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Research on traffic sign image enhancement model under severe weather conditions

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Abstract. With the development of intelligent transportation and intelligent connected vehicles, the accuracy of traffic sign recognition directly affects intelligent driving decision-making and driving safety. Nevertheless, traffic sign recognition suffers from issues such as blurred images, reduced contrast and difficult feature extraction under severe weather including rainy, foggy and nighttime conditions. To tackle the above problems, this paper proposes a joint model integrating image enhancement and recognition. A coding-attention-decoding structured image enhancement module is adopted to strengthen the edges of traffic signs against image quality degradation caused by severe weather. Meanwhile, a loss optimization model based on YOLO is established to reduce the missed detection rate and false detection rate of target recognition. Finally, severe weather data are simulated based on public datasets, and experiments verify the effectiveness of the proposed joint model, which provides effective support for the subsequent technological development of intelligent vehicles.

Keywords: severe weather, image enhancement, traffic sign recognition, joint model

1. Introduction

1.1. Research background

With the integration and implementation of intelligent technologies across the entire automotive industry, vision-based image recognition technology [1] plays an exceptionally critical role in smart transportation and driving. Traffic sign images contain traffic prohibition rules and various traffic passage instructions; hence, the recognition performance of such images is closely correlated with the accuracy of driving decision-making and the improvement of traffic efficiency. In real complex and variable environments, severe weather such as fog scattering, rain occlusion, low illumination at night and backlight glare readily leads to degraded collected image data featuring declined contrast, blurred edges and deteriorated details. These defects cause missed and false judgments during recognition and decision-making, which restricts the adaptive environmental response capacity of intelligent driving systems.

1.2. Domestic and international research status

Existing research mainly falls into two separate directions: image enhancement for severe weather and traffic sign target recognition, while few studies integrate both directions simultaneously. In terms of severe weather image enhancement, the atmospheric scattering physical model is commonly adopted to restore corresponding features for image recovery. For heavy fog scenarios, fog refractive indices are estimated to recover occluded image content [2], yet this algorithm tends to produce estimation distortion in high-brightness traffic sign regions. For rainy conditions, guided filtering is widely applied to separate high-frequency and low-frequency rain streaks for rain removal [3], but this method fails to properly handle traffic sign edges. In low-light environments, image contrast is adjusted by simulating human visual luminance perception; however, this approach involves massive computation and delivers limited image enhancement effects. Overall, the above methods lack generalization capability. Most adjustments merely fit human visual perception rather than meeting the requirements of traffic sign recognition. Although deep learning can deliver partial image enhancement effects to satisfy certain target recognition demands, existing deep learning models are mostly used for image restoration without introducing supervised recognition mechanisms, so restored images tend to lose fundamental traffic sign features.

Regarding traffic sign target recognition, early research relied on SVM classifiers, which only apply to road images with uniform illumination and distinct signs. When images are contaminated by haze, rain streaks and other interferences that drastically reduce contrast, such methods fail to identify relevant traffic signs. Current research solely depends on feature compensation within detection networks, which cannot offset image quality degradation caused by severe weather, resulting in obvious deficiencies in recognition performance.

For studies combining image enhancement and recognition, fog-specific detection networks are constructed, which only adapt to single foggy scenarios and fail to cope with complex weather such as rainy days and dim light. Some research processes lanes, vehicles and signs simultaneously, yet their enhancement modules ignore the unique geometric and color characteristics of traffic signs, as well as the variable sizes of distant signs.

1.3. Research content

Targeting the above deficiencies in traffic sign recognition research, this paper carries out research from the following aspects:

1. Comprehensively analyze the degradation rules and feature failure laws of traffic sign images under severe weather such as fog and rain;
2. Design an adaptive lightweight image enhancement model to restore edge, texture and color features;
3. Construct a joint model integrating image enhancement and traffic sign recognition to process images captured under special weather conditions;
4. Verify the effectiveness of the proposed model through comparative experiments and ablation experiments.

