Robust License Plate Recognition in OCC-based Vehicle Networks using Image Reconstruction

Weiye Zhu*, Ziwei Liu*, Yixin Zuo, Linyue Hu, Yimao Sun, *Member, IEEE*, and Yanbing Yang *Member, IEEE*

***Abstract*—With the help of traffic lights and street cameras, optical camera communication (OCC) can be adopted in the Internet of Vehicles (IoV) applications to realize communication between vehicles and roadside units. However, the encoded light emitted by these OCC transmitters (LED infrastructures on the roadside and LED-based headlamps embedded in vehicles) will bring stripe patterns in image frames captured by existing license plate recognition systems. Since the OCC stripes dramatically interfere with the license plate feature, the accuracy of the recognition system is severely affected. In this paper, we propose and experimentally demonstrate a method that is able to reduce the interference of OCC stripe patterns in the image frames captured by the license plate recognition system. We innovate a pipeline scheme with an end-to-end image reconstruction module to learn the distribution of the image without OCC stripes and provide high-quality license plate images for recognition under OCC circumstances. In order to solve the problem of insufficient data, we model the OCC strips as multiplicative noise and propose a method to synthesize a pairwise dataset under OCC using the existing license plate dataset. Moreover, we also build a prototype to simulate real scenes of the OCC-based vehicle networks and collect data in such scenes. Overall, the proposed method can achieve a recognition performance of 81.58% and 72.12% on the synthesized dataset and that captured from real scenes respectively, which is improved by about 31.18% and 23.14% respectively compared with the conventional method.**

***Index Terms*—Internet of vehicles, optical camera communication, license plate recognition, computer vision.**

I. Introduction

COMBINING the visible light communication (VLC) technology with cameras, optical camera communication (OCC) systems provide both multiple functionalities including data communications [1]–[3], with LED lighting infrastructures as transmitters and embedded cameras (e.g., smartphone cameras) as receivers [4], [5]. Due to its feasibility of deployment, the OCC systems have been widely investigated for the Internet of Vehicle (IoV) applications, whether the Vehicle-to-Vehicle (V2V) or the Infrastructure-to-Vehicle (I2V) and the Vehicle-to-Infrastructure (V2I) [6]–[9].

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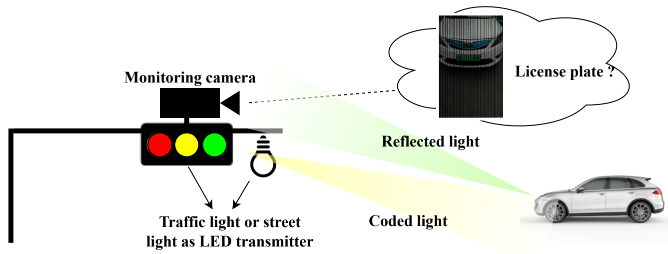

Fig. 1. In applications of the IoV that adopt OCC, license plate recognition cameras can be interfered with by coded light emitted by OCC devices, thus the recognition performance is affected.

Considering that more and more vehicles are being fitted with LED-based headlamps, optical camera communication is adopted in V2V communications to transmit information including the given vehicle longitude, latitude, and safety information [10], [11]. Besides, note that camera-based traffic monitoring systems are already available and deployed in many cities [12], OCC systems can also be used as the V2I or the I2V communication networks with the help of traffic lights and roadside infrastructure [1], which can be seen as the cornerstone technology enabling the construction of the future-generation highly functional and intelligent transportation system [13]. The camera is often fixed on the roadside as a receiver, and a typical example of the roadside unit receiver is the road camera which is originally designed to perform other functions such as capturing images for license plate recognition (LPR). The shutter speed of the cameras should be more than twice as fast as the frame rate to realize secure OCC [14], and the existing road cameras often set the exposure time to less than 0.001 seconds to avoid capturing blurry images when the targets are moving at an excessive speed [15].

These optical camera communication infrastructures adopted in applications of the IoV(such as LED infrastructure on the roadside and LED-based headlamps embedded in vehicles) transmit information via switching the LED on and off with a high frequency exceeding the perception of the human eye [5], while the monitoring camera-based OCC receivers embedded in the license plate recognition system will yield bright-dark bands in captured frames owing to receiving the LED transmitted information via the rolling shutter effect [5], [16], [17]. Fig. 1 describes a typical scenario where LED-based infrastructure on the roadside (e.g. traffic light or streetlight) is the optical signal transmitter that conveys visual information to the driver and digital information to the receiver embedded in vehicles [18], then the monitoring camera plays the role of OCC receiver to capture image frames including reflected light formed OCC stripes and license plates. Although the stripe patterns represent optical signals and can be decoded for information transmission, the bright and dark stripes dramatically interfere with the feature of the license plate, and occupy a large area in the captured frames, easily misleading the license plate recognition system to produce an incorrect result, thus severely degrading the performance of the existing license plate recognition systems and other applications or infrastructures in the IoV that adopt optical cameras. Some works also proved that these bright and dark stripes caused by OCC are strong interferences on computer vision tasks like object recognition [16], [19].

