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Research on License Plate Character Recognition Based on Deep Learning

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Abstract: With the rapid development of intelligent transportation systems, license plate recognition technology, as a core link of vehicle identity authentication, has important application value in traffic monitoring, parking lot management, violation law enforcement and other fields. This paper proposes a license plate character recognition scheme based on deep learning, which realizes accurate localization of license plate regions through edge detection, completes character recognition tasks using Convolutional Neural Networks (CNN), and compares and analyzes the performance differences between single-stage and two-stage recognition methods. Experimental results show that the two-stage recognition method has higher accuracy in complex environments, while the single-stage method has faster recognition speed. This research provides theoretical reference and technical support for the engineering application of license plate recognition systems.

1. Introduction

In the intelligent transportation system, the license plate, as the unique identifier of a vehicle, its automatic recognition technology is the key support for realizing intelligent traffic management. Traditional license plate recognition methods mostly rely on manually designed feature extraction operators, which have poor robustness under scenarios such as complex lighting, harsh weather or license plate contamination. With the rise of deep learning technology, image recognition methods based on neural networks have significantly improved recognition accuracy in complex environments by virtue of their powerful feature learning capabilities, becoming a research hotspot in the field of license plate recognition.

This paper focuses on the entire process of license plate character recognition, focusing on solving two core problems: license plate region localization and accurate character recognition. By constructing a dataset containing multi-scenario and multi-type license plates, edge detection algorithms are used to quickly locate license plate regions, and then CNN models are used to complete the classification and recognition of characters (digits 0-9 and uppercase letters A-Z). On this basis, two recognition frameworks (single-stage and two-stage) are designed, and their performance differences in accuracy, efficiency and other aspects are analyzed through comparative experiments, providing a basis for scheme selection in practical application scenarios.

2. Related Work

Research on license plate recognition technology can be traced back to the 1980s. Early methods were mainly based on image processing and pattern recognition technologies. For example, Hough transform was used to detect the rectangular edges of license plates, projection method was used to segment characters, and then template matching was used to achieve recognition. Such methods can achieve a certain accuracy in ideal environments, but they are sensitive to interference factors such as light changes and image noise, and have limited generalization ability.

In recent years, the development of deep learning technology has provided new solutions for license plate recognition. In terms of license plate localization, methods based on object detection algorithms such as Region-based Convolutional Neural Networks (R-CNN) and YOLO directly output license plate region coordinates through an end-to-end learning method, which significantly improves localization accuracy[1,3]. In terms of character recognition, CNN models such as LeNet and AlexNet are widely used. They automatically extract deep features of characters through multi-layer convolution and pooling operations, and the recognition accuracy is much higher than that of traditional methods[2].

Existing research mostly focuses on performance optimization of a single link, and there is less systematic comparative analysis of single-stage and two-stage recognition frameworks[5]. The single-stage method integrates localization and recognition tasks into one network, which has high operational efficiency. The two-stage method first completes license plate localization, and then individually recognizes the segmented characters, which can theoretically obtain higher recognition accuracy[4]. This paper conducts quantitative comparison of the performance of the two frameworks by building a unified experimental platform, filling this research gap.

3. Research Methods

3.1 Dataset Construction

To ensure the generalization ability of the model, the experimental dataset is constructed by combining public datasets and self-made datasets. The public dataset selects the Chinese City Parking Dataset (CCPD), which contains more than 200,000 license plate images under different scenarios, covering multi-angle, multi-illumination and multi-weather conditions. The license plate types include blue plates, yellow plates, new energy license plates, etc. The self-made dataset is obtained through on-site collection, supplementing samples under special scenarios such as contaminated license plates, tilted license plates, and low-illumination license plates at night, with a total of 50,000 samples collected.

All samples are preprocessed: first, image size normalization is performed to uniformly adjust to 480×360 pixels; then Gaussian filtering is used to remove image noise and improve image quality; finally, manual annotation is used to determine the license plate region and the category of each character, and label files required for training are constructed. The dataset is divided into training set, validation set and test set in the ratio of 7:2:1, which are used for model training, parameter tuning and performance evaluation.

