Research on Traffic Sign Image Recognition Algorithms Under Complex Weather Conditions

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Abstract. In the transportation system, the influence of haze is more significant, such as license plate recognition, real-time monitoring, etc. The visibility of both people and equipment is greatly affected in foggy weather, leading to the emergence of foggy image processing. We analyzed the recognition requirements of traffic signs in foggy weather and conducted research on algorithms for removing fog from foggy images and extracting image edges. This topic mainly improved on the traditional Retinex algorithm, recognizing the loss of detail information in images under Gaussian filtering conditions. We applied guided filtering to the estimation of illumination images to achieve the preservation of image edge information. In terms of image recognition, the currently best performing LOG operator and Canny edge extraction algorithm were applied to achieve the extraction of detail information. Then, based on the background knowledge of Convolutional neural network, a small Convolutional neural network model is designed for training to realize the recognition and classification of traffic sign images. The experimental results show that the method proposed in this paper can achieve good functions in fog removal and traffic sign recognition.

Keywords: Haze · Edge detection · Retinex · Guided filtering · LOG operator · Convolutional neural network

1 Introduction

Traffic signs are the most important source for drivers to obtain road information during driving. As an important auxiliary facility in the road traffic system, traffic signs play an irreplaceable role. Haze inevitably reduces atmospheric visibility, and the accuracy and timeliness of driver information acquisition will be greatly negatively affected. Countless traffic accidents occur every year as a result. In addition, in foggy weather, the implementation of technologies such as intelligent monitoring, intelligent recognition, automatic navigation, and target tracking in outdoor environments has a significant negative impact. Therefore, in order to minimize the impact of haze weather on images, studying the implementation of traffic sign recognition algorithms under haze weather has extremely important theoretical value and practical significance [1].

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Among the existing defogging algorithms, the retinex method has good performance and adaptability in image defogging. However, traditional retinex methods have drawbacks such as high computational complexity, difficulty in parameter selection, and limited effectiveness [2]. To address the problems of traditional retinex, we propose an improved retinex image clarity algorithm for image defogging and recognition of traffic signs in the image.

2 Related Work

Wang introduced traffic sign images into Convolutional neural network as training data to realize the classification function of traffic sign images. This method uses Convolutional neural network to study and classify the features of traffic signs, and can accurately recognize and classify different types of traffic signs. Li et al. proposed a method called FusedGAN to overcome the limitations of traditional defogging algorithms. This method combines the Generative adversarial network (GAN) and traditional image defogging technology, and restores images with complex haze by introducing multi-scale and multi-channel information fusion. FusedGAN can better remove the haze effect in the image and improve the image clarity and contrast [3]. Liu et al. proposed a single image defogging method based on the Recurrent Squeeze and Extraction Context Aggregation Network (R-SECA-Net). This method improves the quality and detail retention ability of image defogging by introducing attention mechanism and context aggregation. R-SECA-Net can adaptively adjust defogging processing, effectively reducing the problem of detail loss caused by haze [4]. Huang et al. proposed a traffic sign recognition algorithm based on CNN networks [5, 6]. The algorithm uses Convolutional neural network to extract and classify the features of traffic sign images, which can achieve high accuracy of traffic sign recognition.

3 Methodology

3.1 Traditional Retinex Algorithm

Among traditional Retinex image enhancement algorithms, the most common ones are single scale SSR algorithm, multi-scale MSR algorithm, etc., followed by iterative McCann algorithm and multi-scale Retinex algorithm with color restoration (MSRCR) [7–9]. The SSR algorithm needs to maintain a balance between contrast and image features, but the images to be processed vary in terms of shooting environment and imaging results. Therefore, the MSR algorithm is proposed based on the single scale algorithm. In order to compensate for the color deviation caused by interference such as haze and noise, a color restoration factor parameter C is added to the multi-scale MSR algorithm to adjust for the color deviation problem caused by the enhancement of local area contrast in the image. This corresponding algorithm is called the multi-scale Retinex algorithm with color restoration (MSRCR) [10–12].