In this article, we propose and demonstrate a simple and effective license plate recognition scheme with an advanced image reconstruction (IR) module to achieve the restoration of local pixel details of the image corrupted by OCC stripes. The image reconstruction module involves an end-to-end deep denoising network trained to learn the distribution of the images without OCC stripes. To solve the problem of insufficient data in the scenarios of the OCC-based vehicle networks, we model the OCC noise as multiplicative noise and propose a method to synthesize a pairwise dataset under OCC using the existing license plate dataset, we also build a prototype and collect data to evaluate the performance in real scenes of the OCC-based vehicle networks. We conduct extensive experiments and the results show that the proposed method significantly repairs the local details of the corrupted license plate. The reconstructed license plate frames achieve an average recognition accuracy of about 80% under various experimental settings.

The rest of the paper is organized as follows. We give a brief related work summary in Section II. Section III presents the architecture of our license plate recognition scheme and introduces each main module in this scheme respectively. Section IV explains the implementations including a prototype and dataset building. Section V reports the performance of the proposed scheme in terms of detection accuracy and recognition accuracy, and then discusses the experimental results. Finally, Section VI concludes the whole paper.

II. Related Work

Owing to the convenience of deployment, the OCC systems have been extensively utilized in applications of the IoV. Nguyen *et al.* [20] propose an integration of OCC and cloud-based communication for the IoV to achieve fast communication and ensure safety in the vehicular environment. In their work, the architecture exchanges information on the basic status of vehicles and some emergency messages. The cloud server store and broadcast information in the vehicle network. Cheng *et al.* [21] propose a LED detection algorithm based on deep learning to reduce the inference signals in captured images from environmental factors. They adopt a lightweight backbone to detect the LED positions of vehicles at different communication distances with efficient computation. Moreover, the LED segmentation recognition algorithm is optimized to reduce the bit error rate and enhance the reliability of the OCC system in the IoV. Ali *et al.* [6] propose a method that uses OCC to realize pothole detection and road banking angle estimation by measuring the angle between the two rear LEDs of a vehicle. In their work, the OCC is expected to provide advanced driver assistance functions in addition to communication in applications of the IoV. However, these works mostly focus on expanding the application scenarios of OCC in the IoV or improving the security and efficiency of communication in OCC systems in the IoV, while ignoring the interferences on the visual functions of the infrastructures of optical cameras caused by OCC systems during the information transmission.

As for stripe noise elimination in image recognition, some researchers propose to use filter-based methods to eliminate noise stripes in images. For example, Zhang *et al.* [22] construct a kind of adaptive frequency filter based on 2-D fast Fourier Transforms for image de-striping. Münch *et al.* [23] combines wavelet and Fourier analysis to eliminate the horizontal or vertical stripes in images. Lee *et al.* [24] use a method built upon a framework that includes denoising and rectification to get the high-quality license plate image from the low-quality one. Moreover, a method is proposed to leverage optimization with the auxiliary tasks for multi-task fitting and novel training losses. They view high-quality images as ground truths and obtain low-quality images through downsampling for training. Besides, aiming to eliminate the impact of noise and get high-quality images free from varying lighting due to other car beams and street lights, some works consider the simultaneous enhancement for nighttime license plate images by integrating the ability of quotient image for overcoming the illumination variations and the homomorphic filtering for removing noises under one framework [25]. Nevertheless, these methods either focus on removing noise of known distribution or manually reduce the quality of license plate images for recovery, while current license plate recognition systems are interfered with by OCC stripe patterns, these stripes emerge a non-temporal variation and belong to an uncertain distribution, thus current works are unable to cope with this challenge effectively.

III. LPR scheme in vehicle network

Fig. 2 briefly shows the proposed pipeline scheme architecture and modules for the vehicle networks enabled by OCC technology. The scheme is composed of three main components: the image reconstruction module, the license plate detection module, and the license plate character recognition module. Firstly, the images captured by the LPR cameras in the OCC-based vehicle networks with a mixture of vehicle objects and OCC stripe patterns are fed into the image reconstruction module to generate images without the interference of OCC stripe noise, then the reconstructed images are fed into the license plate detection module to build affine matrixes that transform the certain square area into the warped license plate region [26]. After the region of the license plate is extracted, perspective transformation is adopted to rectify the distorted license plate due to oblique views into a positive perspective. At

