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# Fuzzy License Plate Recognition Based on Recurrent Convolutional Neural Network and Generative Adversarial Network

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## Abstract

Fuzzy license plate recognition is a difficult problem in the field of license plate recognition. In view of the difficulties in collecting fuzzy license plate images, the large license plate recognition algorithm model, and the shortcomings of mobile or embedded devices, this paper proposes a lightweight fuzzy license plate recognition method, which uses deep convolutional generation adversarial network to generate fuzzy license plate images. The algorithm mainly consists of two parts, namely fuzzy license plate image generation based on optimized convolutional generation adversarial network and lightweight license plate recognition based on deep separable convolutional network and bidirectional long short-term memory. Combined with the lightweight license plate recognition model with depth separable convolution, the recognition rate is comparable to that of the license plate recognition method based on the standard convolutional recurrent neural network (CRNN) after being improved by the images generated in this paper. However, the size and recognition speed of the model are better than that of the standard CRNN model, which is used to solve the problem that it is difficult to collect fuzzy license plates in the real scene, and improves the recognition accuracy of the algorithm while improving the deployment generalization ability. Using generative adversarial network to generate images can effectively solve the problem of insufficient fuzzy license plate image samples. Combined with the depth separable convolution of lightweight license plate recognition model, it has good recognition accuracy and better deployment generalization ability.

**Keywords:** Fuzzy license plate recognition; recurrent convolutional neural network; generative adversarial network; deep separable convolutional network

## 1. Introduction

License plate recognition is one of the important applications in the field of intelligent transportation and computer vision. As the main identifier of motor vehicles, license plate recognition algorithms need to be efficient and fast in traffic control, electronic payment, criminal investigation and other fields [1-3]. At present, most license plate recognition algorithms can achieve a good recognition effect for clear license plate images, but for fuzzy license plate images, the recognition effect needs to be further improved.

With the continuous development of deep learning, it has brought new research directions for license plate recognition. Thanks to the strong ability of convolutional neural networks to extract image features and the good contextual learning ability of recurrent neural networks to input targets, Alghyaline et al. [4] used these methods to gradually move the license plate recognition process from the segmentation based method to the end-to-end recognition method. However, the license plate recognition using deep learning algorithm has two difficulties: 1) The size of the model is much larger than that of the traditional license plate recognition algorithm. Because the license plate recognition algorithm needs to be deployed in mobile devices or embedded devices in many applications, the model is too large, which limits the algorithm's deployment generalization ability. Therefore, the measurement between recognition efficiency and model size becomes one of the difficulties in using deep learning technology to solve license plate recognition problems. 2) The deep learning algorithm requires a large amount of training data, but license plate recognition is a task with regional characteristics [5,6]. Different countries and regions have certain differences in the local license plate design specifications, and the universality of images is not good. If a large number of license plate images are collected manually in each region, the cost is too high. Therefore, the lack of training images has become another difficulty in using deep learning technology to solve the task of license plate image recognition.

Generative adversarial network [7], as one of the typical networks of deep learning technology, has been one of the research hotspots of most researchers due to its outstanding performance in image generation tasks. Various generative adversarial network models have been used to generate ultra-high quality images. Although generative adversarial networks have achieved impressive results, there is little research on the use of generative adversarial networks to generate "low-quality" images for other deep learning tasks that lack training samples. In this paper, a lightweight fuzzy license plate recognition algorithm is proposed by using generative adversarial networks to generate "low quality" fuzzy license plate images.

Taking domestic license plate recognition as the entry point, the main contributions of this paper are as follows: 1) Aiming at the difficulty of manual license plate collection, it is proposed to use the license plate image generated by the generation adversarial network to fill the training set required by the recognition model, so as to solve the problem of insufficient training samples; Wasserstein distance [8,9] loss is used to optimize the convolutional generation adversarial network, which not only ensures the quality of the original image generation, but also greatly improves the training stability of image generation, that is, the generated images have good diversity and fewer duplicate samples. 2) On the basis of convolutional recurrent neural networks [10,11], combined with deep separable convolutions [12-14] designed a lightweight license plate recognition model. Compared with the basic convolutional recurrent neural network, under the condition of improving the recognition accuracy, the size of the final recognition model is effectively compressed, which greatly improves the recognition speed of the license plate and enhances the practical value of the algorithm.