3.2 Improved Retinex Algorithm

The traditional Retinex algorithm uses Gaussian filtering for implementation, which has the effect of smoothing the image after processing. During the enhancement process of the image, there will be a loss of detail information, resulting in blurred information in the logo. So when calculating the illumination information of an image, we use guided filtering to estimate the illumination information of the image. Guided filtering is an edge preserving filter, and here we use guided filtering for illumination estimation [13, 14].

$$q_i = \sum_j W_{ij}(I)p_j \tag{1}$$

where p is the input image to be processed; I is the guiding image; q is the filtered output; W_{ij} is the filtering kernel, equivalent to $F(x, y)$, W_{ij} in the traditional Retinex algorithm is a function of guide image I. In actual calculations, we generally consider the output image q as the linear calculation result of guide image I. Assuming The output and input of the $W_{ij}(I)$ function are in a two-dimensional window Satisfy linear relationship within W_k:

$$q_i = a_k I_i + b_k, \forall i \in w_k \tag{2}$$

Among them, a_k and b_k is the constant term coefficient that needs to be calculated by us, and it is also the coefficient when the window center is located at k; w_k is the window; i and k are pixel indices.

As a local linear model, guided filtering is defined as the following Loss function in order to find linear correlation and minimize the difference between the output value of the fitting function and the true value p:

$$E(a_k, b_k) = \sum_{i \in \omega_k} \left((a_k I_i + b_k - p_i)^2 + \varepsilon a_k^2 \right) \tag{3}$$

ω_k is right for a_k Correction compensation when the value is too large; The parameters about ε are used to adjust the blurriness of the image and the detection accuracy of edge information; εa_k^2 is used to suppress a_k value is too large. In terms of results, if the guide map does not contain edge information, the corresponding output mean filtering fuzzy result; If the guide map contains more edge information, the edge information will be reflected in the output image to achieve the preservation of edge information [15]. When calculating the coefficients of each window, a single pixel is usually described by multiple calculated linear functions. When calculating the output value of a single point, we take the mean of all calculated coefficients, and the final output result is as follows:

$$q_i = \frac{1}{|\omega_k|} \sum_{i \in \omega_k} (a_k I_i + b_k) = \overline{a}_i I_i + \overline{b}_i \tag{4}$$

Calculate the value of the linear coefficient from this. The algorithm flow of the guided filter is as follows:

1. Read in the guidance image I and the pending image P;
2. Calculate the mean and variance of I, the mean of the image P to be processed, and the product IP of I and P;
3. Calculate the linear correlation coefficient based on this $a_k = (IP - I_{mean}P_{mean})/(I_{Var} + \varepsilon)$; $b_k = P_{mean} - aI_{mean}$;
4. Calculate the mean of a_k and b_k;
5. Export filtering results: $q = a_{mean} * I + b_{mean}$;

This method uses guided filtering instead of Gaussian filtering to estimate illuminance images, ultimately resulting in an improved Retinex algorithm.

3.3 LOG Filtering Method

The edge detection algorithm of images requires both noise suppression and accurate positioning of edge information, and the LOG filtering method is an effective edge detection method. The LOG filter operator, also known as the Laplacian of Gaussian operator, and its corresponding operator, also known as the LOG operator, is the optimal filter for detecting image edge information based on image signal-to-noise ratio. This method comprehensively considers noise suppression and edge detection [16–18].

Perform the LOG operator on the test image to extract edge information, and the effect is shown in Fig. 1.

Fig. 1. Edge information extraction using LOG operator

Due to the extraction results being not suitable for observation, the pixel values of the resulting image were increased by a bias of 20 for observation. It can be seen that the LOG operator can effectively extract edge information from images.

3.4 Traffic Sign Image Recognition Based on CNN Network

This part will use Convolutional neural network (CNN) based on deep learning to implement a traffic sign image classification and recognition algorithm [19]. The training data is based on the BelgiumTS traffic sign dataset, which includes both training and testing sets. The training set contains 62 sets of images, each containing a certain number of logo images for training, with a total of 4575 images; The test set is also divided into 62

Table 1. Network Architecture Diagram

Hierarchical network	feature maps	Convolutional kernel/pooling size	step
Conv2D	64 × 5	5 × 5	5
MaxPool2d	32 × 5	2 × 2	2
Conv2D	32 × 5 × 5	5 × 5	5
MaxPool2d	16 × 5 × 5	2 × 2	2
Fully connected layer	120	–	None
Fully connected layer	84	–	None
Fully connected layer	62	–	None

sets of images, including a total of 2520 images. The design and implementation of the training model are coded in the Python environment and PyTorch dependency package, which includes two convolutional layers, two maximum pooling layers, and three fully connected layers. A CNN network is implemented to achieve traffic image classification.