2. Related theories and key technologies

2.1. Image degradation principle under severe weather

The core theoretical basis for image degradation under severe weather is the atmospheric scattering imaging model for fog, which also serves as the fundamental framework for image enhancement. Massive tiny water mist particles in fog absorb and refract natural light, altering imaging results and causing degraded image quality, namely image degradation. The physical model formula for foggy weather is shown in Formula (1):

$$I(x) = J(x)t(x) + A(1 - t(x)) \tag{1}$$

Where $\mathrm{I}(x)$ denotes the degraded foggy image captured by the camera, $J(x)$ represents the original clear fog-free image, $t(x)$ stands for atmospheric transmittance characterizing the transmission ratio of scene light penetrating the fog medium with a value range of (0,1), and A refers to global atmospheric light intensity, representing the constant background light formed by environmental scattering.

Compared with the complex image quality degradation induced by fog, rainy and dim light conditions exert relatively simpler impacts on image quality. Rain degrades images through rain streak occlusion and pixel coverage, while dim light leads to deteriorated pixel quality, contrast and saturation due to insufficient exposure. In summary, fog triggers holistic and uniform image degradation, which constitutes the core processing challenge among all severe weather image conditions.

2.2. Classical image enhancement technologies

Traditional image enhancement algorithms rely primarily on image statistical features to modify images, and represent the mainstream methods for processing severe weather images. Three classic conventional approaches include dark channel prior dehazing, Retinex enhancement and adaptive histogram equalization.

The dark channel prior dehazing algorithm is widely used for foggy image processing [4]. Based on statistics of natural fog-free images, this algorithm estimates the refractive index distribution of atmospheric light via image dark channels, and restores clear fog-free images combined with the fog physical model to realize dehazing. Nevertheless, this algorithm delivers suboptimal performance for traffic sign recognition in heavy fog; traffic signs generally feature high saturation, yet images restored by this method suffer severe color distortion.

The Retinex enhancement algorithm decomposes images into environmental illumination components and physical reflection components. It eliminates light interference and retains original reflection features to achieve image enhancement. While this method can enhance images, it severely damages fine edges and textures of traffic signs, failing to meet the visual clarity requirements for traffic sign recognition.

The adaptive histogram equalization algorithm improves upon basic histogram enhancement. It divides images into multiple local patches and performs localized enhancement on each patch to resolve local detail loss. However, this algorithm cannot eliminate overall image whitening caused by fog in traffic sign scene images.

In general, traditional classical image enhancement technologies [5] conduct enhancement targeting specific local conditions and exhibit poor adaptability to special traffic sign scenarios. Although partial local detail optimization is achievable, they fail to deliver adaptive enhancement across all severe weather types.

2.3. Target detection algorithms

This paper adopts lightweight YOLO algorithms [6, 7] to build the target detection framework, which demonstrates favorable performance in extracting target features, conducting detection and classification, and adapting to traffic sign scenarios. A typical lightweight YOLO network framework consists of three collaborative modules: backbone network, feature fusion network and detection head, which jointly generate final detection results.

Despite the strong detection capability of this target detection algorithm for traffic sign recognition, it suffers obvious defects in feature extraction under foggy, rainy and other severe weather conditions. The algorithm cannot handle image recognition interferences from variable weather and is prone to missed detection of small-size targets. This paper optimizes the framework by adding a front-end feature extraction module to remedy the above recognition flaws of the target detection framework.

2.4. Joint optimization concept

This paper adopts an end-to-end joint training mechanism for enhancement and recognition, which delivers remarkably superior performance compared with the conventional two-stage independent training mode for separate image enhancement and traffic sign recognition. Independent two-stage reasoning leads to redundant feature extraction and excessive computational overhead, while separate training cannot realize collaborative processing effects. Relying on multi-task parallelism and feature compensation mechanisms, joint training prioritizes retaining critical feature information including traffic sign contours and color saturation, fundamentally resolving poor scene adaptability and missed detection issues during training.

The joint optimization mechanism proposed in this paper integrates three synergistic modes: shared feature extraction, joint loss constraint and end-to-end training. The shared feature mechanism breaks the feature isolation limitation of traditional two-stage pipelines. It extracts both image degradation features induced by severe weather and semantic features of traffic signs to boost image recognition quality. The joint loss constraint avoids inaccurate recognition precision caused by single-model training via a weight balancing strategy, eliminating the drawbacks of independent single-task training. The end-to-end integrated training mode shares feature parameters throughout the whole pipeline to prevent information loss and cumulative data errors, satisfying the real-time and high-precision requirements of traffic sign recognition.