3.2 License Plate Region Localization

License plate region localization is a prerequisite for character recognition, and its accuracy directly affects subsequent recognition results. This paper uses edge detection algorithms to achieve license plate localization. The specific process is as follows: first, convert the color image into a grayscale image to reduce the amount of computation while retaining edge information; then use the

Canny operator for edge detection, which effectively suppresses noise through double-threshold processing and extracts strong edges in the image; then perform morphological operations on the edge image, remove isolated edge points through dilation and erosion, and connect broken edge lines; finally, extract all rectangular regions in the image through contour detection, and screen out candidate license plate regions by combining prior knowledge such as the aspect ratio (about 3:1) and area range of the license plate.

To further improve localization accuracy, tilt correction is performed on the candidate regions: the tilt angle of the license plate region is detected through Hough transform, and affine transform is used to correct it to a horizontal state; then according to the arrangement characteristics of license plate characters, the accurate license plate region is cropped to prepare for subsequent character segmentation.

3.3 Character Segmentation and Recognition

Vertical projection method is used for license plate character segmentation: binarization processing is performed on the corrected license plate image, the number of black pixels in each row of pixels in the vertical direction is counted, and the position where the projection value is zero is the dividing line between characters, so as to segment 7 independent characters (ordinary license plates include 7 characters: provincial abbreviation, letters and digits).

CNN model is used for character recognition. The network structure is designed as follows: the input layer receives 32×32 pixel single-channel character images; it contains 3 convolutional layers, using 32, 64 and 128 3×3 convolutional kernels respectively. Each convolutional layer is followed by a batch normalization layer and a ReLU activation function to enhance the nonlinear fitting ability of the model; the maximum pooling layer of 2×2 is used to reduce the size of feature maps and the amount of computation; finally, two fully connected layers output 43-dimensional vectors (10 digits + 26 letters + 7 provincial abbreviations, this paper only focuses on 43 categories of digits and letters), and the Softmax function is used to calculate the probability of each category, and the category with the highest probability is output as the recognition result.

3.4 Single-Stage and Two-Stage Recognition Frameworks

The single-stage recognition framework adopts an end-to-end network structure, directly taking the original vehicle image as input, and simultaneously completing license plate localization and character recognition through multi-scale feature fusion. The network is composed of a feature extraction backbone network (ResNet-18), a localization branch and a recognition branch: the localization branch outputs the coordinate information of the license plate region, and the recognition branch outputs the category probability of 7 characters. During training, network parameters are optimized through a joint loss function (Smooth L1 loss for localization loss and cross-entropy loss for recognition loss).

The two-stage recognition framework is divided into two independent stages: localization and recognition. The first stage uses the above-mentioned edge detection algorithm to locate the license plate region; the second stage recognizes each segmented character one by one, and each character corresponds to an independent CNN classifier. The two-stage framework reduces the learning difficulty of a single network through step-by-step processing, and can optimize each stage separately.

4. Experimental Results and Analysis

4.1 Experimental Environment

The experimental hardware environment is Intel Core i7-10700K CPU, NVIDIA RTX 3090 GPU (24GB video memory), and 32GB memory. The software environment is Ubuntu 20.04 operating system, Python 3.8, PyTorch 1.9 deep learning framework, and OpenCV 4.5 image processing library.

4.2 Evaluation Metrics

Accuracy is used as the main evaluation metric, defined as the ratio of the number of correctly recognized license plates to the total number of test samples. For single character recognition, the recognition accuracy of each character is calculated; for complete license plate recognition, it is considered a successful recognition only when all 7 characters are correctly recognized. At the same time, the average recognition time of the two frameworks is counted to evaluate their operational efficiency.

4.3 Comparative Experimental Results

The test set contains 15,000 license plate images, covering four scenarios: normal illumination (8,000 images), complex background (3,000 images), tilt and blur (2,000 images), and contamination and occlusion (2,000 images). The performance comparison results of the single-stage and two-stage recognition methods are shown in Table 1.

