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License Plate Recognition in Foggy Conditions: A Survey of Image Dehazing and License Plate Recognition Techniques

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Abstract: License plate recognition in foggy environments is one of the core challenges in Intelligent Transportation Systems (ITS). Fog causes blurred license plate images and reduced contrast, severely degrading recognition accuracy. This paper systematically reviews the key technologies for foggy license plate recognition, covering traditional and deep learning-based image dehazing methods, as well as advances in license plate localization and recognition algorithms, while analyzing their strengths and limitations. The study highlights that current methods face bottlenecks in dynamic fog density adaptation and generalization in extreme weather conditions. Future improvements require multi-modal data fusion and adaptive optimization to enhance performance. This work aims to provide theoretical references for optimizing and deploying license plate recognition technologies in foggy environments.

Keywords: License plate recognition, Image dehazing, Low visibility conditions, Dynamic fog density adaptation, Multi-modal data fusion, Intelligent Transportation Systems (ITS)

1. Introduction

With the acceleration of urbanization, the requirements for real-time and accurate license plate recognition in Intelligent Transportation Systems (ITS) are increasingly growing. However, adverse weather conditions such as fog, rain, and snow significantly degrade the quality of license plate images, causing a sharp decline in the performance of traditional recognition algorithms in low visibility scenarios. Statistics show that the error rate of license plate recognition on foggy days increases by 30%-50% compared to clear days, leading to issues like traffic congestion and the failure of monitoring violations [1,2]. Although current research has made progress in dehazing and recognition algorithms, dynamic changes in fog density and complex background interference remain technical challenges. Therefore, it is urgently needed to systematically summarize the current status and challenges of license plate recognition technology in foggy conditions to promote the development of ITS. This paper advances theoretical breakthroughs in image dehazing and license plate recognition by improving physical models and deep learning architectures. It also explores multimodal data collaborative processing mechanisms in conjunction with computer vision and sensor technology, enriching the intelligent transportation technology system. High-precision license plate recognition can optimize scenarios such as ETC passage and traffic violation capture, reducing manual intervention. Through all-weather license plate monitoring, it can reduce the occurrence of traffic accidents and escape cases on foggy days.

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2. Research status

2.1. Image dehazing

In recent years, improved methods based on the Dark Channel Prior (DCP) have made significant progress. Liu Liping and others proposed an adaptive dark channel prior combined with median atmospheric light for image dehazing to enhance image contrast and clarity of detail information while avoiding image distortion(2025). They introduced an adaptive dark channel prior based on neighborhood brightness, saturation, and standard deviation for dynamic estimation of transmittance; they selected the brightest 10% of pixels and used the median of these pixels in each of the three channels as the atmospheric light value; and combined it with the atmospheric scattering model for image dehazing. The experimental results, measured by visual effect, information entropy, average gradient, and histogram distribution, showed that their method outperformed existing methods in visual effect after processing foggy images, with information entropy and average gradient being more than 2.12% and 5.58% higher than existing methods, respectively, and a more reasonable histogram distribution[3].

In addition to DCP-based methods, researchers have also explored color transfer-based methods. For instance, Wang Qiaoyu and others proposed an innovative color transfer-based dehazing method, particularly targeting the recognition issue of license plate images in foggy environments. This method utilizes the Monge-Kantorovitch Linear (MKL) color mapping algorithm to statistically analyze the color information between clear license plate images and foggy blurred license plate images, establishing a linear mapping relationship. The core of this method is to change the minimum number of colors to achieve effective color transfer, restoring the color information of foggy license plate images and achieving the dehazing effect. The experimental results showed that the algorithm performed well in dehazing both synthetic and natural fog images, especially in the recognition of natural fog images, where 0-error reached 88.05%[4].

These traditional methods do not rely on large amounts of data and have strong interpretability of physical models. However, they depend on manual parameter tuning and have poor adaptability to non-uniform fog and extreme scenarios.

Deep learning methods significantly improve dehazing effects by learning the mapping relationship between fog distribution and clear images through end-to-end networks. Zhang W and others proposed a Multi-scale Perceptual Generative Adversarial Network (MPGAN) model based on multi-scale convolution and perceptual loss for dehazing tasks. MPGAN uses a Generative Adversarial Network (GAN) architecture to directly learn the nonlinear mapping from foggy images to clear images through adversarial training of the generator and discriminator, without relying on atmospheric scattering models for parameter estimation. Its core lies in the design of multi-scale convolution and perceptual loss. Multi-scale convolution extracts multi-scale detail information of images through convolution kernels of different sizes (e.g., 3×3 and 7×7), which helps to more comprehensively restore details obscured by fog. Perceptual loss compensates for the shortcomings of traditional mean squared error (MSE) in being sensitive to outliers, enhancing dehazing effects. Experimental results show that MPGAN achieves a PSNR of 21.82 dB and an SSIM of 0.895 on the O-HAZY dataset, significantly outperforming traditional dehazing methods[5].

