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A Refined Traffic Light Detection Method for Challenging Low Visibility Scenarios with CS-YOLOv10 Algorithm

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Abstract— To address the challenge of traffic light detection under low visibility conditions, this paper proposes an improved algorithm, CS-YOLOv10. Based on the YOLOv10 framework, it embeds the CA attention mechanism to enhance feature extraction, and builds a small object detection layer to improve recognition accuracy. By preprocessing the dataset with the dark channel prior defogging algorithm, combined with comparative and ablation experiments, the algorithm achieves an mAP of 98.32%, a 5.68% improvement over the original YOLOv10. This significantly enhances the robustness and accuracy of traffic light detection for autonomous vehicles in rainy and foggy environments.

Keywords-component; object detection and recognition; YOLOv10; CS-YOLOv10 (an improved algorithm); visibility; autonomous vehicles

I. INTRODUCTION

Traffic light detection and recognition is of importance for safe operations of autonomous vehicles. However, low visibility, as one of the main factors contributing to traffic accidents, poses a potential safety hazard for intelligent vehicles. Visibility, in the context of transportation, refers to the distance at which one can identify objects ahead under a complex meteorological condition [1]. It is not only an important weather indicator, but also a pivotal factor for ensuring the safety of transportation [[2]].

Two main factors influence visibility: (1) illumination difference, and (2) atmospheric transparency. Natural and artificial lights are two factors affecting illumination. The illumination value is directly proportional to the visibility value, higher illumination corresponds to greater visibility. Severe weather conditions, such as heavy rains, snows, fogs, and sandstorms, can make the atmosphere turbid [[3]]. Atmospheric transparency is directly proportional to visibility, and reduced transparency leads to decreased visibility. Generally, visibility below 300 meters is considered as low visibility, implying a challenging environment for autonomous vehicle systems. A long distance between a traffic light and a small target may diminish brightness contrast between the object and the background, making them difficult to be detected. Additionally, adverse weather conditions, such as rains, snows, and smogs, significantly reduce atmospheric transparency. These factors, which contribute to poor visibility, can detrimentally impact a driver's field of vision, making driving more challenging and potentially leading to severe traffic accidents [[3]]. Given the essentiality of traffic light detection in low visibility conditions, this paper proposes an algorithm for improving the capabilities of detecting and recognizing traffic lights when visibility is below 300 meters. This algorithm is to increase the safety of autonomous vehicles operations.

The proposed algorithm, namely CS-YOLOv10, which is devoted to addressing the challenges posed by traffic lights at a far distance and low visibility caused by rains, snows, and blurred nighttime lighting. The CS-YOLOv10 was designed to improve the performance to the YOLOv10. The CS-YOLOv10 algorithm integrates the CA attention mechanism to adaptively focus on more critical features, thereby enhancing the algorithm performance. Additionally, it adds a small object detection layer to improve the accuracy of detecting small traffic light targets. This is followed by preprocessing the created traffic light image dataset using the Dark Channel Prior dehazing algorithm, which effectively enhances the visual contrast threshold. Finally, comparison and ablation experiments are conducted between the CS-YOLOv10 algorithm and the YOLOv10 to validate the effectiveness of the proposed algorithm.

II. TRAFFIC LIGHT DATASET

A. Creating Dataset

We collected 3,053 traffic light samples in low visibility, filtering images and creating a manual dataset. It includes various times, rainy conditions, and different light intensities for straight, left, and right turns (Fig. 1). The dataset was enhanced through operations like flipping, translation, rotation, cropping, scaling, noise addition, and random occlusion. LabelImg annotated the images, categorizing lights into "red," "yellow," "green," and "off." The dataset was divided into 80% training, 10% validation, and 10% testing sets.

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Figure 1. Sample images from the generated traffic light datasets [5].