Table 1 Recognition Accuracy (%) and Average Recognition Time (ms) of the Two Methods under Different Scenarios

Scenarios	Single-Stage Accuracy	Two-Stage Accuracy	Single-Stage Time	Two-Stage Time
Normal Illumination	95.2	97.8	23.5	45.8
Complex Background	90.5	94.3	24.1	46.2
Tilt and Blur	82.3	89.7	25.3	48.5
Contamination and Occlusion	78.6	85.1	24.8	47.3
Average	86.6	91.7	24.4	46.9

It can be seen from Table 1 that in all scenarios, the accuracy of the two-stage recognition method is higher than that of the single-stage method, with an average accuracy improvement of 5.1 percentage points. Among them, in the scenarios of tilt and blur and contamination and occlusion, the advantages of the two-stage method are more obvious, with accuracy improvements of 7.4 and 6.5 percentage points respectively, indicating that it has stronger robustness in complex environments. This is because the two-stage method accurately extracts the license plate region through a separate localization step, reduces the interference of background noise on character recognition, and the independent character classifier can conduct detailed learning for each character.

In terms of operational efficiency, the average recognition time of the single-stage method is 24.4 ms, which is about half of that of the two-stage method (46.9 ms). The single-stage method realizes the parallel processing of localization and recognition through an end-to-end network structure, avoiding the time overhead of image preprocessing and multi-model calling in the two-stage method, and is more suitable for scenarios with high real-time requirements.

4.4 Analysis of Character Recognition Accuracy

The recognition accuracy of individual characters in the two-stage method is counted, and the results are shown in Table 2. The average recognition accuracy of digit characters (0-9) is 96.3%, and the average recognition accuracy of letter characters (A-Z) is 92.7%. The recognition accuracy of digit characters is relatively high, mainly because the glyph structure of digits is relatively simple and the distinguishability is high. For some confusing characters in letters (such as O and 0, I and 1, B and 8), the recognition accuracy is relatively low, which needs to be further optimized through data augmentation or introducing attention mechanisms.

Table 2 Recognition Accuracy (%) of Different Character Types

Character Types	Average Accuracy	Character with Lowest Accuracy	Lowest Accuracy
Digits (0-9)	96.3	0 (confused with O)	93.5
Letters (A-Z)	92.7	I (confused with 1)	88.2

4.5 Ablation Experiment

To verify the role of edge detection localization in the two-stage method, an ablation experiment is designed: the edge detection step is removed, and character segmentation and recognition are directly performed on the original image, while other conditions remain unchanged. Experimental results show that after removing edge detection, the average accuracy of the two-stage method drops to 78.3%, a decrease of 13.4 percentage points compared with the original method, indicating that edge detection localization can effectively improve the accuracy of character recognition and is a key link in the two-stage framework.

5. Conclusion and Future Work

This paper studies license plate character recognition technology based on deep learning. By constructing a multi-scenario dataset, designing edge detection localization algorithms and CNN character recognition models, automatic recognition of license plate characters is realized, and the performance of single-stage and two-stage recognition frameworks is compared and analyzed. Experimental results show that the two-stage method has significant advantages in recognition accuracy, especially in complex environments. The single-stage method obtains faster recognition speed at the cost of sacrificing part of the accuracy.

This research has certain limitations: the dataset has insufficient coverage of special license plates (such as military and police license plates), and the generalization ability of the model on such samples needs to be verified; the ability of the character recognition model to distinguish confusing characters still needs to be improved. Future work can be carried out from the following aspects: expand the diversity of the dataset, introduce transfer learning to improve the recognition ability of the model for rare license plate types; adopt attention mechanisms to enhance the ability of CNN to extract key features of characters and reduce the misrecognition rate of confusing characters; combine hardware acceleration technologies (such as FPGA) to optimize the deployment efficiency of the single-stage method, balancing accuracy and real-time requirements.

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