Research and Application of License Plate Recognition Technology Based on Deep Learning

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Abstract. There are many types of vehicle license plates in China, including new energy license plates, large truck license plates, government vehicle license plates, and military license plates. The existing commercial license plate recognition system only targets common license plates and does not completely cover the full range of license plates. Therefore, this paper proposes an SSD-based end-to-end license plate recognition system (LPR-SSD). The LPR-SSD network architecture consists of upper and lower classification networks: the upper layer network is used for vehicle license detection and classification, and the lower layer network is used for license plate character detection and classification. In order to enhance the generalization performance of the LPR-SSD network, in addition to the real license plate image captured by the camera, this paper synthesizes 50K simulated license plates for each type of license plate according to the legal document [1]. Experiments show that LPR-SSD achieved a faster convergence speed during training. After the test set verification, the accuracy of license plate location detection and classification reaches 98.3%, and the character recognition accuracy rate reaches 99.1%.

1. Introduction

With the advancement of industrialization, vehicles have become the preferred means of transportation for people to go out. There are also higher requirements for the task of license plate recognition. The license plate recognition is mainly divided into two parts, one is to accurately locate the license plate in the picture, and the other is to perform character recognition on the positioned license plate. In order to improve the accuracy of license plate location and character recognition, academic researchers and commercial companies have implemented a series of license plate recognition methods that have color-based [2], texture-based [3], edge detection based [4], and template-based matching [5]. Nowadays, many papers [7, 8, 10, 11, 15] propose a method based on deep learning. The method of using the convolutional neural network to extract the license plate and character features for positioning and recognition is more robust than the traditional method [10]. The paper [6] proposed a license plate location method based on contour features, and used a deep learning model for character recognition in character recognition tasks. A. Abd et al. [7] performed pre-processing on the correction of the picture, and then used CNN for character segmentation, which increased the recognition time. Huang. Z.J. et al. used two different neural networks (VGG-16 and ResNet-50) to integrate Faster-RCNN [9] in [8] to realize the task of locating the vehicle logo. Recurrent neural networks (RNNs) with long short-term memory (LSTM) are trained to recognize the sequential features extracted from the whole license plate via CNNs [10]. Xu, Z.B. et al. [11] used a self-built data set to train a convolutional neural network based on Faster R-CNN for detecting and locating license plates. Under...
the existing object detection model, the migration learning method is used to train license plate recognition [12]. Although these methods avoid character segmentation, the license plate recognition system does not completely cover all categories in the task of identifying multiple types of license plates in China. In the natural environment, the license plate imaging is complicated, the license plate characters are complex, the font size is different, and the colors are different, as shown in Figure 1.

![License Plate](image1.png)

Figure 1. License plate in different situations

Figure 2. LPR-SSD identifies the license plate

These problems are not well handled in the deep learning methods that have been proposed. The main contributions of this paper are summarized as follows: Convolutional neural networks show excellent performance and generalization capabilities in terms of license plate location. This paper proposes an SSD-based license plate recognition system for identifying various types of license plates in China. The license plate recognition is decomposed into two subtasks: license plate location and classification. It can be seen from Fig. 2 that the upper layer of the network architecture adopts an SSD-based object detection algorithm, and a new feature extraction layer and a classification layer are designed to detect the position of the license plate and output the classification result of the license plate. The lower layer network classifies the input license plate image. The two convolutional neural networks are combined to achieve an end-to-end license plate recognition process without split characters.