## 2. Related works

### 2.1 License plate recognition task

The existing license plate recognition algorithms can be divided into segmentation based recognition algorithms and segmentation free recognition algorithms. The segmentation based license plate recognition algorithm firstly divides the characters in the license plate image into a single character by the segmentation algorithm, and then uses the classifier to recognize each character. Segmentation algorithms mainly include projection-based segmentation algorithms [15,16] and a segmentation algorithm based on connected regions [17,18], using template-based matching after segmentation [19,20] algorithm or learn-based algorithm classifies the segmented individual characters. Among them, learn-based algorithms include support vector machines, improved hidden Markov features, and neural networks, because of its ability to learn image features, the final recognition effect is better than the recognition algorithm based on template matching. However, the segmentation based license plate recognition algorithm is subject to the segmentation performance of the segmentation algorithm, and will also lose the overall information inside the license plate image. It can still meet the practical requirements for the clear license plate recognition effect, but for the fuzzy license plate image, its recognition ability is not satisfactory. Segmentation free license plate recognition algorithm, also known as end-to-end recognition algorithm. Ma et al. [21] proposed a convolutional recurrent neural network based on sliding Windows for segmentation free recognition of license plates. However, the use of sliding window to extract license plate image will eventually lead to a huge amount of computation of the whole network model, and the deployment cost of the algorithm in practical application is too high. Tang et al. [22] adopted the combination of convolutional neural network and recurrent neural network to extract image features first, then convert feature maps into feature sequences, and input them into the bidirectional long short-term memory (LSTM) network for learning. Thus, an end-to-end recognition effect is achieved, but the network calculation parameters of this method are large, and the size and speed of the final recognition model still have further optimization space.

In this paper, the license plate recognition algorithm uses depth-separable convolution to improve the standard convolution in the convolutional neural network. Instead of using the sliding window, the features of the entire license plate image are directly extracted, and then input into the bidirectional LSTM network for marking and prediction. On the one hand, free segmentation makes use of the overall information of the license plate image, which can achieve better recognition effect, especially for fuzzy license plate. On the other hand, the network based on the separable convolutional layer can reduce the model size and improve the recognition speed, so that the algorithm has a good efficiency. Finally, the proposed algorithm is combined with EasyPR and convolutional recurrent neural network (CRNN). The two license plate recognition algorithms are compared from the aspects of recognition speed, recognition accuracy and recognition model size, among which EasyPR is a segmentation based license plate recognition algorithm, while CRNN is a segmentation free license plate recognition algorithm.

**2.2 Generative adversarial network (GAN)**

The concept of generative adversarial network (GAN) was first proposed by Goodfellow et al.. Inspired by the idea of zero-sum game, a generative model and a discriminant model are set up in the artificial neural network, and the discriminant model and the generative model are trained at the same time, so that the two can compete with each other in the training process. Finally, the distribution of samples generated by the generative model in the sample space gradually approximates the distribution of real samples in the sample space. Convolutional generative adversarial network uses deconvolution layer and convolutional layer in generative model and discriminant model, which makes the whole network generate better effect on the basis of the original.

Wang et al. [23] proposed conditional GANs, which adjusted the generation model and discriminant model so that the network could generate images with specific label classes. Perarnau et al. [24] used GANs to construct text-to-image or image-to-image generation conditioned on text descriptions and images conditioned on images. DeVries et al. [25] designed new training strategies and loss calculation methods based on GAN networks, which improved the stability of network training and the diversity of generated samples. In addition, GANs have made remarkable achievements in the field of image restoration. However, GANs are mainly used to generate high-quality images, and there are few researches on using GAN-generated images to fill some early training sets of deep learning with few samples, and even fewer applications and researches on generating low-quality images. Taking license plate recognition as an example, license plate images involve regional issues and personal privacy issues, and it is difficult to collect a large number of manual images. In this paper, GANs are used to generate "low-quality" fuzzy license plate images, and then these generated images are used to fill the training data set required for license plate recognition models. Experiments show that using Wassetstein distance loss to improve the loss function in the convolutional generation adversative network can make the generated license plate images more diverse and stable, and using the generated images as training samples can effectively improve the accuracy of fuzzy license plate recognition.