Additionally, Liu W and others proposed an Image Adaptive YOLO (IA-YOLO) framework that significantly improves detection performance in foggy scenes by jointly optimizing dehazing and detection tasks through a differentiable image processing (DIP) module. IA-YOLO includes a small convolutional neural network (CNN-PP) that can adaptively predict the hyperparameters of the DIP module based on the brightness, color, hue, and weather information of the input image. The DIP module consists of six differentiable filters that follow the principle of differentiability and enhance images for object detection through backpropagation training. Although CNN-PP increases the

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model parameters (165K), the model remains lightweight, with a detection speed only 13ms slower than YOLOv3. Experiments show that IA-YOLO performs well on synthetic test sets (VOC_Foggy, VOC_Dark) and real-world datasets (RTTS, ExDark), with an average precision (mAP) increase of over 40% compared to YOLOv3, demonstrating superior adaptability to adverse weather conditions. Its key advantage lies in its ability to adaptively process both normal and adverse weather images without affecting detection performance under normal weather conditions[6].

Deep learning-based methods have strong generalization capabilities, adapt to complex fog distributions, and support end-to-end optimization. However, they have high computational complexity and rely on high-quality datasets.

2.2. License plate recognition

Traditional methods rely on image preprocessing and feature engineering to locate and recognize license plates, depending on manually designed features. For instance, edge detection and morphological processing are common techniques. Among these, Wang Junzhou and others proposed a license plate localization method combining improved Canny edge detection and Hough transformation. This method uses an optimized Canny algorithm to extract image edges, enhancing the accuracy and robustness of edge detection, and then utilizes Hough transformation to correct the tilt angle of the license plate, standardizing it for subsequent character segmentation and recognition. Experimental results show that this method achieves a localization accuracy rate of 93.2%, significantly improving the success rate of license plate recognition in complex environments[2]. Zhang Ailing adopted Canny edge detection combined with morphological operations to enhance the connectivity and integrity of the license plate area, and performed an "AND" operation with the color features and edge detection results to narrow down the search range. Ultimately, candidate areas were screened based on the aspect ratio to identify regions that match the license plate ratio. This method achieved a localization accuracy rate of 96% for blue license plates in foggy weather, demonstrating good robustness and anti-interference capabilities[1].

In addition, projection segmentation and template matching are also methods used in license plate recognition. Li Fei, in response to the over-segmentation problem of Chinese characters in license plate recognition under foggy conditions, proposed an improved vertical projection method. The traditional vertical projection method often leads to segmentation errors when dealing with complex-structured Chinese characters due to internal gaps, which is particularly prominent when image quality decreases in foggy weather. To address this, Li Fei designed a character box model based on separators, avoiding over-segmentation of Chinese characters by presetting character box ratios and thresholds. The specific method involves: first, converting the license plate image to grayscale and binarizing it, then using horizontal projection to remove the upper and lower borders, followed by vertical projection to remove the left and right borders to obtain the character area. For the first Chinese character, four character boxes were designed, based on standard size ratios (such as the width ratio of Chinese characters to separators), and by counting the number of pixels and width of the separator area, the first two characters were accurately segmented when reaching the preset threshold, with subsequent characters continuing to use the traditional vertical projection method for segmentation. This method effectively solved the problem of over-segmentation of Chinese characters, significantly improving the accuracy and robustness of character segmentation[7].

Traditional methods have low computational resource requirements and are suitable for simple scenarios, but they have poor robustness against foggy weather blur and complex backgrounds.

Deep learning methods achieve license plate detection and recognition through end-to-end networks, significantly enhancing adaptability to complex scenarios. Among the improved models of the YOLO series, Luo S and others proposed a license plate recognition method based on the

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enhanced YOLOv5m and LPRNet. This method uses the K-means++ algorithm for multi-dimensional clustering of anchor boxes, optimizing the matching degree between anchor boxes and detection targets, reducing computational load, and improving detection accuracy. In the recognition phase, a lightweight LPRNet network is employed to achieve end-to-end license plate character recognition, avoiding the impact of character segmentation on the results. Experiments indicate that this method achieves an average recognition accuracy of 98.56% across various complex scenarios (frontal, tilted, nighttime, strong light interference), with a processing speed of 32 FPS, which is significantly better than models such as YOLOv3-LPRNet and YOLOv4-LPRNet[8]. Xu Wangming and others proposed a lightweight license plate detection and recognition algorithm based on image adaptive enhancement. This algorithm improves the accuracy of detection and recognition by enhancing YOLOv5s and LPRNet through a hybrid attention mechanism (Shuffle Attention, SA). The core module is the Image Adaptive Enhancement Module (IAE-M), which provides dehazing and texture enhancement parameters for foggy images through an Adaptive Parameter Prediction Module (APPM), optimizing detection outcomes. Experimental results show that this algorithm achieves an mAP@0.5-0.95 of 70.6% for license plate detection and a recognition accuracy of 93.5% on synthetic foggy weather license plate datasets, with good real-time performance, meeting the needs of practical applications[9].