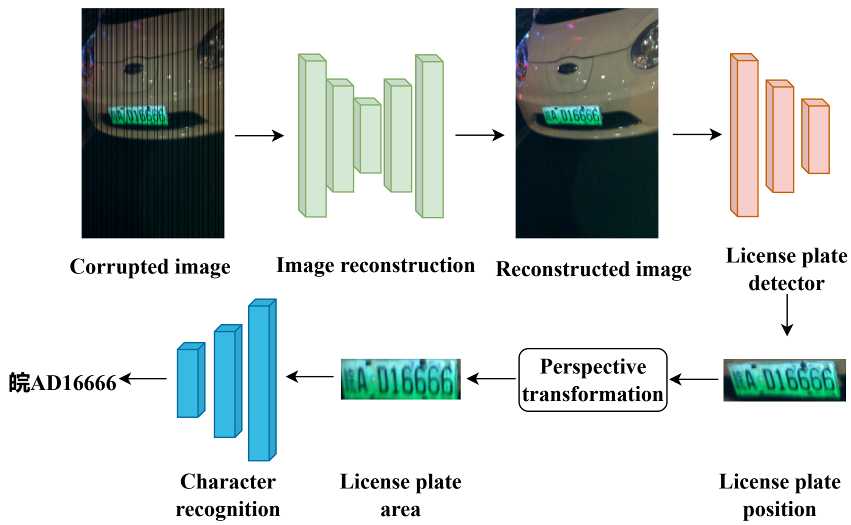

Fig. 2. Diagram of proposed license plate recognition scheme workflow in the vehicle networks with integrated image reconstruction module.

last, the license plate character recognition module recognizes the text information from the view-corrected license plate. These modules make up the proposed license plate recognition scheme that is suitable for the OCC-based vehicle networks, and we will detail them in the following sections.

A. Image Reconstruction Module for Corrupted License Plate

In the OCC-based vehicle networks, the captured corrupted images contain the mixture (or overlapping) with the original image and the OCC stripe patterns. Here let $\mathbf{x_{original}}$ be the image without OCC stripes and $\mathbf{y}$ means the corrupted image.

For the image reconstruction module, we adopt the NAFNet [27] structure which could achieve great denoising performance and computationally efficiency at the same time using the classic single-stage U-shaped architecture with skip connections. Moreover, the NAFNet uses a convolution network instead of a transformer in the stacked blocks considering that depthwise convolution is simpler than the self-attention, it also replaces the ReLu activation function [28] with designed SimpleGate which directly divides the feature map into two parts in the channel dimension and multiply them:

$$\mathit{SimpleGate}(\mathbf{X}, \mathbf{Y}) = \mathbf{X} \odot \mathbf{Y}, \tag{1}$$

where $\mathbf{X}$ and $\mathbf{Y}$ are feature maps divided in channel dimension of the same size and $\odot$ means the element-wise multiplication. Then the channel attention is replaced with simplified channel attention (SCA) in order to further simplify the whole structure and its complexity in the calculation:

$$\mathit{SCA}(\mathbf{X}) = \mathbf{X} * W_{pool}(\mathbf{X}) \tag{2}$$

where *pool* indicates the global average pooling operation which aggregates the spatial information into channels. With the preparations above, the NAFNet accepts the corrupted image captured in the OCC-based vehicle networks $\mathbf{y}$ as input and gives an estimation of the clean image written as $\mathbf{x_{recon}}$. Since ℓ_2 loss gets stuck more easily in a local minimum while ℓ_1 could get a better minimum [29], we choose Charbonnier penalty function [30], [31] as the loss function, for it could get better performance and require fewer iterations compared with the ℓ_2 loss function [31]. Here it can be implemented as:

$$\mathit{loss}(\mathbf{x_{recon}}, \mathbf{x_{original}}) = \sqrt{\|\mathbf{x_{recon}} - \mathbf{x_{original}}\|^2 + \epsilon^2}, \tag{3}$$

where ϵ is a constant that maintains the gradient of loss function presence and smooth convergence. The module is trained on patches set as 256×256 cropped from images randomly, and is tested on the full-resolution images. Notedly, this operation brings performance degradation and patch boundary artifacts if we choose to test on patches. To solve the problem, we adopt the Test-time Local Converter (TLC) to convert the global operations in the network to local operations only during inference [32].

B. Reconstructed License Plate Detection Module

License plates are usually captured as irregular quadrilaterals during the recognition process, in order to appropriately capture the shape of the license plate, the license plate detection module adopts the Wpod-Net [26] which accepts the vehicle images as input and results in an 8-channel feature map, these parameters in the 8-channels indicate whether there exists an object to be detected at each point in the feature map and coefficients for affine transformations.

We first consider an image of a vehicle with $\boldsymbol{p}_i = [x_i, y_i]$, for $i = 1, 2, 3, 4$ as the four corners of the area of a license plate, and let $\boldsymbol{q}_1 = [-0.5, -0.5]^T, \boldsymbol{q}_2 = [0.5, -0.5]^T, \boldsymbol{q}_3 = [0.5, 0.5]^T, \boldsymbol{q}_4 = [-0.5, -0.5]^T$ be the corresponding vertices of a canonical unit square centered at the origin. For each point (m, n) in the $M \times N$ feature map, Wpod-Net give 8 values and the first two values indicate the confidence concerning the existence of objects, and the last six values are then used to build the affine transformation T_{mn}:

$$T_{mn}(\boldsymbol{q}_i) = \begin{bmatrix} max(v_3, 0) & v_4 \\ v_5 & max(v_6, 0) \end{bmatrix} + \begin{bmatrix} v_7 \\ v_8 \end{bmatrix}, \tag{4}$$

