurry and over-dark license plates are less than 30%, then it is determined to be a white background. Otherwise, it is judged to be a black background.

B. Image Inpainting Model

Fig. 3 describes the architecture of the pix2pix model.

The pix2pix model is designed based on conditional-GAN (cGAN), which differs from the traditional GAN in that it utilizes image for conditions to achieve image-to-image translation.

The generator of the pix2pix model adopts the U-Net, which uses skip connections to enable each layer to share information, saving more features during training.

On the other hand, the discriminator of the pix2pix model uses PatchGAN, which differs from a typical discriminator in its way of judging. While a typical discriminator judges whether an entire image is real or fake and outputs 0 or 1, PatchGAN outputs a matrix of elements of 0 or 1 and takes the average to judge the reality of the image.

III. Experiment

Far Eastern Electronic Toll Collection Co. (FETC) provides license plate images that contain blurry, overexposed, and over-dark license plates. The data was split into 80% for training and 20% for testing. Then the training data are augmented to 20,000 and resized to 256x256.

We evaluate PSNR and SSIM for our approach. A higher value of PSNR and a value of SSIM closer to 1 indicate nearer to the ground truth. Table I displays the average evaluation metrics for each result, where "Original" and "Inpainted" represent the damaged and restored images compared to the ground truth, and "blur white" refers to a blurry image with a white background, and so on. The proposed model increases PSNR in most cases, especially exposure cases with black plates. The PSNR improves from 5.66 to 15.07. Some restoring examples are shown in Fig. 4 and Fig. 5. Initially, the input is unreadable. After the stage 1, the contours become more apparent. Subsequently, in the stage 2, noise is removed, and details are restored to get a complete restoration of the license plate.

IV. Conclusion

In this paper, we proposed LPRS, which categorizes license plates into black and white backgrounds, restored blurry, overexposed, and over-dark license plates, and raised PSNR and SSIM by 3.8094 and 0.0137.

Acknowledgment

This work is jointly sponsored by Far Eastern Electronic Toll Collection Co. (FETC), Innovation Center for Big Data and Digital Convergence of Yuan Ze University, National Central University, and National Science and Technology Council (NSTC) under the project NSTC 110-2222-E-008-008-MY3.

References

[1] Karel Zuiderveld, "Contrast limited adaptive histogram equalization," *Graphics gems*, pp. 474–485, 1994.

[2] Phillip Isola, Jun-Yan Zhu, Tinghui Zhou, and Alexei A Efros, "Image-to-image translation with conditional adversarial networks," in *IEEE/CVF Conference on Computer Vision and Pattern Recognition*, 2017.

[3] David F Malin, "Unsharp masking.," *AAS Photo Bulletin*, vol. 16, pp. 10–13, 1977.