Realization of Anti-glare Algorithm Based on Stagnant Water Reflection of Automobile Headlights on Rainy Day

1st Yu-Jian Xu
School of Information Engineering
Wuhan University of Technology
Wuhan,China
yuginchui@foxmail.com

2nd You-Yu Wu*
School of Information Engineering
Wuhan University of Technology
Wuhan,China
wuyouyu1@whut.edu.cn

3rd Wen-Long Yuan
School of Information Engineering
Wuhan University of Technology
Wuhan,China
longwy@whut.edu.cn

4th Lin-Cheng Jiang
School of Information Engineering
Wuhan University of Technology
Wuhan,China
897058630@qq.com

***Abstract*—This project proposes to develop an algorithm founded on YOLOv5 to detect water accumulation at night,to eliminate the glare that results from car headlights reflecting off of standing water while people are driving at night on rainy days.Use the histogram equalization enhancement algorithm to process the night driving image to improve the contrast between the stagnant water and the road surface.Then use the YOLOv5 target detection algorithm to accurately identify where the water is located.Through the Freescale MCU to control the high and low beam switching and angle adjustment of the automobile headlights, purpose to avoid the glare of stagnant water at night.Experimental findings indicate that the histogram equalization enhancement algorithm can increase the contrast between stagnant water and road surface by 40.35%. The precision of the YOLOv5 target detection algorithm reaches more than 80%, and the precision is sufficient for practical applications.This project has high flexibility as a whole, and at the same time improves the safety of driving on rainy days at night.**

Keywords-stagnant water; anti-glare headlights; target detection; computer vision; image enhancement

I. INTRODUCTION

In the process of driving at night, not only the strong high beam lights are easy to dazzle the driver when meeting cars, but also the reflected lights generated by the light reflection medium directly irradiated by the lights are also easy to dazzle the driver.Especially on rainy days, road conditions are much more complicated than those in sunny days.If there is a lot of stagnant water in front of the vehicle on the road, it can produce pieces of "mirror surface" at night,forming a light-reflecting medium, which makes the lights reflect and interferes with the driver's vision.At the same time, the flooded area illuminated by the light of the own car will also dazzle the driver of the oncoming car, which will bring certain risks to the other driver.As society has grown and science and technology have continued to expand, the traditional high and low beams and directional shifting car headlights have been unable to meet people's growing driving safety needs.At present, polarized light anti-glare technology [1] and liquid crystal dimmer devices are mostly used to solve the glare problem of meeting cars in the world.Polarized light anti-glare technology is to install polarizers on the windshield of the car and the glass of the headlight lamp shade, so that the strong light of the other party's car lights cannot pass through the windshield.However, the polarizer not only has poor light transmittance, which greatly limits the driver's field of vision, but also requires high cost and processing accuracy, making it difficult to be widely used.The liquid crystal dimming device uses a light sensor to convert the strong light signal into an electrical signal, so that the liquid crystal panel located between the driver's eyes and the front windshield changes color.[2] So the driver does not feel the glare of the strong light, but The device has poor applicability to different road conditions and is more likely to cause visual fatigue of the driver. [3] Due to the complex road conditions at night on rainy days, and there is no good solution to the glare caused by stagnant water reflection at night in the world.Therefore, develop a device that can detect the road surface information ahead in real time, determine the center position information of the water accumulation area through feature detection, and extract the area of the water accumulation area is very necessary because it can control the automobile headlights of the car to weaken the glare caused by the road surface water reflection to the oncoming drivers.

Digital image processing uses a histogram processing technique called histogram equalization enhancement method, and the histogram processing is also the basis of various spatial domain processing techniques, which is of great significance in image gray scale transformation and enhancement processing.First of all, the classification of levels of intensity is primarily divided into four levels: image in the dark, image in the light, image with low contrast, and image with high contrast.In dark images, At the low end (dark end) of the intensity levels, the histogram's constituent parts are concentrated. The corresponding components of the bright images histogram tend to be at the high end of the gray scale.The low-contrast image has a narrow histogram, which is concentrated in the middle of the gray level, while the histogram components in the high-contrast image cover a

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wide range of gray levels and the pixel distribution is relatively uniform. [4] For the system studied in this paper, it is required to be able to accurately identify the road water situation and the area where it is located at night, and it is inevitable to perform dark image enhancement processing.Using the histogram equalization algorithm to highlight the brightness of a specific gray scale range in the photograph that was taken and enhance the corresponding water features, so that the dark image can be converted into a high-contrast image is of great significance for determining the scope of the water accumulation area.