3. Design of the joint model

3.1. Overall framework design

Severe weather leads to low contrast, blurred details and severe noise interference in traffic sign images, and conventional processing methods struggle to extract valid features from original images, resulting in degraded traffic sign recognition accuracy. To address this problem, this paper proposes a joint model comprising four modules: image enhancement, feature fusion, target recognition and joint loss optimization. The overall framework diagram is shown in Figure 1.

First, severe weather traffic scene images are input into the image enhancement module. This module adopts an encoder-decoder structure, extracts semantic features via convolutional neural networks, and restores images degraded by fog, rain, snow and other severe weather to improve contrast, saturation and edge sharpness. To boost traffic sign recognition performance, an attention mechanism is embedded in the enhancement module to focus processing on traffic sign regions and suppress interference from background impurities.

Enhanced images and intermediate features are then fed into the traffic sign recognition module. Based on a lightweight YOLO model, a multi-feature fusion strategy implemented by the feature fusion module strengthens the integration of semantic and detailed information, improving recognition accuracy for small-size traffic sign targets.

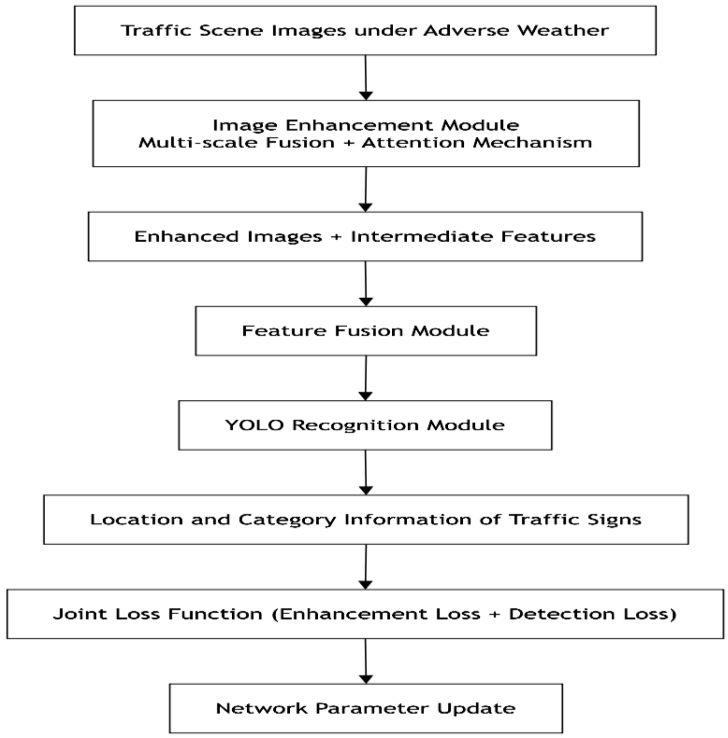


Figure 1. Framework

A joint optimization strategy is adopted during model training, which simultaneously optimizes image quality loss and traffic sign detection loss by constructing a joint loss function. This collaborative optimization of the two tasks ultimately provides technical support for intelligent transportation applications.

3.2. Adaptive image enhancement module

Traffic sign images captured under severe weather suffer degraded saturation, contrast and lost details. To solve these problems, this paper designs an encoder-attention-decoder image enhancement architecture. The attention mechanism embedded in this architecture focuses on fine details of traffic signs and improves image restoration capacity.

The encoder is primarily responsible for extracting valid feature content from traffic sign images, providing abundant feature data for subsequent image processing. The attention mechanism assigns different weights to diverse image features by analyzing feature information, accurately reflecting pixel-level image information for each regional position. Based on the image information extracted by the encoder, the decoder restores original image content to the maximum extent, and optimizes fine image details via convolutional neural networks to recover images as close to real scenes as possible.

3.3. Recognition module

Traffic signs are characterized by small sizes, numerous categories and dense distribution, and they are vulnerable to blurring induced by rain, fog and other severe weather factors. To improve traffic sign recognition performance under harsh environments, this paper builds an efficient target recognition network based on an improved lightweight YOLO model, with optimizations implemented in three dimensions: backbone network, feature fusion and loss function. The specific processing flow is illustrated in Figure 2.