The structure of the designed network training model is shown in Table 1.

As shown in the above figure, after each convolutional layer is extracted, a pooling layer is added to reduce the dimensionality of feature information, thereby reducing computational complexity and accelerating network training speed.

After the training is completed, the model parameters are used to predict the test set, and the prediction accuracy for the test set can reach 92.73%. But for practical application requirements, this accuracy is not high. The CNN network model designed in this section is only a simple pre trained network, and its recognition performance still has room for improvement.

4 Experimental Results

4.1 Display and Analysis of Experimental Results of Defogging Algorithm

Here we use traditional single scale Retinex algorithm, multi-scale Retinex algorithm, and improved Retinex algorithm for experiments. In the traditional Retinex algorithm experiment, different Gaussian scales c are continuously adjusted to achieve better processing results. The final scale selection is: the scale in the single scale SSR algorithm is set to 15% of the image size; The multi-scale MSR algorithm has a mesoscale setting of 5% of the image size for small scales, 15% for medium scales, and 40% for large scales.

As shown in Fig. 2, the experimental example is shown in the original image. 4–2 shows the processing results of the single scale SSR algorithm, 4–3 shows the processing results of the multi-scale MSR algorithm, 4–4 shows the guided filtering processing results, and 4–5 shows the weighted guided filtering processing results (Figs. 3, 4, 5, 6):

It can be seen that both the traditional Retinex algorithm and the improved guided filtering algorithm can achieve good defogging results, achieving image enhancement results. However, the processing quality of edge information in each group of experimental results is difficult to compare with the naked eye.

Fig. 2. Original image

Fig. 3. SSR processing results

Fig. 4. MSR processing results

Therefore, two parameters, edge intensity factor and peak signal-to-noise ratio (PSNR), are selected as the comparison criteria, the images were divided into two groups for processing in the experiment. The average values of the experimental results of the two groups of images are shown in Tables 2 and 3 [20, 21]:

Among them, the edge intensity factor reflects the amount of edge information contained in the image. The larger the edge intensity factor, the clearer the image edges and the more edge information it contains; PSNR represents the ratio of signal to noise and is often used to evaluate noise and signal strength. A larger PSNR indicates less

Fig. 5. Guiding Filter Processing Results

Fig. 6. Weighted Guided Filtering Processing Results

Table 2. Experimental Results of the First Group

algorithm	picture	Edge intensity factor	PSNR
SSR	pic (c)	82.8520	13.0193
MSR	pic (e)	83.5945	13.1975
Guided filtering	pic (g)	85.5671	13.9176
Weighted guided filtering algorithm	pic (i)	84.5239	13.8082

image noise. It can be seen that the experimental results of the algorithm combined with guided filtering contain more detailed information than the traditional Retinex algorithm. Therefore, it can be concluded that the improved Retinex algorithm can achieve edge information preservation to a certain extent.

4.2 Presentation and Analysis of Experimental Results on Traffic Sign Recognition

This part uses the Convolutional neural network pre training model designed in Sect. 3 to predict the test set, as shown in Fig. 7, the terminal output results of some kinds of test

Table 3. Experimental Results of the Second Group

algorithm	picture	Edge intensity factor	PSNR
SSR	pic (d)	41.0715	16.2509
MSR	pic (f)	42.0565	16.2701
Guided filtering	pic (h)	42.2539	16.7990
Weighted guided filtering algorithm	pic (j)	43.0994	16.8973

set graph prediction. In the figure, Input represents the true group identifier of the group of images to be predicted, while Prediction represents the predicted group identifier.

Fig. 7. Prediction Results of Test Set Part

It can be seen that there was an error in the recognition of the third image, but overall, the recognition rate can be maintained at a high level. After predicting all 2520 images in the test set, the accuracy of the prediction result is 92.73%.

Figures 8 show the prediction results of some traffic sign images processed by the improved Retinex defogging algorithm in this recognition algorithm, with two images showing recognition errors.