B. *Preprocessing Dataset*

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Due to the influence of atmospheric scattering in low visibility environments, such as foggy weather, the recognition and detection processing for traffic lights may be slower and less accurate. Therefore, this study utilized the Dark Channel Prior dehazing method [6] for image preprocessing in order to enhance the clarity and obtain clearer dehazed images. In the field of image dehazing in computer vision, the imaging model of haze is simplified as

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

where J(x) represents the dehazed image, A the global atmospheric light, I(x) the hazy image, and t(x) the transmission rate of light. From the haze imaging model expressed in (1), it is known that the key to obtaining a dehazed image J(x) lies in calculating the transmission rate t(x) and the global atmospheric light value A.

The Dark Channel Prior algorithm can be used to improve images' quality, and the dehazing effect of a sample image is shown in Fig. 2.

(a) (b)

Figure 2. An Example of (a) hazy image; (b) dehazing image.

III. PROPOSED CS-YOLOV10 ALGORITHM

The YOLOv10 algorithm consists of three main components: backbone, neck, and head. It is widely used in real-time target detection applications, and has good detection performance. However, the YOLOv10 algorithm still suffers from slow detection speed and low accuracy in poor weather conditions for detecting traffic lights. Therefore, built upon the YOLOv10 algorithm, the CS-YOLOv10 is developed to enhance the detection and recognition ability for traffic lights. The integrated architecture of the proposed CS-YOLOv10 algorithm is depicted in Fig. 3.

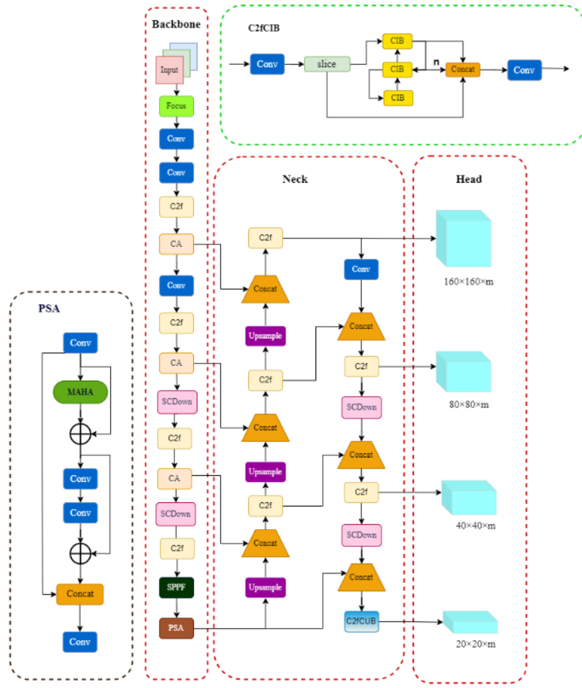


Figure 3. Architecture of CS-YOLOv10.

A. *Adding the Attention Mechanism*

The CS-YOLOv10 algorithm enhances the performance of YOLOv10 as the base algorithm by embedding an attention mechanism in the backbone of the algorithm. Comparing various attention mechanisms, such as CA, CBAM, EMA, MCA, and SimAM, through a comparative experiment, the optimal one is selected. The chosen optimal attention mechanism is then incorporated into the traffic light detection algorithm to improve the perception of critical regions, thereby increasing the model's accuracy and achieving the best detection effect. The results derived from the comparative experiment are shown in Table Ⅰ.

From the experimental results of the attention mechanism, it can be seen that adding CA leads to better detection performance and a smaller model parameter size. Therefore, we chose to add a CA attention mechanism to improve the performance of the YOLOv10 model.

TABLE I. A COMPARISON OF PERFORMANCE MEASURES OF THE YOLOV10 ALGORITHM WITH VARIOUS ATTENTION MECHANISMS.