YOLO (You Only Look Once) algorithm is a target detection algorithm with a single stage, which can be regarded as a single regression algorithm.Finding all areas of interest in an image and determining their position and class probability are the tasks of object detection.The current mainstream deep learning object detection algorithm is primarily split into two-stage and one-stage detection algorithms. The two-stage detection algorithm is a target detection algorithm based on candidate regions represented by the R-CNN series; the one-stage detection algorithm.It is a regression-based target detection system, represented by YOLO and SSD. [5] Compared with the two-stage target detection algorithm, because of its faster processing speed, the YOLOv5 algorithm is frequently utilized in business and other time-sensitive applications.Compared with the YOLOv4 algorithm, the YOLOv5 algorithm is optimized by using Mosaic data enhancement, adaptive anchor box calculation, adaptive image scaling, etc. in the model training phase. Integrates the Focus structure and the CSP structure in the benchmark network.The FPN+PAN structure is inserted between BackBone layer and the final Head outputlayer, which further improves the precision of the algorithm.Therefore, the YOLOv5 algorithm has a high recognition accuracy while having a fast running speed, which is more suitable for the detection speed and accuracy requirements when driving in a complex environment at night. This project uses the YOLOv5 algorithm as the core processing algorithm.

This project uses the camera to collect road information in front of vehicles driving at night on rainy days. The histogram equalization enhancement algorithm is used on the personal computer terminal to improve the contrast between the stagnant water and the road, the YOLOv5 algorithm is used to identify the specific area where the stagnant water is located and generate a control signal. The control module composed of the Freescale MC9S12XET256 chip can adjust the LED headlights to avoid glare caused by the reflection of the headlights directly irradiating the stagnant water, and improve the safety of driving at night on rainy days.

II. System Structure

The project system is mainly composed of vehicle camera, personal computer terminal, control module based on Freescale MC9S12XET256 chip and LED automobile headlights. Figure 1 displays the diagram of the system architecture.The overall workflow of this project is as follows:The images of stagnant water at night collected by the camera are directly processed on the personal computer terminal to generate control strategy signals.The personal computer terminal communicate with the Freescale control module through the CAN bus. The control module catches the corresponding information and processes it and then communicates with the LED driver module through the SPI protocol. Finally, the LED driver module adjusts the angle of the automobile headlights to avoid irradiating the water accumulation area to cause reflections.

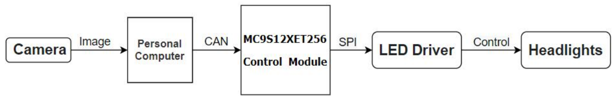

Figure 1. Example of the system structure.

III. Histogram Equalization Enhancement

A. Basic Theory

Since the automobile headlights are generally used in the process of driving at night, but the night environment is usually the weak link of the machine vision system, there will be a large gap in accuracy compared with that in a well-lit environment.Therefore, in order to better identify road water on rainy days and nights, we use a histogram equalization algorithm to preprocess the road image information collected by our vehicle camera.The histogram equalization enhancement algorithm can convert the part of the original image whose gray intensity value distribution is too concentrated into a uniform distribution, that is, the process of equalization,which broadens the dynamic range of the original image's gray intensity value difference. Consequently, the overall contrast of the image is increased. It is more convenient to identify.The basic theory of histogram equalization enhancement algorithm is as follows.

