Super-resolution Restoration of Single Vehicle Image Based on ESPCN-VISR Model

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Abstract. In the process of image acquisition monitoring in vehicle license plate recognition system, the accuracy of license plate recognition will decrease which is caused by the complicated application scenarios, poor performance of the equipment and system, and the degeneration of surveillance images. In order to overcome the shortcoming, a super-resolution restoration method for single vehicle image based on efficient sub-pixel convolutional neural network (ESPCN) model is proposed (hereinafter referred to as ESPCN-VISR method). In the experiments, ESPCN-VISR method was proved to be superior by four indexes of quantitative assessment which are peak signal to noise ratio (PSNR), structural similarity (SSIM), vehicle license plate recognition accuracy (VLPRA), and calculation time of reconstruction (CTR). Compared with the methods based on sparse dictionary learning and deep convolutional neural network SRCNN, the ESPCN-VISR method can improve the performance of vehicle license plate recognition system with vehicle license plate sample image dataset LPI-1000.

1. Introduction
In vehicle license plate recognition system, the task of super-resolution restoration technology application is aiming at the increase of license plate recognition accuracy. There are the following disadvantages such as the complicated application scenarios, poor performance of the equipment and system, and the degeneration of surveillance images in the process of image acquisition monitoring in vehicle license plate recognition system. Through signal and information processing (software) to restore and reconstruct the high resolution target images, the clearer images can be provided for vehicle license plate recognition and the accuracy of license plate recognition will be improved. Currently the super-resolution restoration methods applied to vehicle license plate recognition system are mostly based on the reconstruction and shallow learning (e.g., the method based on sparse dictionary learning). The application of super-resolution reconstruction method based on deep learning developed in vehicle license plate recognition system research has still rare been reported[1-4]. Compared with multi images super-resolution, the advantages of single image super-resolution reconstruction are simpler process and faster speed. In order to further improve the image reconstruction quality, reconstruction calculation time and other super-resolution restoration performance indicators, in this paper, the vehicle-license plate sample image training set LPI-1000 dataset was specially constructed, and a single vehicle image super-resolution restoration method based on ESPCN model (referred to as ESPCN-VISR method) was proposed.

2. The Construction of Vehicle License Plate Image Dataset: Training Set and Test Set
In order to show the better performance of vehicle license plate recognition by the proposed method, the LPI-1000 dataset was specially constructed. The dataset with 1000 vehicle license plate images
sample data is divided into 7 classes, which include different models, shooting angle, distance, fuzzy degree, day/night and rain and fog, image size and resolution, image luminance and chrominance, that reflect as far as possible the characteristics information of image block or video frame of license plate of all kinds of types. Partial sample images of LPI-1000 dataset are shown in Figure 1. Parts of LPI-1000 dataset is divided into training set LPI-1000/train (500 images) and test set LPI-1000/train (500 images).

3. The Proposed ESPCN-VISR Model
Referring to an efficient sub-pixel convolutional neural network (ESPCN) architecture proposed by Wenzhe Shi et al.[5], ESPCN-VISR model of super-resolution for vehicle image was designed as a 4-layer network structure, which is divided into three convolutional layers and one sub-pixel convolutional layer. The network architecture of ESPCN-VISR model is shown in Figure 2.

Input images of ESPCN-VISR are 3-channel JPG image format and firstly converted from RGB (red, green and blue) color space to YCbCr (an international video standard) color space before training. The first layer of convolution uses a total of 64 convolution kernels with $5 \times 5$, and outputs the feature images of 64 channels after convolution. In the second layer, a total of 32 convolution kernels with $3 \times 3$ is used to convolve the 64-channel feature map of the previous layer, and the output images is 32-channel. The third layer uses a total of $3 \times r^2$ convolution kernels with $3 \times 3$, and the convolution
output $3 \times r^2$ feature images. Finally, the sub-pixel convolution layer is used to reconstruct the super-resolution image from the feature image\[4, 5\]. The parameters of ESPCN-VISR model are listed in Table 1. ESPCN-VISR model was trained under Tensorflow platform which is a deep learning integrated running environment. 1 GB GPU version was used, and the algorithms were developed in Python3.5.2 programming language.

### Table 1. The parameters of ESPCN-VISR model.

| Parameter                        | Value | Parameter                        | Value |
|----------------------------------|-------|----------------------------------|-------|
| Batch-size                       | 32    | Learning rate                    | 0.001 |
| Epoch                            | 100   | Sub-image size                   | 17×17 |
| Image size preprocessing:        |       | Step length cutting              | 9     |
|                                  |       | Edge                             | 8     |

LPI-1000/train training set (500 images) of license plate images were selected for training, and the training process of ESPCN-VISR model converged to a stable state before 100 epochs.

### 4. Performance Evaluation of ESPCN-VISR Algorithm

#### 4.1. Evaluation of Algorithm Performance Using Conventional Quantitative Indicators

The performance of ESPCN-VISR algorithm was evaluated through simulation experiments, and was compared with three super-resolution restoration algorithms including bicubic interpolation, sparse dictionary learning SDL\[6\] and deep convolutional neural network SRCNN\[7\]. From the seven categories of LPI-1000 dataset, 3 sample images were selected for each category, with a total of 21 vehicle images. The process of image degradation is that gaussian blur is applied to the sample image firstly, then twice down-sampling is conducted to obtain 21 degraded vehicle images. In the simulation experiments, the algorithm based on deep convolutional neural network (SRCNN) and the ESPCN algorithm based on single vehicle image (ESPCN-VISR) were trained and tested by LPI-1000/train and LPI-1000/test datasets.