Attention Mechanisms	AP				mAP	F1				Params/M	FLOPs/G
	Red	Green	Yellow	Off		Red	Green	Yellow	Off		
YOLOv10	0.9876	0.9598	0.9336	0.8647	0.9264	0.96	0.95	0.89	0.85	7.277	17.156
YOLOv10_CA	0.9707	0.9789	0.9900	0.9400	0.9399	0.98	0.97	1.00	0.75	7.314	17.172
YOLOv10_CBAM	0.9799	0.9588	0.9227	0.8922	0.9384	0.98	0.95	0.90	0.80	7.322	17.163
YOLOv10_EMA	0.9917	0.9772	1.0000	0.9600	0.9822	0.99	0.96	1.00	0.88	7.331	18.129
YOLOv10_MCA	0.9938	0.9765	1.0000	0.9500	0.9801	0.99	0.96	1.00	0.89	7.277	17.168
YOLOv10_SimAM	0.9938	0.9765	1.0000	0.9500	0.9801	0.99	0.96	1.00	0.89	7.277	17.168

B. Small Object Detection Layer

Many traffic lights are spotted at a considerable distance, occupying a small size in the image. In low visibility scenarios, it becomes even more challenging for in-vehicle cameras to recognize distant traffic lights. To address this problem, the CS-YOLOv10 algorithm incorporates a small object detection layer, represented as the box in red dashed line shown in Fig. 3. The original three-scale feature fusion in the YOLOv10 algorithm is modified to a four-scale feature fusion. The 80×80 feature detection layer is upsampling by a factor of two and then fused with the newly added 160×160 feature detection layer, a prediction head for tiny object detection is introduced, enhancing the semantic information and feature representation of small targets.

IV. RESULTS AND DISCUSSION

To examine the performance of the proposed CS-YOLOv10 algorithm, a benchmark is conducted experimentally by comparing this algorithm with the YOLOv10 and its variants. Once again, for simplicity, we treat the YOLOv10 and its variants as different algorithms. This section introduces the experiment set-up, ablation experiments, and comparison experiments.

A. Experiment set-up

The experiments are conducted on the operating system, Windows 11, using an NVIDIA GeForce RTX 4060 Laptop GPU, with 16 GB memory. Python 3.9 is employed as the programming language, and the training is based on the deep learning framework PyTorch 1.12.1. During the training process, to further enhance the detection and recognition speed of the model, we improved the optimizer in the original YOLOv10 model by adopting the Sophia optimizer, with an initial learning rate of 0.001. A cosine annealing scheduler is employed to adjust the learning rate [7]. Label smoothing is applied to traffic light classification labels to prevent overfitting, with a smoothing value of 0.01.

B. Ablation experiments

To evaluate the performance of the CS-YOLOv10 algorithm, a series of ablation experiments are designed to compare it with the YOLOv10 algorithm and its variants. During training, label smoothing is applied to the images to accelerate the convergence of the CS-YOLOv10 algorithm and ensure the stability of the experimental sample data. The evaluation is performed every 10 epochs, and the experiment is trained for a total of 300 epochs. Table Ⅱ provides the results derived from the ablation experiments. Given the results, the performance measures of the CS-YOLOv10 algorithm can be directly compared against those of the YOLOv10 and its variants.

In the case of YOLOv10_F, no dehazing processing is made on the dataset. For the YOLOv10_C, the CA attention mechanism is embedded. In the YOLOv10_S, the small object detection layer is introduced. Finally, the proposed CS-YOLOv10 algorithm incorporates the CA attention mechanism, and the small object detection layer.

Introducing the CA module, and the small object detection layer leads to improved performance in mAP and F1. For simplicity, it is assumed that the YOLOv10 is baseline algorithm. Compared with the YOLOv10 algorithm, the CS-YOLOv10 outperforms in: 1) achieving the mAP of 98.32%, increasing by 5.68% from the baseline value of 92.64%; 2) attaining F1 scores on traffic light dataset for red, green, yellow, and off with the values of 98%, 97%, 96%, and 97%, increasing by 4%, 2%, 7%, and 12% from their baseline values of 96%, 95%, 89%, and 85%, respectively. Among all the algorithms listed in Table Ⅱ, the CS-YOLOv10 algorithm exhibits the best overall performance in AP, mAP and F1 with the comparable measures of Params and FLOPs.