2. The Proposed Method for License Plates Detection

Figure 3. LPR-SSD network architecture. The license plate detection feature extraction layer consists of 5 convolution layers and one max pooling layer. The feature map for each convolutional layer output is used for the offset of the default box and the prediction of the different license plate category scores. On these feature maps, training and prediction of license plate location and classification are performed to achieve multi-scale detection. After the feature of the license plate is extracted, the license plate position and the license plate type are output. Finally, through the Non-Maximum Suppression (NMS) screening, the final positioning and classification results are output.
In the field of image processing, the method based on convolutional neural network has made remarkable achievements in the subject of object detection, such as Faster-RCNN [9], YOLO [14], SSD [13] and so on. Faster-RCNN, YOLO and SSD are very effective convolutional neural network architectures for object detection. The comparison of the three network architectures is as follows: (1) Faster-RCNN uses a sliding window mechanism based on selective search, which is computationally intensive for each proposal region. Recognition speed is not as fast as YOLO and SSD; (2) Although YOLO can achieve real-time effects, each network can only predict one object, which is easy to cause missed detection. In addition, the generalization ability of objects with large scale changes is poor; (3) SSD borrows the idea of YOLO and the idea of the anchor box of Faster R-CNN, and utilizes the characteristics of multi-layer network to achieve multi-scale detection, and takes into account mAP and Real-time requirements; (4) Unlike Faster-RCNN's first extraction of the proposal region, the SSD uses the anchor to directly classify and bounding box regression. The network architecture diagram of LPR-SSD is shown in Figure 3.

3. The Proposed Method for License Plate Recognition

The second step in license plate recognition is to identify the characters on the license plate, i.e., character recognition. Traditional character recognition schemes use character segmentation and identify each character separately. This non-end-to-end recognition method will cause error accumulation. On the contrary, some researchers use end-to-end character recognition schemes to eliminate such errors, and like to recognize character recognition as sequence recognition [15]. The disadvantage of this scheme [15] is that character sticking will cause recognition errors and affect the recognition result.

| Category       | Content                                      | Total |
|----------------|----------------------------------------------|-------|
| Chinese character | Provinical abbreviations and other abbreviations[1] | 73    |
| Digital        | 1234567890                                   |       |
| Alphabet       | ABCDEFGHIJKLMNOPQRSTUVWXYZ (Without I and O)  |       |

The solution proposed in this paper is to treat character recognition as a regression classification problem, and output each character as a category. From the first step, we got a license plate with different colors, different sizes, different characters and possibly containing distortion, tilt, blur and other noise. Next, a deep convolutional neural network for character detection and classification is constructed using the target detection scheme. The LPR-SSD network treats each character as an object to be detected and performs training classification. The order of the output class names is the number of the license plate. It can be known from [1] that the number of characters required for LPR-SSD regression classification is 73. Table 1 lists all the characters. Figure 4 shows the partial sample character recognition classification result and confidence percentage.

![Figure 4. Character recognition results and confidence percentage ratio.](image1)

![Figure 5. Location and classification of license plate detection and its percentage of confidence.](image2)
4. Experiments Results

4.1 Data set
The role of the big data set is to enable the convolutional neural network model to summarize the license plate characteristics law to obtain a stronger generalization ability. In order to accurately locate and classify multiple license plates in a natural scene image, the data set contains 16 types of license plates. In order to enhance the data set, uncommon license plates were synthesized by technical means, and these license plates were randomly added to operations such as twisting, fogging, and tilting. Table 2 shows the types and quantities of license plates.

| No. | Class | Number of real license plates | Number of synthetic plates | Remarks |
|-----|-------|-------------------------------|----------------------------|---------|
| 1   | EP_D52009 | 28320                        | 50K                        | New energy vehicle license plate (A) |
| 2   | A_B2532  | 30956                        | 50K                        | General car license (B)            |
| 3   | Q_E2732  | 22453                        | 50K                        | Truck head license plate (C)       |
| 4   | K0433    | 1865                         | 50K                        | Police car license plate (D)       |
| 5   | AA_0042  | 265                          | 50K                        | Consulate License Plate (E)       |
| 6   | 0_26100  | 259                          | 50K                        | Embassy license plate (F)         |
| 7   | GB_Y80U5 | 385                          | 50K                        | Coach car license plate (G)       |
| 8   | D_RE32   | 455                          | 50K                        | Guangdong and HK license plates (H)|
| 9   | K_0312   | 375                          | 50K                        | Guangdong and Macau license plates (I)|
| 10  | AE88Y2   | 149                          | 50K                        | Ordinary black license plate (J)  |
| 11  | T_3500B  | 345                          | 50K                        | Armed Police License Plate (K)    |
| 12  | H_V2032  | 0                            | 50K                        | Army license plate (L)            |
| 13  | B0254    | 2689                         | 50K                        | Truck tail license plate (M)      |
| 14  | F58Y2    | 1441                         | 50K                        | Hangable license plate (N)        |
| 15  | J00U6    | 256                          | 50K                        | Armed Police License Plate (O)    |
| 16  | S73R9    | 0                            | 50K                        | Army license plate (P)            |