Conventional quantitative indexes were used to evaluate the performance of each super-resolution algorithm. PSNR, structural similarity (SSIM) and calculation time of reconstruction (CTR) are listed in Table 2.

### Table 2. The average of PSNR, SSIM and CTR for vehicle images by different algorithms.

| Evaluation index | Algorithm            | Bicubic interpolation | SDL      | SRCNN    | Proposed algorithm |
|------------------|----------------------|-----------------------|----------|----------|--------------------|
| PSNR (dB)        |                      | 25.82                 | 27.40    | 28.27    | 28.46              |
| SSIM             |                      | 0.9182                | 0.9423   | 0.9433   | 0.9445             |
| CTR (s)          |                      | 0.650                 | 183.0    | 0.386    | 0.020              |

Based on the evaluation of the bicubic interpolation algorithm, SDL algorithm based on sparse dictionary learning, SRCNN based on deep convolutional neural network, and ESPCN-VISR based on single vehicle image are successively superior to the bicubic interpolation algorithm. By comparison, the recovery quality and reconstruction speed of ESPCN-VISR algorithm is the best. From Table 2, it can be seen that the proposed algorithm has the largest PSNR value (28.46dB) and SSIM value (0.9445). This show that the proposed algorithm has the best reconstruction performance which is beneficial for vehicle plate recognition.
4.2. Performance Evaluation of the Algorithm Using the Accuracy Index of License Plate Recognition

The super-resolution of vehicle or license plate image are served to the vehicle license plate recognition system, and the evaluation of image quality should also aim at improving the accuracy of license plate recognition. Therefore, the accuracy rate of license plate recognition VLPRA is designed to be used as the quantitative evaluation index and verified in EasyPR Chinese license plate recognition experimental system.

4.2.1. EasyPR-SR Chinese license plate recognition experimental system. EasyPR (easy to do plate recognition) is an open source license plate recognition software system. EasyPR system is developed by C++ language, which is based on the open source OpenCV (open computer vision) computer vision library, and developed by the Chinese team. The system has a interactive graphical interface, and support Chinese license plate recognition and batch image license plate target recognition. The EasyPR-SR Chinese license plate recognition experimental system is specially developed to evaluate the performance of the super-resolution algorithm. A single image recognition software module and a batch recognition software module were developed in the EasyPR-SR experimental system. EasyPR-SR can give the signal of character segmentation of vehicle license plate, the recognition effect of vehicle license plate and the total recognition accuracy. Figure 3 shows the license plate recognition interface of the EasyPR-SR experimental system.

![Figure 3. The license plate recognition interface of EasyPR-SR experimental system.](image)

4.2.2. Simulation experiment and performance evaluation. From the LPI-1000/test set, 120 original images that can be correctly recognized by the EasyPR-SR experimental system were selected, which means that after being sent to the EasyPR-SR experimental system, VLPRA, the accuracy rate of license plate recognition after recognition processing, was 100%.

The degraded images are firstly obtained from the 120 images by gaussian blur and twice down-sampling degradation. Then superresolution images are reconstructed by bicubic interpolation, SDL algorithm based on sparse dictionary learning, SRCNN algorithm, ESPCN-VISR algorithm of a single vehicle image reconstruction, respectively. After reconstruction by each algorithm, images are sent into EasyPR system for identification and statistics. The statistics of the results by the EasyPR -SR are listed in Table 3.

It can be seen from Table 3 that the EasyPR-SR system has an accuracy rate of 100% for the license plate recognition of the original HR image. Because the resolution of the degraded images is reduced, the recognition effect is significantly lower than that of original HR images. The average license plate recognition accuracy VLPRA using ESPCN-VISR algorithm reached 79.46%, while the Chinese character recognition error rate dropped to 14.05%. Compared with other algorithms, ESPCN-VISR algorithm is more helpful to improve the accuracy rate of license plate recognition.
Table 3. The average of VLPRA index by different algorithms in the EasyPR-SR experimental system (%).

| Evaluation index | Images sent to EasyPR-SR experimental system |
|------------------|---------------------------------------------|
|                  | Original | Degradation | BIC  | SDL  | SRCNN | Proposed |
| Recognition accuracy VLPRA | 100      | 70.48       | 74.00 | 77.08 | 79.14  | 79.46     |
| Error rate of Chinese character recognition | 0        | 21.91       | 18.00 | 17.19 | 14.97  | 14.05     |

5. Conclusion
Aiming at the super-resolution restoration of single vehicle monitoring image in the vehicle license plate recognition system, the ESPCN-VISR method proposed in this paper was verified by multiple simulation experiments and EasyPR-SR system experiments. According to four quantitative indexes including PSNR, SSIM, VLPRA and CTR, ESPCN-VISR method was superior. Especially, ESPCN-VISR takes only 20ms to calculate the reconstruction, which can meet the embedded application of front-end device of video monitoring system. The performance of the VLPRA is also optimum, which can provide support for the performance improvement of vehicle license plate recognition system. Therefore, the application of super-resolution reconstruction method based on deep learning in vehicle license plate recognition system research is worthy of study.

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