where the v_i represent the sorted 8 values, and then the $\boldsymbol{p}_i$ is re-centered according to the point (m, n) in the feature map:

$$A_{mn}(\boldsymbol{p}_i) = \frac{1}{\alpha}\left(\frac{1}{N_s}\boldsymbol{p} - \begin{bmatrix} n \\ m \end{bmatrix}\right), \tag{5}$$

where α is a scaling constant that represents the side of the fictional square and N_s represents the total stride of the downsampling process of the network, thus the whole loss function of Wpod-Net can be expressed as:

$$\begin{aligned} loss(\boldsymbol{p}, \boldsymbol{q}, v) &= \sum_{m=1}^{M}\sum_{n=1}^{N}[\mathbb{I}_{obj} f_{affine}(m, n) + f_{probs}(m, n)] \\ &= \sum_{m=1}^{M}\sum_{n=1}^{N}[\mathbb{I}_{obj}\sum_{i=1}^{4}\|T_{mn}(\boldsymbol{q}_i) - A_{mn}(\boldsymbol{p}_i)\|_2 \\ &- \mathbb{I}_{obj} log(v_1) + (\mathbb{I}_{obj} - 1) log(v_2)], \end{aligned} \tag{6}$$

the loss function first makes the warped unit square and normalized annotated points close enough and then measures the confidence concerning the object's appearance in a certain point with the cross-entropy function.

Normally, the object to be detected is considered at the point of (m, n) if its rectangular bounding box presents an IoU larger than the given threshold, and $\mathbb{I}_{obj}$ in the loss function is a state function which returns 1 if the object exists or returns 0 otherwise [26]. After obtaining the inference of the location of the license plate, we then adopt perspective transformation to rectify the possibly distorted license plate due to oblique views into a positive perspective, and this function was built with the help of OpenCV [33].

C. License Plate Character Recognition Module

After locating the specific plate area, the next process is character recognition. Character segmentation is often used in traditional text recognition algorithms such as fixed character spacing, connected component analysis and so on [34]. However, possible errors in segmentation may affect the recognition process, thus degrading the accuracy of the entire module [34]. Compared with algorithms that require character segmentation, the algorithms without character segmentation processes could effectively avoid these errors considering the complex distribution of noise in the OCC-based vehicle networks. The segmentation-free methods transform the license plate recognition problem into a character sequence labeling problem utilizing the global information of the input image. Li *et al.* [35] uses bidirectional RNNs and CTC loss to label the sequential feature, later Li *et al.* [36] uses a convolutional neural network to get features of the input and then the LSTM is trained to recognize text features. Inspired by these works, we adopted a CNN [37]+Transformer [38] based character recognition module, where the CNN extracts the image features and the transformer is used to decode these features into text.

IV. Implementation and Dataset

A. Prototype and Network Training

To verify our idea, we build a prototype as shown in Fig. 3. Specifically, to simulate the LED infrastructures on the roadside in the OCC-based vehicle network systems, we use a 30W LED luminaire as the OCC system transmitter which is controlled by an ARM Cortex-M4 GD32F330G8U6 microcontroller to generate the digitally controlled signal for light modulation. On the receiver side, we employ Redmi K40 to capture modulated light reflected from the observation plane with different parameter settings.

As for the software settings, we adopt the NAFNet architecture with a width of 32 in the image reconstruction module, the number of stacked encoder blocks and decoder blocks are $2, 2, 4, 8$, and $2, 2, 2, 2$ respectively. The module is trained for 200 epochs upon patches size 256×256 randomly cropped from the original images using AdamW [39] optimizer with $\beta_1 = 0.9, \beta_2 = 0.9$, the initial learning rate is $1e^{-3}$ and gradually reduces to $1e^{-6}$ with the cosine annealing schedule [40].

To obtain a detection model with better generalization ability, we adopt ResNet-18 [41] as the feature extraction module of Wpod-Net. We first train the model upon the CCPD-base dataset [42] which has over $200,000$ unique images with annotations for LPR, and then fine-tune on the CCPD-db dataset which is a subset of the whole CCPD dataset and contains over $10,000$ images where the illuminations are dark or uneven. We also adopt random Gaussian noise for data augmentation to improve the robustness of the module. After locating the area of the license plate, we then adopt the license plate character recognition module to recognize the characters on the license plate. The license plate character recognition module consists of a ResNet structure and two stacked transformer blocks with hidden dimensions of 512, and is trained for over $10,00$ epochs. Since it is unrealistic to collect substantial labeled license plate images for the license plate character recognition module, we randomly generate simulated license plate images which are annotated during the generation process.