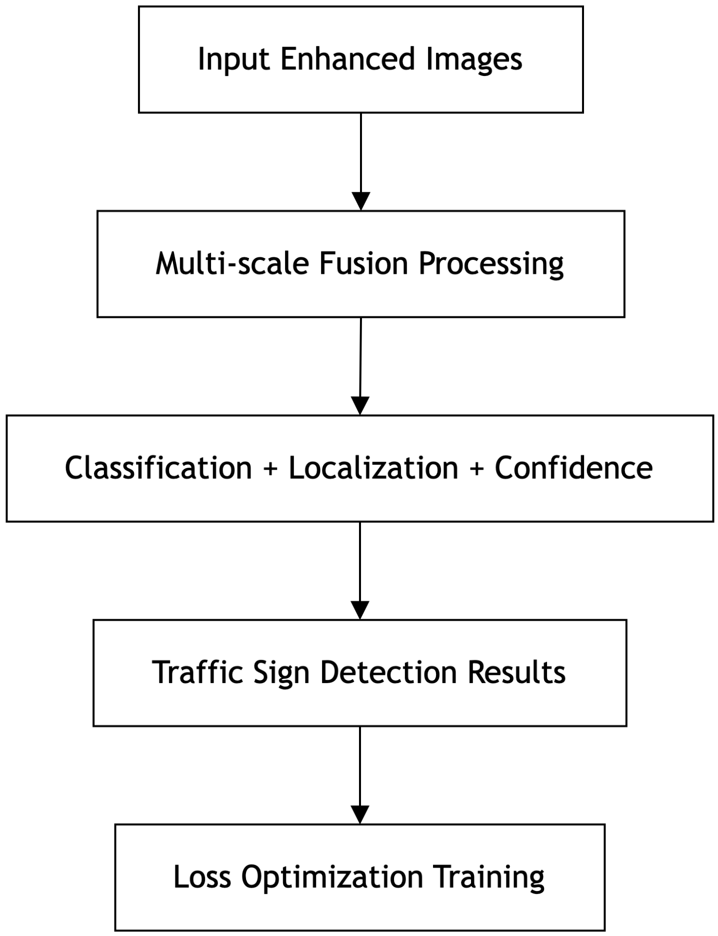


Figure 2. Image recognition process

The backbone network extracts multi-layer feature information from input images, and embeds convolutional attention modules to strengthen feature representation. The feature fusion module integrates high-level semantic features and low-level detail features, and extracts complex features of multi-category traffic signs across diverse scenarios via weighted fusion of multi-scale semantics, thereby reducing the missed detection rate. The loss function module addresses ambiguous bounding boxes and indeterminate boundary discrimination. Targeting the small-size attribute of traffic signs, it optimizes boundary ranges by calculating errors between predicted and ground-truth bounding boxes to enhance localization precision and realize accurate traffic sign identification.

In summary, the embedded attention mechanism, multi-scale fusion strategy and loss function optimization proposed in this paper strengthen feature extraction and precise localization for traffic signs under severe weather, and deliver superior adaptability especially for tiny and small-size traffic sign targets.

3.4. Joint training strategy

The conventional two-stage training mode isolates information flow between processing phases, easily causing image feature loss and biased model localization precision. To maximize synergistic effects between enhancement and recognition tasks, this paper adopts a joint training paradigm that integrates the image enhancement module and traffic sign recognition module, and optimizes the model via a joint loss function to strengthen the network's target recognition capacity. The joint optimization model consists of image enhancement and target detection branches, and the joint loss function is defined in Formula (2):

$$L = L_{enhance} + \lambda L_{detect} \tag{2}$$

Where $L_{enhance}$ denotes the image enhancement loss, L_{detect} represents the target detection loss, and λ stands for the loss weight coefficient.

In the joint training model, images are first fed into the image enhancement module. After encoding and processing, enhanced images and extracted feature maps are generated and transmitted to the recognition module for traffic sign feature extraction. Finally, the loss function optimizes model parameters to elevate recognition precision.

3.5. Model advantage analysis

The joint model for traffic sign image enhancement and recognition under severe weather proposed in this paper highly integrates image enhancement and feature processing to realize collaborative optimization of image quality improvement and target recognition. Compared with traditional models, the proposed method achieves superior performance in image quality restoration, detection accuracy and real-time inference speed.