For a digital image with gray intensity levels range of $\left[0, L-1\right]$,its histogram can be expressed as a discrete function $h(r_k) = n_k$,where r_k is the the k-th gray intensity value and n_k is the number of pixels with the the k-th gray intensity value r_k .In practical applications, if the dimension of the image is $Rows \times Cows$ .Then $N = Rows \times Cows$ is the number of pixels in this picture, and the normalized histogram function of the picture is able to be expressed as

$$p(r_k) = n_k / N, k = 0,1,\ldots,L-1 \tag{1}$$

where $p(r_k)$ is the probability estimate of gray intensity value r_k appearing in the picture, and the normalized histogram's total component count is 1. [6]

Assuming that the gray intensity value is continuous initially, r and s indicate respectively the histogram equalization algorithm's processed gray intensity value and the original image's normalized gray intensity value.Therefore, when $r = s = 0$, it is represented as a black pixel;When $r = s = 1$, it is represented as a white pixel;When $r, s \in (0,1)$, it means that the color of the pixel is between black and white.Then, for the histogram equalization algorithm, any r in range of $[0, L-1]$ can get a corresponding s through the transformation function $T(r)$ as

$$s = T(r) \tag{2}$$

For equation (2), $T(r)$ should be satisfied the following two conditions :

(1) When the range of r is $0 \le r \le 1$, $T(r)$ is a monotonically increasing function;

(2) The range of r has $0 \le T(r) \le 1$ within $0 \le r \le 1$;

The above two conditions are explained as follows.

(1) Condition (1) ensures that the image's post-equalization gray intensity level does not change from black to white;

(2) Condition (2) ensures the equalized intensity of image's pixel gray value falls within the acceptable range.

If the known random variable's probability density function r is $p_r(r)$,and the random variable s is a function of r .Then the probability density function $p_s(s)$ of the random variable s can be derived from the probability density function $p_r(r)$ of the random variable r .Assuming that the random variable's distribution function s is represented by $F_s(s)$,we have

$$F_s(s) = \int_{-\infty}^{s} p_s(s)ds = \int_{-\infty}^{r} p_r(r)dr \tag{3}$$

Since the probability density function is the derivative of the distribution function, there are

$$\begin{aligned} p_s(s) &= \frac{dF_s(s)}{ds} = \frac{d\left[\int_{-\infty}^{r} p_r(r)dr\right]}{ds} \\ &= p_r(r)\frac{dr}{ds} = p_r(r)\frac{dr}{d[T(r)]} \end{aligned} \tag{4}$$

The equation above demonstrates that the probability density function $p_s(s)$ of the random variable s is adjusted by changing the function $T(r)$,improving the overall image's gray intensity level in the process.

The above method studies the histogram equalization of grayscale images. For color images, we can convert the RGB space of color images into HSV (Hue, Saturation, Value) space and then perform histogram equalization and enhancement on V (Value) alone, [7] so as to ensure the undistorted image color .

B. *Results*

The effect of the nighttime stagnant water image processed by the histogram equalization enhancement algorithm is depicted in Figure 2.

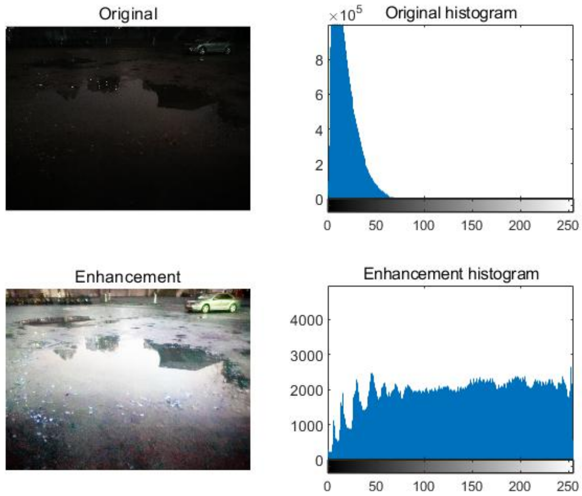

Figure 2. Comparison of enhancemental image and orignal image.

Through the comparison of the above original nighttime stagnant water image and the enhanced image after histogram equalization, it is evident that the contrast between the stagnant water part of the enhanced image and the road has been significantly improved, the contrast improvement has reached 40.35% after testing. At the same time, by comparing the histograms of the images before and after enhancement, it can be found that the original nighttime stagnant water image's histogram is concentrated in the lower intensity gray value region. After applying the histogram equalization, the gray intensity value distribution of the picture is more uniform, and the detection results of the night water target detection algorithm are also improved.