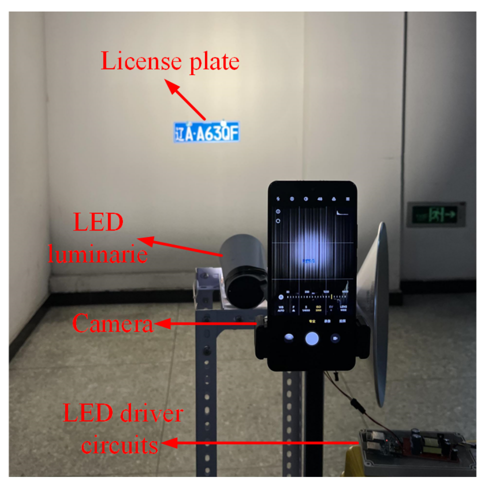

Fig. 3. We build a prototype that consists of a 30W LED to simulate the LED infrastructures on the roadside in the OCC-based vehicle network, and a Redmi K40 to simulate the LPR camera. We use this prototype to collect frames that are then used to build our dataset.

B. Dataset

To train the image reconstruction module, we need a pair-wise dataset that contains the OCC noised images and clean images. As there is no available public dataset for license plate recognition under the interference of OCC, we first design a method that adopts the existing license plate recognition dataset (such as the CCPD) to build a new dataset for our work as shown in Fig. 4. Mathematically, let $\mathbf{x}_{\mathbf{original}}$ be the clean image from the license plate dataset without the inference of OCC and $\mathbf{x}_{\mathbf{occ}}$ means the stripe pattern noise under the interference of OCC, then we build the corrupted image $\mathbf{y}$ as:

$$\mathbf{y} = \mathbf{x}_{\mathbf{original}} \odot \mathbf{x}_{\mathbf{occ}}, \tag{7}$$

where $\odot$ means the element-wise multiplication.

The noise of stripe structure can distort the brightness of the original frames in multiplicative form according to the difference in the distribution of its gray values, thus generating the visual effects of the background objects interfered by the OCC light, so these captured frames were used as multiplicative noise to build a pairwise dataset with the CCPD dataset. We remove some images of poor quality and randomly choose $1,000$ images from CCPD-db to test and use the rest to build the pairwise dataset and train the image reconstruction module.

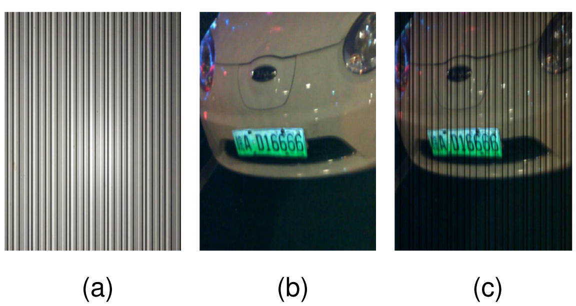

Fig. 4. Synthesize a dataset of OCC noise and original image. (a) OCC noise. (b) Original image. (c) Synthesized image.

Moreover, to evaluate the performance of the proposed scheme in real scenes of the OCC-based vehicle networks, we also adopt the prototype to make a dataset in these scenes as shown in Fig. 5. Given the variety of distances and angles between the vehicle and the license plate recognition system in such scenes, we mainly explore the impact of distance and angle changes between the license plate and the camera on system performance. For each combination of the two parameters, we collect 200 images, so the dataset end up containing about 1600 images.

V. Experimental results and discussions

In this section, we extensively evaluate the performance of the proposed license plate recognition scheme on the synthesized dataset and in real scenes of the OCC-based vehicle networks, the baseline is defined as directly detecting and recognizing the license plate in OCC images. We first attempt to adopt the band-pass filter to eliminate the OCC stripes in images, the band-pass filter converts the OCC noised image from the time domain to the frequency domain via fast Fourier transform, then uses a filter to remove the features related to OCC stripes. To quickly verify the OCC noised image restoration performance, we show a visualization comparison

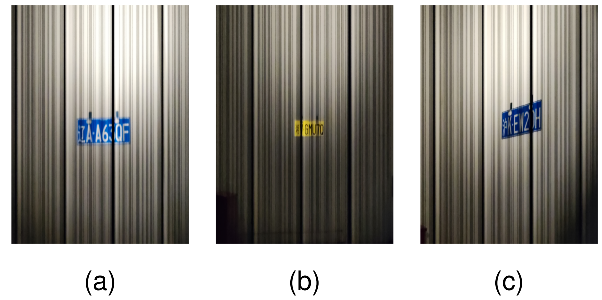

Fig. 5. Examples of the captured dataset from real OCC-based vehicle network scene. (a) Distance 2m, angle 0°. (b) Distance 4m, angle 0°. (c) Distance 3m, angle 60°.

between the band-pass filter method and the IR module as shown in Fig. 6. We can find that the band-pass filter method results in distortions in some pixel spaces and brings gray stripes, while the IR module basically eliminates the occlusion of stripes leaving a clean license plate. In particular, the peak signal-noise-ratio (PSNR) scores of the recovered images by our IR module are almost over 30dB, getting an improvement of about 8.84dB over the band-pass filter method, which is able to preliminarily demonstrate the effectiveness of the proposed scheme in terms of mitigating OCC's negative effect on license plate recognition, we report the performance of the proposed license plate recognition scheme in detail following.