## 3. **Proposed Method**

In this paper, the image generation adversarial network is first trained with real license plate samples, then a large number of license plate images are generated using the trained adversarial network, and finally the validity of the generated license plate samples in the recognition task is verified. The generative adversarial network consists of two sub-networks, generator and discriminator, and its training process is a minimization and maximization game process: both sub-networks aim to minimize their own loss functions and maximize other loss functions. As the algorithm converges, the images generated by the generator become more realistic. In this paper, Wasserstein distance loss is used to improve the convolutional generation adversarial network, which improves the diversity and stability of the generated images.

In the convolutional generation adversary-network, the structure of the discriminator is composed of 4 layers of full convolutional network, no pooling layer is set behind the convolutional layer, but the convolution kernel with step length and size of 5 × 5 is used in the convolutional layer for convolution operation, instead of the feature graph downsampling, the discriminator uses LeakyReLU as the activation function. The generator is composed of 4 deconvolution layers and uses 5×5 convolution kernel for deconvolution operation. Use backpropagation to update weights for generators and discriminators during training. The schematic diagram of the generator structure is shown in Figure 3. Firstly, a 100-dimensional vector z is randomly extracted from the latent layer space and converted into a tensor of 4×4×1024. Then, an image of 64×64×3 is formed through 4-layer deconvolution operation (convolution kernel is 5×5). Based on deepconvolutional adversarial networks (DCGAN), the convolutional adversarial network in this paper modifies the network structure of generators and discriminators. The loss calculation method of generator and discriminator is followed, that is, the game centered on the training of convolutional generative adversarial networks is as follows:

$$\min_G \max_D V(D,G) = E_{x\sim p_r(x)}(logD(x)) + E_{z\sim p_g}(log(1-G(z))) \tag{1}$$

Where $V(D,G)$ represents the difference degree between the real sample and the generated sample, $E$ is the expected value, $x$ represents the input image, $z$ represents the noise of the input generator, $G(z)$ represents the image generated by the generator, $D(x)$ represents the probability of the discriminator judging whether the input image is the real image, and $p$ represents the distribution of the sample. The training process of generating adversarial network is the process that the distribution of generated samples in space approximates to the distribution of real samples in space. DCGAN uses Jensen-Shannon (JS) divergence and Kullback-Leibler (KL) divergence to measure the distance between two samples.

The license plate recognition algorithm based on character segmentation is limited by the segmentation performance of the segmentation algorithm, and can not recognize the fuzzy license plate well. The segmentation free recognition algorithm can retain the overall information inside the license plate image and is not affected by the segmentation results, which has certain advantages for fuzzy license plate recognition. However, the traditional segmentation free license plate recognition algorithm using deep learning needs to be further improved in terms of recognition speed due to the excessive parameters calculated by the network. At the same time, the final recognition model of such methods is too large and is not suitable for deployment to embedded devices or mobile devices, limiting the practical value of the algorithm.

In order to improve the efficiency of fuzzy license plate recognition and reduce the deployment cost of the algorithm, this paper proposes a lightweight fuzzy license plate segmentation free recognition algorithm. The algorithm flow is shown in Figure 1. First, the license plate image is input into the convolutional neural network to extract the feature map. In the convolutional neural network, depth-separable convolution is used instead of standard convolution to reduce the amount of computation in the network, and then the final model size is reduced. After obtaining the feature map of the license plate image, it is converted into the feature sequence, and the bidirectional recurrent neural network is used to learn and predict the feature sequence extracted by the convolutional neural network.