IV. YOLOv5 Algorithm

A. *Network Architecture*

The YOLOv5 algorithm is a target detection algorithm released by Ultralytics in May 2019. The inference speed can reach 140FPS, and the detection performance has been further improved. It is currently one of the most advanced target detection technologies. [8] Due to the complex road conditions at night, the precise position of stagnant water must be known, this project uses the YOLOv5 algorithm to detect the nighttime stagnant water on rainy days.

Figure 3 depicts the YOLOv5 algorithm's overall network structure. The algorithm network improves Mosaic data over YOLOv4 and includes adaptive anchor frame computation, adaptive picture scaling, and adaptive anchor frame calculation at the input layer.[9] fused the Focus structure and the CSP structure on the benchmark network. The Neck network adds the FPN+PAN module. [10] The output layer primarily enhances the GIOU_Loss loss function during training and the DIOU_nms loss function during prediction box screening. [11]

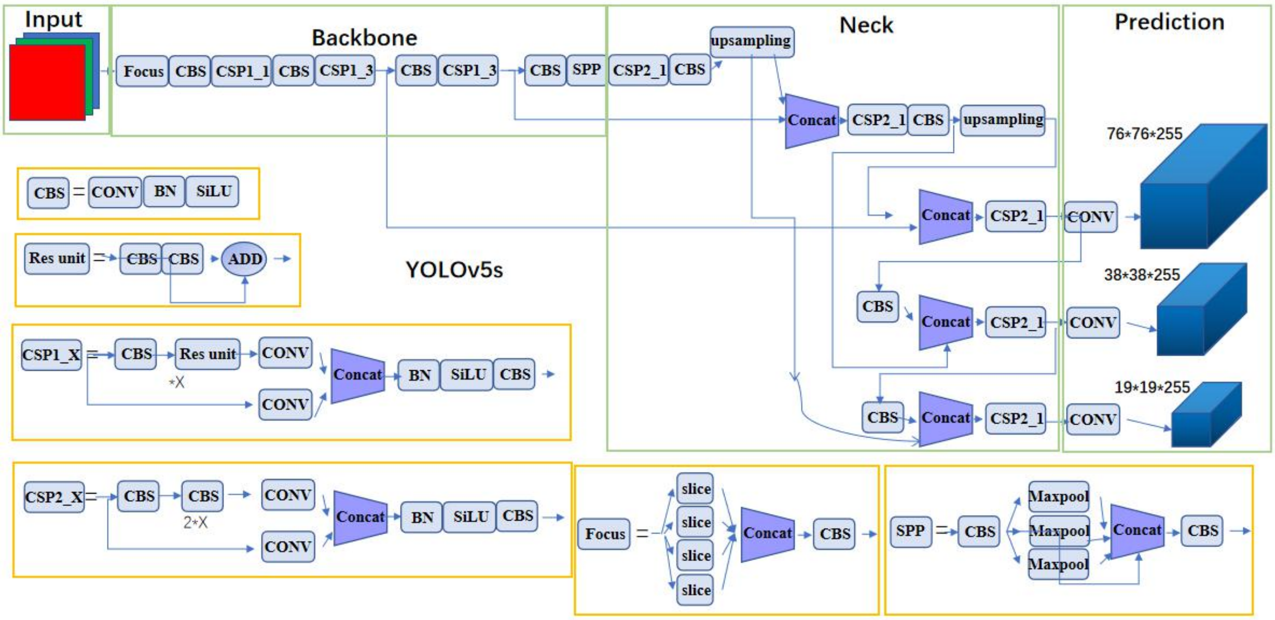

Figure 3. Network architecture of YOLOv5.

B. Implementation Details

1) Benchmark Network: For the benchmark network, it is mainly a Focus structure, and its main idea is to crop the input image through the Slice operation. As shown in Figure 4, the original input picture is 608*608*3, and after Slice and Concat operations, a feature map of 304*304*12 is produced. Then, the output of a convolutional layer with 32 channels is a 304*304*32 feature map.