4.2 Training process
Inspired by the anchor of Faster R-CNN, SSD uses the concept of default box. After the feature map of the convolution output, each point corresponds to the center point of an area of the original image. Based on this point, two kinds of default boxes with different width and height ratios (in accordance with the license plate aspect ratio) are constructed. The default box is to match the ground truth box on the license plate. The default box and the ground truth box IOU greater than 0.5 are selected as positive samples. Others are used as negative samples. In order to speed up the training and convergence, the positive and negative ratios are set to 1:3 according to the probability order of each box category. Finally, the default box whose category probability is lower than the threshold (0.7) is filtered out, and then the NMS non-maximum value suppression is used to filter out the default box with higher overlap. The final output sample is shown in Figure 5.

4.3 Loss function
The loss function is divided into two parts: calculating the confidence of the corresponding default box and target category and calculating the corresponding position regression result. Confidence is achieved with Softmax Loss and position regression with Smooth L1 loss. Equation (1) is the total Loss function.
\[ L(x,c,l,g) = \frac{1}{N} (L_{\text{conf}}(x,c) + \alpha L_{\text{loc}}(x,l,g)) \]

Where: \( N \) represents the number of positive samples.

\[ L_{\text{loc}}(x,l,g) = \sum_{i \in \text{Pos}} \sum_{m \in \{c,x,y,w,h\}} x_{iy}^k \text{smooth}_{L_i}(l_i^m - \hat{g}_{ij}^m) \]

\[ \hat{g}_{ij}^c = (g_{ij}^c - d_{ij}^c) / d_i^c, \hat{g}_{ij}^y = (g_{ij}^y - d_{ij}^y) / d_i^y \]

\[ \hat{g}_{ij}^w = \log \left( \frac{g_{ij}^w}{d_i} \right), \hat{g}_{ij}^h = \log \left( \frac{g_{ij}^h}{d_i} \right) \]

\[ L_{\text{conf}}(x,c) = - \sum_{i \in \text{Pos}} x_{ip}^p \log \left( \hat{c}_i \right) - \sum_{i \in \text{Neg}} \log \left( \hat{c}_i \right) \]

Where

\[ \hat{c}_i = \frac{\exp(c_i^p)}{\sum_p \exp(c_i^p)} \]

### 4.4 Result analysis

This part of the analysis evaluates the performance and accuracy of the LPR-SSD network model on self-built test sets. Model training experiments were performed on 6G GeForce GTX 1070 and Intel(R) Core(TM) i7-7700 CPU @ 3.60GHz and 16G RAM. Table 3 shows the recall rate and accuracy of the test set on the LPR-SSD, as well as the identification time and frame rate of the single license plate.

| Performance of LPR-SSD on test set. |
|--------------------------------------|
| **Location and classification**      |
| 98.30                                |
| 95.44                                |
| 38                                   |
| 55                                   |
| **Character recognition classification** |
| 99.10                                |
| 94.67                                |
| 69                                   |
| 58                                   |
| **Class-A**                          |
| 99.61                                |
| 96.78                                |
| 25                                   |
| 60                                   |
| **Class-B**                          |
| 99.74                                |
| 97.45                                |
| 29                                   |
| 60                                   |

In addition, Class-A and Class-B are the most common types of license plates in daily life, so the identification efficiency of these two types of license plates is specifically tested, as shown in Table 3.

### 5. Conclusion

In this paper, we propose a SSD-based end-to-end identification license plate recognition system for all types of Chinese license plates in the natural environment. The LPR-SSD network is a combination of two SSD-based networks. It mainly optimizes the classification layer for the license plate and removes the full connection layer to improve the efficiency of positioning and classification. Different from the previous license plate recognition network system, the idea of this paper is based on target detection and classification, and the license plate recognition is divided into two parts. The first part is the location and classification of license plate detection, and the second part is the location and classification of character detection. The experimental results show that the modified network architecture accelerates the convergence speed through the training of a large amount of data, and also has a high classification accuracy. The system achieves the most advanced performance in terms of recognition speed and recognition accuracy, meeting the requirements of real-time detection.
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