For severe weather conditions, the encoder-attention-decoder architecture combined with multi-scale feature fusion and attention mechanisms delivers excellent performance in identifying edge features of traffic signs. During joint training, continuous feedback of enhancement effects from the image enhancement branch preserves most edge features of sign images.

Traffic signs feature small dimensions and diverse categories, which easily lead to missed and false detection under severe weather. By sharing image information across all processing stages, the joint model retains original feature information to the greatest extent and minimizes missed and false detection probabilities.

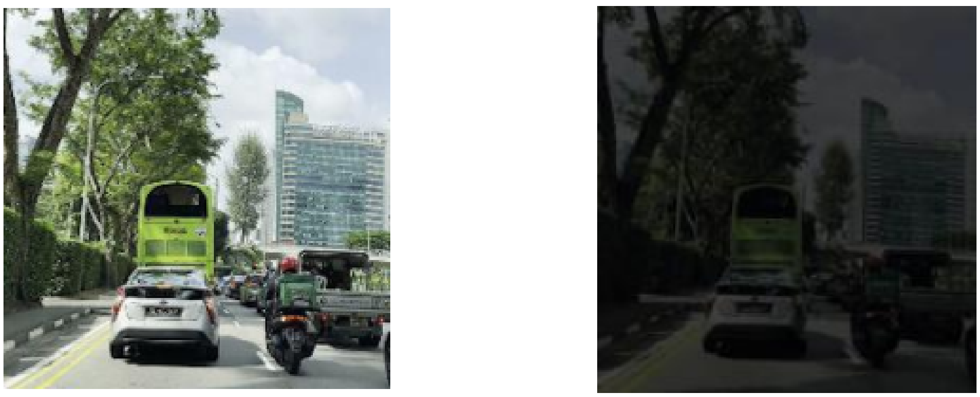
4. Analysis of experimental results

4.1. Experimental datasets and environment

The experimental datasets adopted in this paper combine public datasets and self-simulated severe weather datasets. The base dataset contains Chinese traffic sign [8] samples, and rainy, foggy, nighttime and other complex scene data are generated via image degradation simulation to construct the complete severe weather dataset.

Public datasets contain limited image samples of complex weather scenarios, which fail to meet the data volume demands for research on traffic sign recognition models under severe weather. This paper simulates diverse weather scene data via image transformation: for rainy scenes, rain streaks of variable directions, lengths and densities are superimposed onto original images with additional brightness and noise interference, as shown in Figure 3; for foggy scenes, fog images of varying density are generated by adjusting refractive index and atmospheric light parameters; for nighttime scenes, illumination is reduced with added uneven local light distribution, as shown in Figure 4.

Figure 3. Simulated rainy image



Original Image　　Processed Image

Figure 4. Simulated night image

4.2. Evaluation metrics

Four evaluation metrics are selected to test model performance: Precision, Recall, mean Average Precision (mAP) and Frames Per Second (FPS), which are used to measure target detection performance.

Precision represents the proportion of correctly detected samples among all predicted samples, calculated via Formula (3):

$$P = \frac{TP}{TP+FP} \tag{3}$$

Recall denotes the proportion of successfully detected samples among all ground-truth samples, defined in Formula (4):

$$R = \frac{TP}{TP+FN} \tag{4}$$

Where TP refers to true positive samples (correctly detected targets), FP denotes false positive samples (false detection results), and FN stands for false negative samples (missed targets).

Mean Average Precision measures the comprehensive detection performance across multiple categories. Average Precision (AP) for each category is calculated from Precision and Recall curves, and mAP is obtained by averaging AP values over all categories, as shown in Formula (5):

$$mAP = \frac{1}{N}\sum_{i=1}^{N} AP_i \tag{5}$$

Where N represents the total number of traffic sign categories.

FPS refers to the number of inference frames processed per second, calculated via Formula (6):

$$FPS = \frac{TotalFrames}{TotalTime} \tag{6}$$

4.3. Experimental analysis

To verify the overall performance of the joint image enhancement and recognition model, baseline YOLO models are gradually augmented with the proposed improved modules for comparative experimental analysis. Model performance is evaluated via Precision, Recall, mAP and FPS metrics.