A. License Plate Detection (LPD) Accuracy

As we have to locate the license plates the in received frames before recognition in the OCC-based vehicle networks, we first report the license plate detection accuracies. In our experiments, the bounding box of a license plate is considered to be detected when its IoU with the ground truth bounding box is more than 70%. We mainly explore how the camera's ISO, shutter speed, and data rate impact license plate detection performance, and results are shown in Fig. 7. Generally, the average license plate detection accuracies are close to 97.75% without OCC stripes interference under all settings. However, the stripe pattern caused by the OCC-based vehicle networks has a negative effect on license plate detection accuracy, hence the baseline's performance is dramatically degraded, the average detection accuracy has a maximum 54.75% drop, while the proposed scheme has only slight fluctuation in accuracy. Fig. 7a further shows the results under increasing ISO with a fixed shutter speed of $1/3200$s and data rate at 4kbps, we can find that the detection accuracy of the image reconstruction module is 97.23% on average, which is 6.92% higher than the accuracy of band-pass filter method. Fig. 7b reports the results under varying shutter speeds with fixed ISO of 3200 and 4kbps transmission rate. The average accuracy of baseline is 70.18%, and the band-pass filter method improves the accuracy to 90.20% while the IR module brings an improvement to 96.82%.

Additionally, we can find that the varying ISO and shutter speed settings barely affect the detection accuracies after the image reconstruction module, the results prove that the image

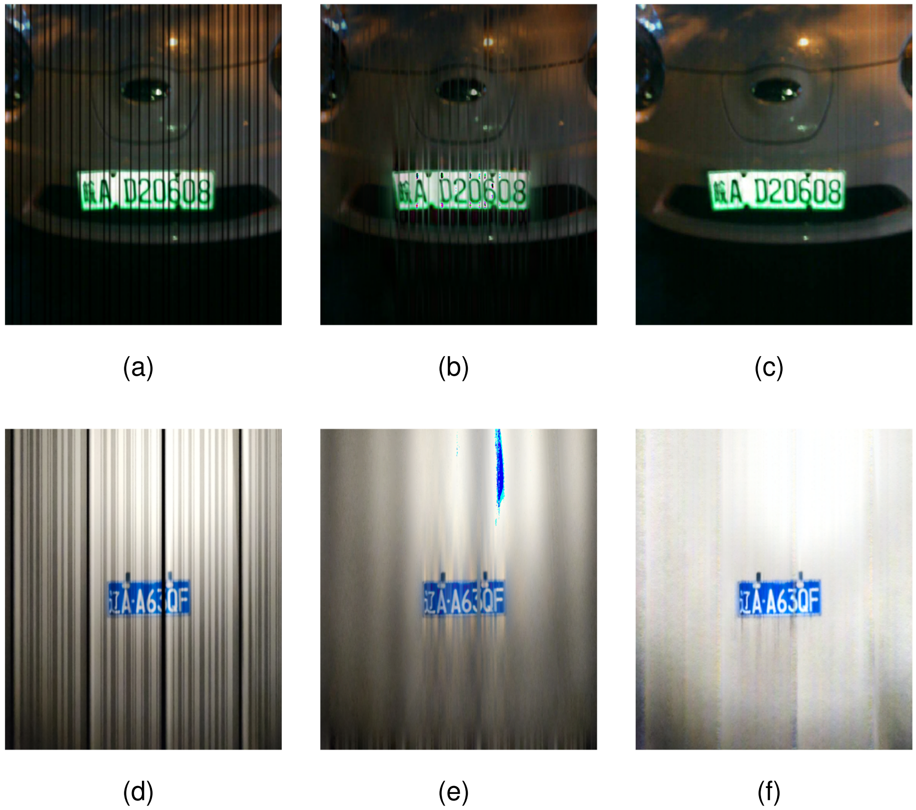

Fig. 6. A visualization comparison on synthesized image and real scene image. (a) Synthesized OCC image. (b) Result of band-pass filter on the synthesized dataset. (c) Result of IR module on the synthesized dataset. (d) Real scene OCC image. (e) Result of band-pass filter in real scenes. (f) Result of IR module in real scenes.