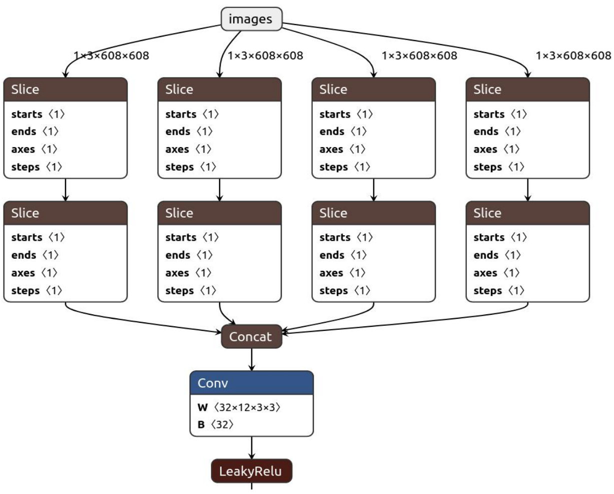

Figure 4. The structure of Focus module.

At the same time, the YOLOv5 algorithm designs two CSP structures, that is, the original input is divided into two branches, and different operations are performed respectively.[12] The Backbone network uses the CSP1_X structure, whereas the Neck network uses the CSP2_X structure.

2) Neck Network: In the YOLOv5 algorithm, the Neck network adds the design of the FPN+PAN structure, and in the same manner draws on the CSP2 structure created by CSPnet to improve the ability of the network to fuse features. The FPN structure can enable the images to transfer semantic information from high dimension to low dimension, making the recognition of large objects more accurate. The PAN structure enables the images to transfer semantic information from low-dimensional to high-dimensional, ensuring that small objects are more accurate. Figure 5 depicts its structure.

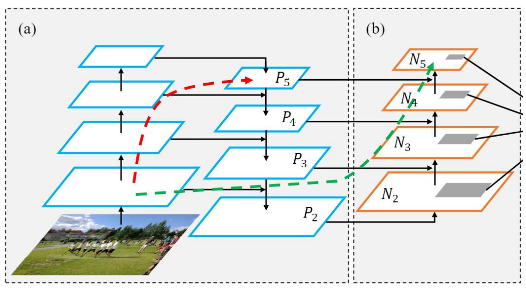

Figure 5. The structure of Neck network.

3) Head Output Layer: For the Head output layer, its function is to predict the image features, forecast the target's category and construct the target's bounding box coordinates. During target detection task training, the most frequent element that significantly influences the algorithm's performance is the imbalance between positive and negative samples. A positive-negative sample mismatch in the target identification algorithm's training phase is an issue that the YOLOv5 method attempts to address by simultaneously assigning the label frame to three anchors during training, which is equal to doubling the initial number of positive samples. Its loss function expression is:

$$\begin{aligned} L_{total} &= \sum_{i}^{N}(\lambda_1 L_{box} + \lambda_2 L_{obj} + \lambda_3 L_{cls}) \\ &= \sum_{i}^{N}(\lambda_1 \sum_{j}^{B_i} L_{CIoU_j} + \lambda_2 \sum_{j}^{S_i \times S_i} I_{obj_j} + \lambda_3 \sum_{j}^{B_i} l_{cls_j}) \end{aligned} \quad (5)$$

Among them, N is the quantity of detection layers, B is the quantity of targets whose labels are assigned to the prior frame, and $S \times S$ is the quantity of grids that the scale is divided into. L_{box} is the bounding box regression loss, which is calculated for each target; L_{obj} is the target object loss, calculated for each grid; L_{cls} is the classification loss, λ_1, λ_2, and λ_3 are also calculated for each target as the weights of these three losses.

C. Model Retraining

1) Hardware Configuration And Datasets: This project uses the tensorflow framework, and Table 1 displays the model training hardware configuration.

TABLE I. HARDWARE CONFIGURATION

CPU	Memory	GPU	Operating System
Intel i5-10300H	16GB	GeForce GTX1650	Windows 10

The images of this project are mainly taken by the vehicle camera when driving on rainy days, including various videos and photos of various road sections such as urban roads and expressways for a total of 5 hours and 15,000 pieces, from which 5,000 clear and suitable photos were selected as for the training set, use LabelImg software to mark the stagnant water and potholes in the selected photos, and finally select 4000 photos as the training dataset and 1000 photos as the test dataset. Use the above-made datasets for model training.

The training procedure involves 300 iterations, with an initial learning rate of 0.001, and it lasts around 26 hours.

D. Results and Analysis

To accomplish better demonstrate the effect of model training, the tensorboard module is added to the program. Using tensorboard module can record the loss value calculated by the loss function and the change of recognition accuracy in real time at the end of each round of training during the training process.