Figures 8 show the predicted results of some traffic sign images in the first set of experimental results of the defogging algorithm mentioned above. In this step, a total of 43 images from the first and second groups of the defogging algorithm results were used as predictive materials, with a total of 39 images predicting accurately, achieving an accuracy rate of 90.69%.

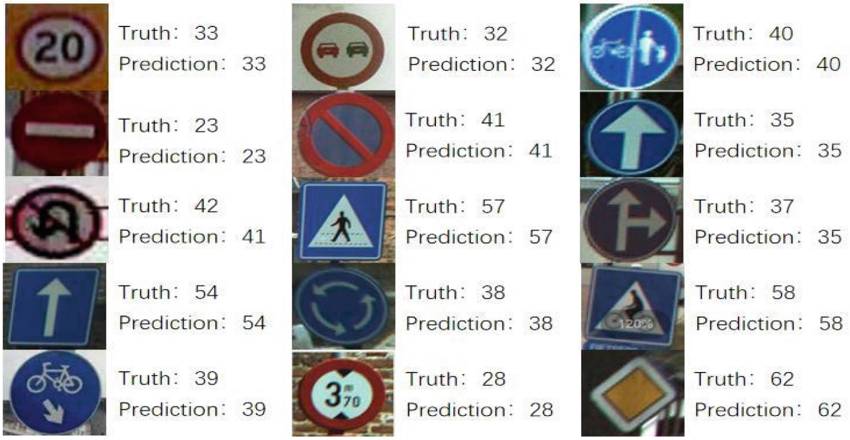

Fig. 8. Partial recognition results of improved defogging algorithm

4.3 Image Defogging and Traffic Sign Recognition System Based on Improved Retinex

The design of the improved Retinex based image defogging and traffic sign recognition system in this article is mainly divided into three parts: haze image selection, image display after defogging, and traffic sign box selection image display.

The Home screen of image processing consists of module selection and system menu, including four controls: button, panel, coordinate axis and text box. Each button has a corresponding callback function to switch the main interface to each module sub interface. The Home screen of GUI image processing system is shown in Fig. 9.

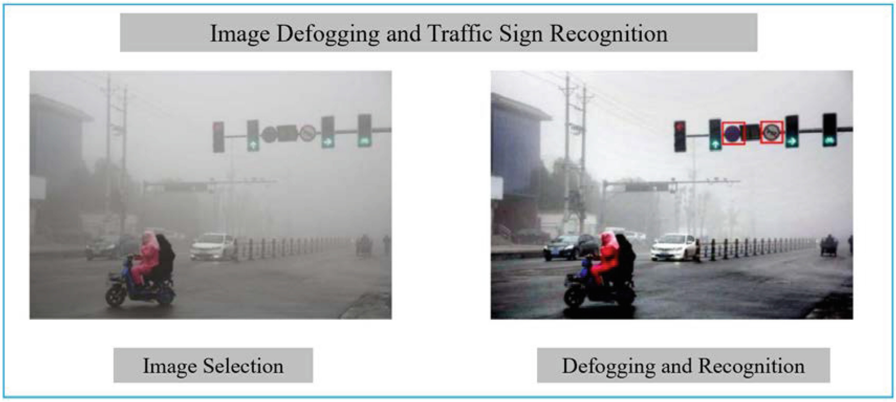

Fig. 9. Image Defogging and Traffic Sign Recognition System

Click to select an image and select the one you want to operate on. Click on 'Identify' to remove fog and recognize traffic signs on the fog map. The image after defogging and recognition will be generated in the right display box.

5 Conclusion

This project mainly focuses on the recognition of traffic sign images in haze weather. Combining the basic theory of digital image processing with traditional Retinex vision theory, research and improvement on image defogging are carried out. A Retinex defogging algorithm with guidance filtering influence factors is designed, and the recognition algorithm for traffic signs is analyzed and implemented. Effective information extraction is carried out on the image. The classification of traffic images is carried out on CNN pre trained networks, and training and learning are conducted using the BelgiumTS traffic sign dataset, Finally, our Convolutional neural network can get 93.89% recognition accuracy, but in practical application, this number still needs to be improved.

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