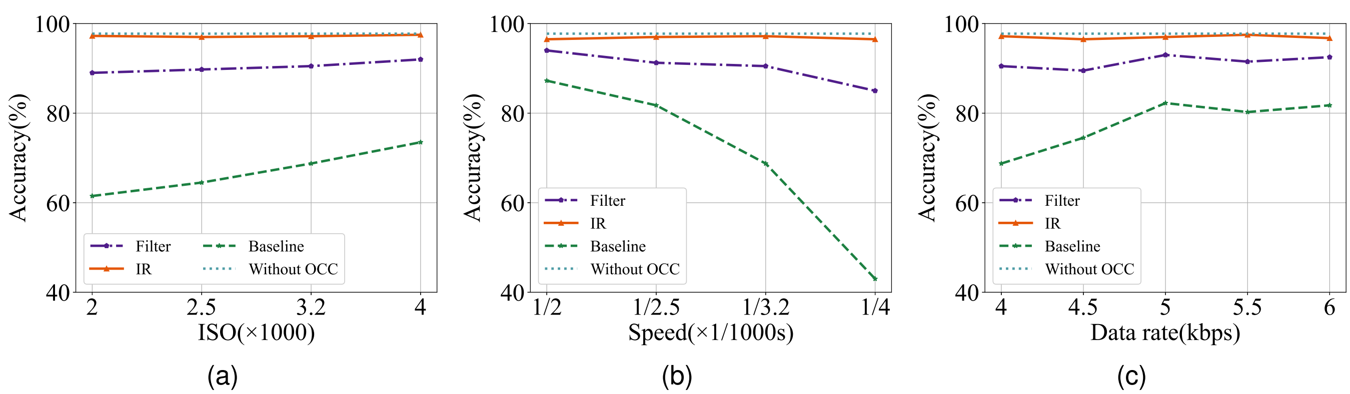

Fig. 7. Detection accuracy under varying settings on the synthesized dataset. (a) Increasing ISO. (b) Increasing shutter speed. (c) Increasing data rate.

reconstruction module is suitable for scenes with different camera parameter settings. We further explore the constructive effect of the band-pass filter method and IR module under varying data rates with fixed 3200 ISO and $1/3200$s shutter speed as shown in Fig. 7c. It can be seen that the average detection accuracy of the band-pass filter method is 91.4%, while the IR module is 96.98%. It should be noted that a low data rate more likely leads to poor detection accuracy, as shown in the baseline's result under 4kbps. It can be explained that a lower data rate means wider OCC stripes in captured images, hence increasing the difficulty of image restoration, while the image reconstruction module maintains high detection accuracies under varying data rates.

The above results strongly verify that our image reconstruction module can effectively improve the license plate detection accuracy under the interference of the OCC stripes in the OCC-based vehicle networks, and has a better performance than the band-pass filter method.

B. License Plate Recognition (LPR) Accuracy

1) LPR accuracy on the synthesized dataset: We first evaluate the license plate recognition accuracy of the proposed scheme on the synthesized dataset. Specifically, we explore the impact of various ISO, shutter speed, and data rates on recognition accuracy, and results are shown in Fig. 8. The average LPR accuracy under various experimental settings is about 92.50% without OCC interference. However, the recognition accuracy of the baseline is only 32.88% on average, proving that the OCC stripes have a significant negative impact on the LPR accuracy in the OCC-based vehicle networks.

Fig. 8a shows the recognition accuracy of the band-pass filter method and our IR module under increasing ISO with a fixed shutter speed of $1/3200$s and 4kbps data rate, we find that the average recognition accuracy of our IR module is 77.61% on average, which is 33.05% higher than the band-pass filter method. Besides, we also study the gain of the band-pass filter method and IR module bring to the recognition accuracy under varying shutter speeds where the ISO is fixed to 3200 and the data rate is fixed to 4kbps. As is shown in Fig. 8b, the band-pass filter method makes the accuracy increase from 34.31% to 50.56% on average, while the recognition of our IR module is 30.24% higher than the band-pass filter method. The recognition accuracy of both the band-pass filter method and IR module tend to raise with the ISO increasing and the shutter speed slower, it can be explained that higher ISO and slower shutter speed means more received light intensity, thus promoting the salience of license plate features. Further, we explore the positive effect of the two methods under different data rates with a fixed ISO of 3200 and a shutter speed of $1/3200$s. It can be seen in Fig. 8c that the average recognition accuracy of the band-pass filter method and IR module are 54.95% and 85.39% respectively. We find that the accuracy of the baseline slightly increases as the data rate increases, and by contrast, the IR module is more insensitive to varying data rates, the recognition accuracy of the IR module hardly changes much no matter how the data rate varies. The result above demonstrates that the image reconstruction module is more robust than the baseline and the band-pass filter method, hence having the potentiality to be applied in real scenes of the OCC-based vehicle networks.

2) LPR accuracy in real scenes: We further evaluate the proposed license plate recognition scheme in real scenes of the OCC-based vehicle networks. Considering the IR module's recognition accuracy is relatively insensitive to varying ISO, shutter speed, and data rates as studied in the synthesized dataset, we fixed them as 3200, $1/3200$s, and 5 kbps respectively. We mainly explore the impact of distance and angle between the license plate and receiver to mimic the realistic scenario of the OCC-based vehicle networks, and results are shown in Fig 9. As illustrated in Fig. 9a, the average recognition accuracy of the IR module is 76.07% under varying distances, significantly exceeding the band-pass filter's 57.59% and the baseline's 32.86%. Furthermore, we find that the results of all methods have a slight drop in relatively close recognition distances, it can be explained that close distances lead to light saturation in captured images, thus degrading the recognition accuracy, this problem can be readily solved by setting automatic adjustment of camera ISO. Meanwhile, longer distance makes it more difficult to recognize the area of the license plate, this problem can be addressed by adding a lens to the LED or increasing the LED power, these adjustments can increase the recognition distance of the system to over ten meters in real scenes of the OCC-based vehicle networks. In our experimental scenario, we finally conclude that the 3 m is the most optimal recognition distance, and fix the distance for the following experiment. We then explore the recognition accuracy under varying angles between the license plate and receiver, and results are shown in Fig. 9b. We find that a larger angle increases the difficulty of recognition, thus reducing the accuracy. For example, in our experiments, we find that the system incorrectly recognizes the character 'D' as '0' when the angle is set to $60°$ like a human-made error. On the whole, the proposed image reconstruction module can achieve a recognition performance of 72.12% in real scenes of the OCC-based vehicle networks with various settings of the distances and angles between the license plate and receiver, which is 23.14% higher than the band-pass filter method. It strongly confirms that our scheme is more feasible in real scenes of the OCC-based vehicle networks than the conventional band-pass filter method.