The effect of the recognition accuracy is depicted in Figure 6.

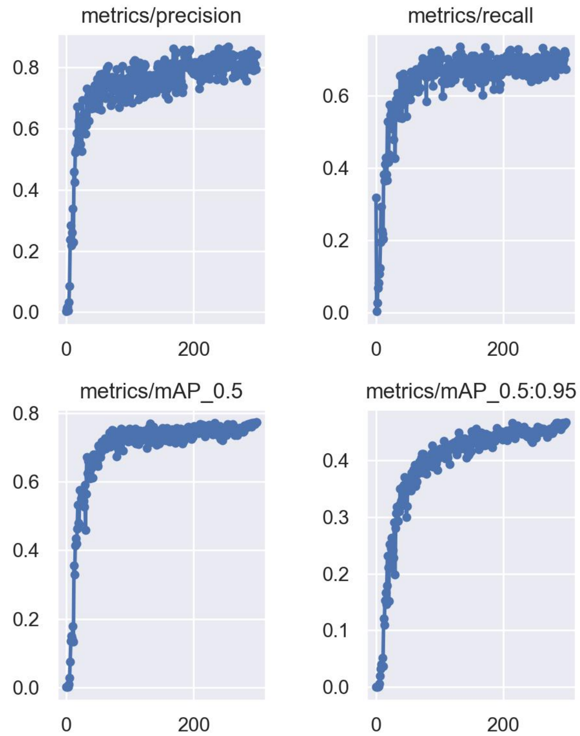

Figure 6. The effect of recognition accuracy.

According to the above renderings,It can be observed that precision may reach more than 85% during the training phase. Analyze the mAP (Mean Average Precision) after model training, that is, calculate the AP (Average Precision) for the training set separately except for the data in the True Negative area that cannot be calculated because there is no mark, and then perform the mean average calculation. The results are depicted in Figure 6, which means that after 300 rounds of training, a good recognition effect has been achieved, and will eventually stay around 0.80. It can be considered that the recognition accuracy of positive samples using this model can reach about 80%.

The effect of the loss function is depicted in Figure 7.

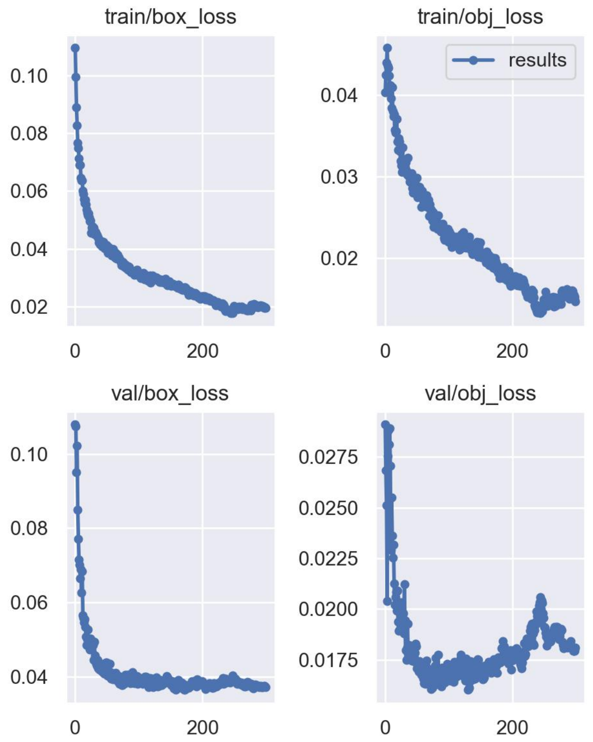

Figure 7. The effect of loss function.

To analyze the error loss of model training from Figure 7. we know that after 300 rounds of training, the frame prediction error has dropped to below 0.02, which shows that after training, it has high accuracy and precision on the data set of stagnant water and potholes. So the location information of stagnant water and potholes can be detected accurately.

V. CONCLUSION

The actual scene test using the trained model is depicted in Figure 8.