Experimental results illustrated in Figure 5 and Figure 6 show that the improved model achieves Precision of 77.98%, Recall of 72.13% and mAP of 77.89%, all outperforming the original baseline model. A slight reduction in model inference speed is observed, which constitutes a normal computational overhead introduced by the added enhancement module. The results verify the superior recognition precision and real-time inference capacity of the improved model for traffic sign detection under severe weather.

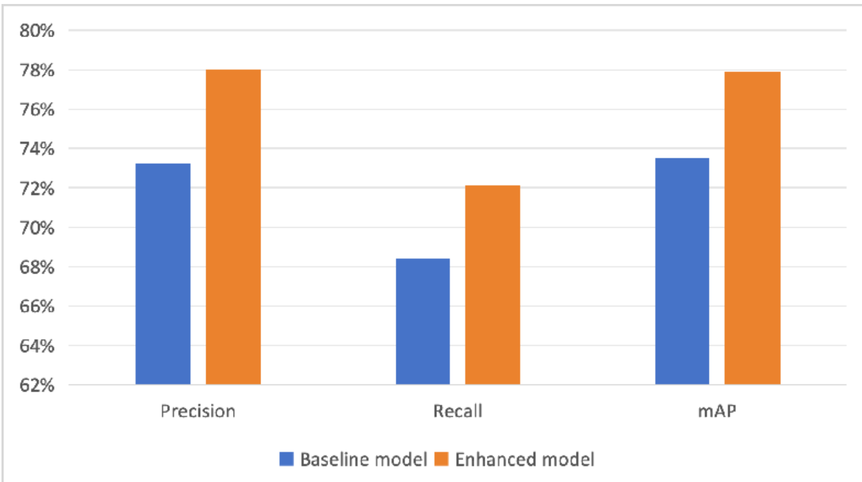


Figure 5. Comparison of various indicators

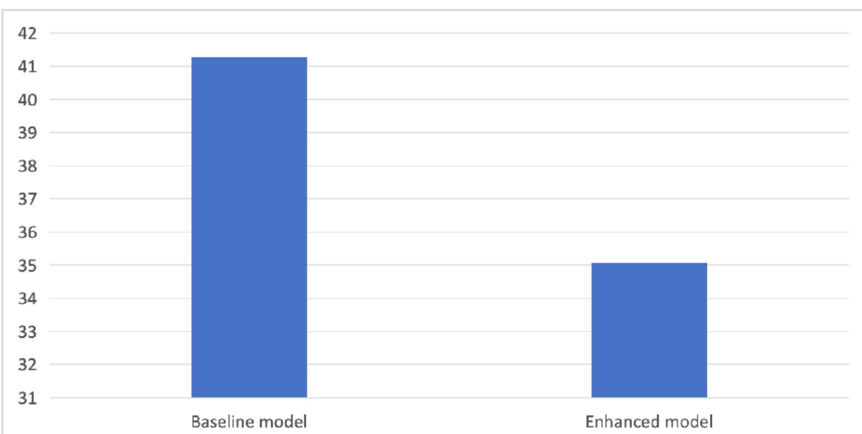


Figure 6. Model frame rate

4.4. Result discussion

Experimental results demonstrate that the proposed joint model integrating traffic sign image enhancement and recognition for severe weather delivers comprehensive favorable performance in recognition precision and real-time processing. The embedded attention mechanism and optimized loss function significantly improve traffic sign recognition accuracy under harsh weather conditions. The image enhancement module effectively restores degraded image quality caused by severe weather, the attention mechanism enhances extraction of critical target features, and the optimized loss function elevates target detection precision.

5. Conclusion

Severe weather conditions cause blurred traffic sign images and degraded detection accuracy, which severely restrict the technological advancement of intelligent driving. To address these issues, this paper constructs a joint optimization model based on YOLOv8. The model adopts an encoder-decoder architecture embedded with attention mechanisms to resolve difficulties in image feature extraction, and integrates image enhancement and target detection branches to mitigate missed and false detection phenomena. Comparative experiments reveal that the proposed model achieves improvements in Precision, Recall, mAP and FPS metrics, verifying its superior target recognition precision and strong adaptability to diverse severe weather scenarios.

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