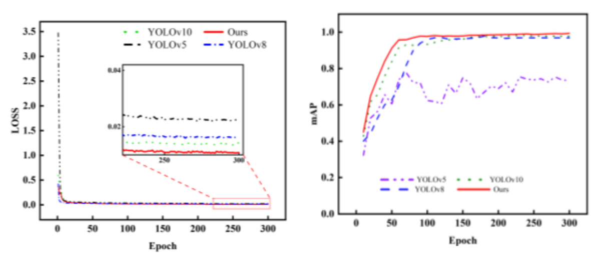
TABLE II. A COMPARISON OF THE PERFORMANCE MEASURES OF THE CS-YOLOV10 ALGORITHM AGAINST THOSE OF THE YOLOV10 AND ITS VARIANTS.

Algorithms	AP				mAP	F1				Params/M	FLOPs/G
	Red	Green	Yellow	Off		Red	Green	Yellow	Off		
YOLOv10_F	0.9703	0.9519	0.9800	0.9512	0.9034	0.98	0.97	0.95	0.89	7.277	17.156
YOLOv10	0.9876	0.9598	0.9336	0.8647	0.9264	0.96	0.95	0.89	0.85	7.277	17.156
YOLOv10_C	0.9707	0.9789	0.9900	0.9400	0.9399	0.98	0.97	1.00	0.75	7.314	17.172
YOLOv10_S	0.9889	0.9703	0.9677	0.9652	0.9730	0.98	0.97	0.93	0.91	7.436	20.734
CS-YOLOv10	0.9863	0.9703	0.9843	0.9922	0.9832	0.98	0.97	0.96	0.97	7.481	20.741

C. Comparison experiments

To further examine the CS-YOLOv10 on the traffic light dataset, a comparison experiment is conducted to compare the proposed algorithm with the YOLOv10. Fig. 4 (a), and (b) show the loss value curve and the mAP curves for each algorithm over the training and testing process, respectively.

Fig. 4 (a) shows that within the first 50 epochs, the loss values for both the algorithms decrease rapidly. After training stabilized, the CS-YOLOv10 outperforms the YOLOv10 in achieving smaller loss value. From the mAP curve in Fig. 4 (b), it is evident that for both algorithms, the mAP values increase rapidly within the first 100 epochs. After training for 200 epochs, both algorithms tend to stabilize, and the CS-YOLOv10 behaves better than the YOLOv10 in attaining higher mAP value.



(a) (b)

Figure 4. Results derived from comparison experiments: (a) loss value curves; (b) mAP curves.

V. CONCLUSIONS

In low visibility conditions, traffic light detection and recognition become more challenging. To enhance the traffic light detection accuracy, this paper proposes and designs an algorithm, called CS-YOLOv10, which is built upon the YOLOv10 algorithm. The CS-YOLOv10 algorithm is distinguished with the following features: 1) embedding CA attention mechanism and introducing a small target detection layer to obtain more crucial traffic light features and improve the detection capability; and 2) using the traffic light image dataset generated with the dark channel prior dehazing algorithm to eliminate foggy image noise, strengthen the detection and recognition capability of weak lighting in night-time, consequently boosting the information content of the images. To evaluate the performance of the proposed algorithm, we conduct numerous experiments.

Experimental results demonstrate that compared with the YOLOv10 algorithm and its variants, the CS-YOLOv10 algorithm exhibits the best overall performance in AP, mAP and F1 with the comparable measures of Params and FLOPs. In particular, the CS-YOLOv10 algorithm achieves the mAP value of 0.9832, increasing by 5.68% from the respective indicator of 0.9264 for the YOLOv10 algorithm. It is indicated that the CS-YOLOv10 algorithm can enhance the detection and recognition capabilities of traffic lights in low visibility conditions. In the near future, the proposed algorithm will be tested and used for autonomous driving systems to explore its capabilities for increasing the safety of these self-driving vehicles.

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