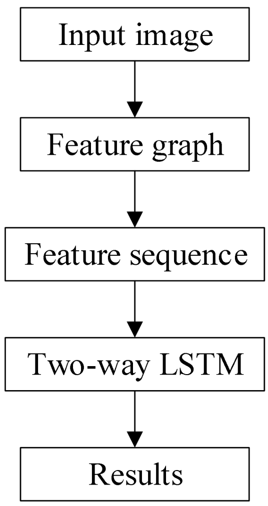


Figure 1. Flow chart of license recognition

The recognition process in this paper consists of three parts: feature sequence extraction, learning and prediction, corresponding to the convolutional layer, loop layer and decoding layer in the network respectively. The overall configuration of the network is shown in Table 1, where K, S and P are the convolution kernel size, stride and padding size respectively.

Table 1. Deep separable convolutional recurrent neural network configuration

| Layer | Configuration |
|---|---|
| Input | 160×48×3 RGB car plate |
| conv | K:3×3, S:1, P:1 |

| | |
|---|---|
| Depthwise conv | K:3×3, S:2, P:1 |
| Pointwise conv | K:1×1, S:1, P:0 |
| maxpooling | K:1×2, S:1×0 |
| Depthwise conv | K:1×1, S:1, P:0 |

## 4. Experimental setup

Two traditional license plate recognition algorithms, EasyPR and standard CRNN, were selected to verify the effectiveness of the generated samples for the training of the recognition algorithm. A total of four experiments were conducted, 5000 sample images were used as the training set each time, and 200 real license plate images were selected for the test, in which the ratio of clear and fuzzy images was 1:1, and the image size was normalized to 160 ×48 pixels, without modifying network parameters, increase the proportion of fuzzy license plate images generated in the training samples successively, train EasyPR and CRNN networks respectively, and compare the recognition rate RA. The experimental results are shown in Table 2.

Table 2. RA results with different number of the generated fuzzy license plate image/%

| Samples | EasyPR | CRNN |
|---|---|---|
| 4700 clear+300 blur | 53.8 | 91.4 |
| 4000 clear+1000 blur | 60.4 | 93.2 |
| 4000 clear+1000 blur | 67.1 | 95.6 |
| 2000 clear+3000 blur | 75.3 | 97.9 |

As can be seen from Table 2, EasyPR's recognition framework adopts a segmentation based license plate recognition scheme, so its overall recognition rate is much lower than the segmentation free recognition method. However, by adding the generated fuzzy license plate samples, the recognition rate is increased from 53.8% to 75.3%. CRNN network is a segmentation free recognition algorithm. When the training sample lacks fuzzy license plate, its recognition rate is better than EasyPR. By adding fuzzy license plate samples generated, the recognition rate is increased from 91.4% to 97.8%. Through the two sets of experiments, it can be seen that if the image generated by the generator is used in the training of the recognition network, the overall recognition rate of the recognition network is of great help, and the problem of difficult collection of training samples can be solved.

## 5. Conclusions

This paper presents a lightweight fuzzy license plate recognition method combined with generated images. Wasserstein distance loss optimization of convolutional generative adversarial network is used to optimize the problems of gradient disappearance and lack of diversity of generated samples in the training process of deep convolutional generative adversarial network, which improves the stability of network training and the efficiency of image generation. The generated images are used to fill the training set of the recognition algorithm, and it is verified that the generated samples can assist the training of the algorithm, which improves the recognition effect of the algorithm in this paper and other algorithms. It can solve the problem that fuzzy license plates are difficult to collect a large number of manual data, and provides a new solution for many deep learning research problems lacking data. This network structure is relatively simple, and the performance of the task of generating vehicle license plate images is reasonable, but for some images with rich details and textures, the quality of the generated samples needs to be improved. A lightweight license plate recognition scheme based on depth-separable convolution is improved with CRNN. On the basis of ensuring recognition accuracy, a depth-separable convolution network combined with bidirectional recurrent neural network is used to realize end-to-end recognition. After extracting the feature map of the input image, each column of pixel values is converted into feature vector from left to right pixel by pixel and input into a bidirectional LSTM network for learning, combined with the powerful learning ability of recurrent neural network to serialize input objects, no need to segment the vehicle license plate characters. To realize the high efficiency recognition of vehicle license plate including fuzzy license plate. Compared with CRNN, the size of the recognition model is nearly doubled on the basis of the original compression, and the recognition speed is nearly doubled.

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**Conflict of Interest**

The authors declare no conflict of interest.

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