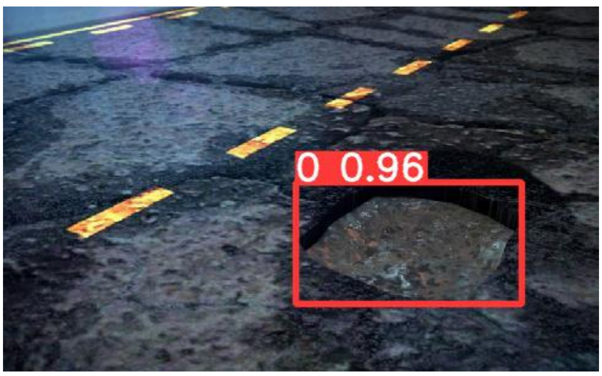

Figure 8. The actual scene test.

This project uses the histogram equalization enhancement algorithm and the object detection method YOLOv5 to identify stagnant water and potholes on the road on rainy days and apply it to the field of automobile anti-glare. Collected and calibrated the data set by ourself and retrained the model to get new model weights , used it to identify road stagnant water and potholes during driving and get their location information, so as to realize intelligent control of automobile headlights.It avoids the glare of the lights reflection caused by the automobile headlights irradiate stagnant water, and reduces the risk of accidents.

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REFERENCES

[1] Dong Tuqiang. Research on Polarization Characteristics of Curved Polarizers [D]. Changchun University of Science and Technology, 2008.

[2] Guo Jianzhong, Liu Dong, Wang Qingmiao, Zhang Guangde.An anti-glare system for meeting cars at night based on the principle of persistence of vision[J]. Mechanical Design and Manufacturing ,2016(05):40-43+47.DOI:10.19356/j.cnki .1001-3997.2016.05.011.

[3] Wang Yuanyu, Zeng Yichen, Li Feiyang, Yan Chen, Zhang Shun. Anti-glare LED car lights at night based on YOLOv3 [J]. Science and Technology and Innovation, 2020 (04): 42-44+46. DOI: 10.15913/j .cnki.kjycx.2020.04.015.

[4] Lu Butao, Hong Qingda, Chen Xuwen, Zheng Shunxin. Research on Track Race Image Enhancement Technology Based on Histogram Equalization [J]. Automotive Practical Technology, 2019 (04): 51-53. DOI: 10.16638/j.cnki.1671-7988.2019 .04.017.

[5] Xu Degang, Wang Lu, Li Fan. A Review of Typical Object Detection Algorithms Based on Deep Learning [J]. Computer Engineering and Applications, 2021, 57(08): 10-25.

[6] Tu Haining, Wei Junwen, Liu Jiansheng, Gu Jia.Design and Implementation of Traceability System for Barcode Image Pattern Recognition[J].Mechanical Design and Manufacturing,2021(07):241-245.DOI:10.19356/j.cnki.1001-3997.2021 .07.057.

[7] Gao Xiaojuan, Mei Xiuzhuang, Bai Fuzhong, Li Ping. Low-illumination color image enhancement and power small component detection for aerial patrol [J]. Journal of Inner Mongolia University of Technology (Natural Science Edition), 2021, 40(06): 461-467.DOI: 10.13785/j.cnki.nggydxxbzrkxb.2021.06.010.

[8] Wang Yulong. Research and implementation of adaptive control strategy for automobile headlights based on machine vision [D]. Wuhan University of Technology, 2021. DOI: 10.27381/d.cnki.gwlgu.2021.001211.

[9] Zhang Xiangqing. Small pedestrian target detection from the perspective of drones based on YOLO algorithm [J]. Information and Computer (Theoretical Edition), 2021,33(15):76-78.

[10] Wu Zijia, Chen Hang, Peng Yong, Song Wei. Visual SLAM Fusion of Lightweight YOLOv5s in Dynamic Environment [J]. Computer Engineering, 2022, 48(08): 187-195+205. DOI: 10.19678/ j.issn.1000-3428.0062294.

[11] Shi Jianting, Li Xu, Liu Wenbin, An Xiangze. Target Detection and Recognition Based on YOLOv4-Efficient [J]. Intelligent Computer and Application, 2022,12(03):123-127.

[12] CY Wang, A Bochkovskiy, HYM Liao. Scaled-YOLOv4: Scaling Cross Stage Partial Network. CSCV.16 Nov 2020.