VI. CONCLUSION

To deal with the problem that existing license plate recognition systems in potential applications of the IoV may be affected by OCC, we propose a pipeline scheme with an image reconstruction module to repair the pixels damaged by

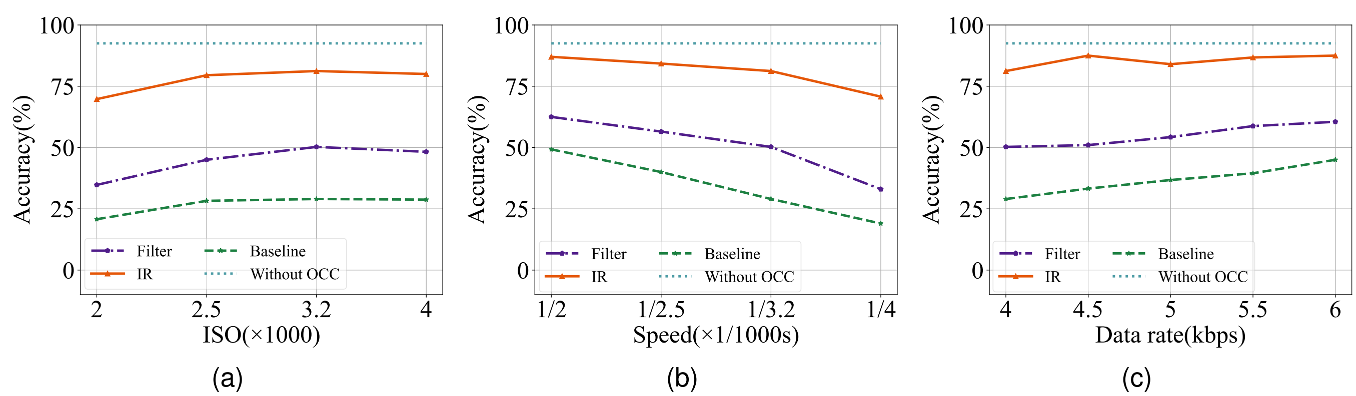

Fig. 8. Recognition accuracy with different settings on the synthesized dataset. (a) Increasing ISO. (b) Increasing shutter speed. (c) Increasing data rate.

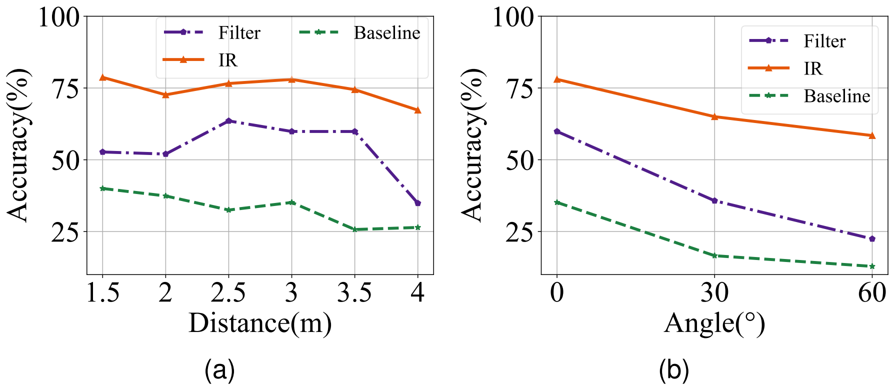

Fig. 9. Recognition accuracy under varying experiments in real scenes of the OCC-based vehicle networks. (a) Increasing distance. (b) Varying angle.

modulated light in captured images in the vehicle networks and minimizes the impact of OCC stripes on license plate frames. We separately make a synthesized dataset of OCC noise and original license plate image, and capture realistic license plate frames with OCC stripes via a real scene prototype, to evaluate the performance of our scheme on license plate recognition. Compared with the band-pass filter method, the experimental results show the proposed image reconstruction module can improve the detection accuracy by over 6.31% on the synthesized dataset. The recognition accuracy is improved by more than 31.18% on average on the synthesized dataset and 23.14% in real scenes, which strongly demonstrates the effectiveness of the proposed scheme. Besides, our image reconstruction takes up less than 110M of storage space and has the potential to be embedded into existing license plate recognition systems and other applications in the IoV. We are actively seeking relevant scenarios in the OCC-based vehicle networks for deploying the proposed scheme to promote the development of intelligent traffic.

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