In the realm of Convolutional Neural Network (CNN) methods, Yang Xiuzhang and others proposed a CNN-based license plate recognition algorithm aimed at addressing the challenges of license plate recognition under complex environments. This method constructs a five-layer CNN model that operates in concert through convolutional layers, pooling layers, activation function layers, fully connected layers, and a softmax layer to achieve character recognition. Experimental results demonstrate that this method achieves an accuracy rate of 86.04%, a recall rate of 82.60%, and an F1 score of 84.29% for license plate area localization under complex environments, outperforming traditional methods and other deep learning algorithms[10]. Kaur and others proposed a CNN-based Automatic License Plate Recognition (ALPR) system capable of recognizing multi-line, tilted, and multi-font license plates, adaptable to various vehicle types, and demonstrating high efficiency in night mode with an accuracy rate of 98.13%. This study addresses the limitations of manual feature extraction in traditional methods by automatically extracting image features through CNN and enhances image contrast through improved preprocessing techniques (such as grayscale scaling and median filtering), ensuring recognition performance under low-light conditions. Experimental results show that the system performs well in a variety of complex environments, providing significant reference for the application of deep learning in the field of license plate recognition[11].

In the aspect of lightweight design, Leng J and colleagues proposed a license plate recognition system (Edge-LPR) based on edge computing and lightweight networks to address the issues of insufficient real-time performance and energy efficiency in traditional systems under cloud computing models, which are caused by high latency and high energy consumption. This system compresses the YOLOv7 model through channel pruning technology, ultimately reducing the model parameter size to 0.606 MB, significantly decreasing GPU resource consumption, making it more suitable for deployment on edge devices. Edge-LPR utilizes the computational resources of the Intel second-generation compute stick to deploy license plate detection and recognition tasks directly on edge gateways. The system integrates attention mechanisms into the C3 module of YOLOv7, enhancing perception capabilities and recognition accuracy, and upgrades three-level detection to four-level detection, improving the accuracy of small target detection by fusing features from various layers. Additionally, Soft-NMS optimization technology is employed to adjust confidence loss, avoiding the reduction in recall rate and the problem of missed detections caused by directly setting to zero due to non-maximum suppression (NMS). Experiments demonstrate that Edge-LPR

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performs excellently on the CCPD standard dataset and real-time monitoring datasets from charging stations, with a license plate recognition accuracy of 97% and an edge recognition speed of up to 187.6 FPS, significantly enhancing real-time performance[12].

Deep learning methods offer high robustness and support real-time processing in complex scenarios. However, their limitations include reliance on large-scale labeled data and limited generalization capabilities under extreme weather conditions.

3. Research conclusion

The current core challenges in foggy weather license plate recognition technology include insufficient adaptability to dynamic fog concentrations, especially in non-uniform fog scenarios; limited cross-scenario generalization capabilities due to significant domain differences between synthetic data and real scenarios; and the balance between real-time performance and accuracy, where lightweight design still requires further optimization. To break through these bottlenecks, future research directions should focus on algorithmic innovation, such as integrating physical models with deep learning through multimodal fusion techniques (e.g., Physics-guided GAN), to construct an integrated optimization framework for "dehazing-detection-recognition" to achieve end-to-end performance improvement (increasing mAP by 10%-15%), and utilizing self-supervised and contrastive learning to reduce reliance on labeled data. In terms of hardware collaboration, the development of edge computing technology should be promoted, deploying lightweight models (e.g., compressing parameters to 30%), while also optimizing imaging devices by developing high dynamic range (HDR) cameras and adaptive lighting systems to enhance image quality in low-light foggy environments. At the system integration level, privacy protection mechanisms should be introduced, combining federated learning with blockchain technology to ensure data security and traceability, and achieving cloud collaboration through 5G and Vehicle-to-Everything (V2X) technology, keeping low-latency recognition times within 50ms. Overall, technological breakthroughs in foggy weather license plate recognition require collaborative innovation at multiple levels of algorithms, hardware, and systems. Future development should focus on deep learning frameworks guided by physical models, lightweight deployment solutions on the edge, and the integration of interdisciplinary technologies to promote all-weather applications of intelligent transportation systems.

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