Journal of Computers Vol. 31 No. 3, 2020, pp. 337-350
doi:10.3966/199115992020063103027

Research on Improving Canny Edge Detection Algorithm in the Binocular Visual Recognition for Hazardous Chemical Warehouse

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Received 30 March 2020; Revised 1 April 2020; Accepted 30 April 2020

Abstract. The safety distance monitoring in the hazardous chemical warehouse is the key to ensure the safe storage of hazardous chemicals. Binocular vision is one of the promising technical means. The Canny edge detection algorithm in the binocular vision of the warehouse is an effective algorithm for the boundary extraction of the dangerous goods used in warehouse, but the algorithm faces the salt and pepper noise interference in the warehouse where has a complex environment. Firstly, adaptive median filtering is used to denoising. Then iterative mean method and Otsu method is used to adaptively set threshold and extract edges. Under normal lighting, night vision, night vision and light interference, carry on experimental research on storage stacks such as warehouse model boxes and cylinders. The results show that the improved algorithm significantly improves denoising effect and edge extraction accuracy.

Keywords: Canny algorithm, hazardous chemicals storage, iterative mean, median filtering, Otsu

1 Introduction

The flammable, explosive and corrosive nature of hazardous chemicals are serious safety hazards. China's existing hazardous chemicals warehouse has not yet formed a real-time automated monitoring and management system, which cannot meet the requirements of enterprise informatization and automation. In the safety of hazardous chemicals, the measurement of "five distances", namely the stomp distance, wall distance, column distance, lamp distance and beam distance [1], is the key to ensure the safe storage of hazardous chemicals, which requires accurate identification of the stack of hazardous chemicals or the edge contour information of the goods, which put forward higher requirements for edge detection [2].

For the edge detection problem, literature [3] proposes to synthesize the Sobel operator to represent the gradient, then use the Bernsen algorithm to obtain the threshold value to link, which has a significant improvement on the problem of uneven illumination but is greatly affected by noise problems; literature [4] uses embedding morphology hat to increase or decrease the edge contrast, and repair some broken edges, but it is not a good way to avoid pseudo-edge. Literature [5] determined the double threshold by continuously increasing the size of the high and low thresholds and using the size of the closed area of the image edge as the standard to detect a more complete image edge, but did not remove the noise, and the image still has more pseudo-edges. Literature [6] proposed a method of generating gradient amplitude by observing the intensity of adjacent pixel values. By calculating the pixel change value and the distance from the adjacent pixel to the central pixel, the intensity of the pixel is obtained, and the quality of the edge detection result is improved.

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2 Improved Canny Algorithm

2.1 Binocular Vision

Binocular vision is an important form of machine vision. It is a method of obtaining the geometric information of the object through calculating the position deviation of the corresponding point of the image by using the machine to imitate the principle of human parallax and using the imaging equipment to obtain two images of the measured object from different positions [7]. The main process of binocular vision includes camera calibration, target extraction, feature extraction, stereo matching, and three-dimensional reconstruction [1-2, 8].

As an important method for image feature extraction, edge detection will recognize the edge contour information of the cargo characteristics and greatly reducing the information that the image needs to process while preserving the shape information of the object. It is a key step to realize the monitoring of the stacking distance of hazardous chemical warehouses and early warning of danger.

The traditional Canny algorithm is one of the mainstream edge detection algorithms. It has good detection effect, strong edge continuity, fast running speed and wide application. The algorithm flow is basically to perform Gaussian smoothing on the image first, then use the differential convolution template to calculate the gradient amplitude and direction, then perform non-maximum suppression on the gradient image, and finally perform double threshold detection and edge connection.

The images acquired by cameras in hazardous chemical warehouses are often disturbed by a lot of salt and pepper noise and different light interference. Salt and pepper noise are one of the main factors that affect edge detection. Salt and pepper noise refer to two kinds of noise-salt noise and pepper noise. Both are white and black light and dark spot noise generated by image sensors, transmission channels, decoding processing, etc. [9]

The traditional Canny algorithm is sensitive to image noise, and it will be affected by the interference of pepper and salt noise in complex environments. Some noises will be considered as edge points mistakenly [10], It will cause weakness of double threshold selectivity and many false edges will appear in the final result [11]. Therefore, this paper improves the traditional Canny algorithm, proposes to use median filtering to improve the noise filtering effect, better protect the image edge information, and then through the Otsu threshold and iterative threshold for adaptive selection of high and low threshold-dual threshold, can remove too much Pseudo-edges and improve the accuracy of edge detection.

2.2 Improved Algorithm Flow Chart

The algorithm in this paper adopts the traditional Canny process and replaces the Gaussian filter with adaptive median filter. Before the double threshold detection step, iterative mean method and Otsu method is used to determine the high and low thresholds. Because the Otsu method is affected by light, the Gaussian filter is added before the Otsu method to smooth the input image. The overall flow chart of the improved algorithm is shown in Fig. 1.

2.3 Adaptive Median Filtering

The median filter is currently one of the effective filters to remove salt and pepper noise, but the conventional median filter, in the processing of hazardous chemicals warehouse images, due to its fixed window, cannot protect image details while denoising [12], needs to be improved.

This paper uses adaptive median filtering to filter out common pepper and salt noise in warehouse monitoring images, smooth other non-impulsive noise, protect image details as much as possible, and avoid image edge coarsening or thinning [13].

There are two processes for the adaptive median filter, which are respectively denoted as A and B: A purpose is to cycle all the time, find the median value of the non-noise point in the process, expand the window to continue the detection if it meets the conditions, otherwise turn to B process; and B is a one-time judgment to find the non-noise point or median. The specific process is as follows: S_{xy} is a rectangular window, $Z_{\min}$ is the minimum gray value in S_{xy}, $Z_{\max}$ is the maximum gray value in S_{xy},

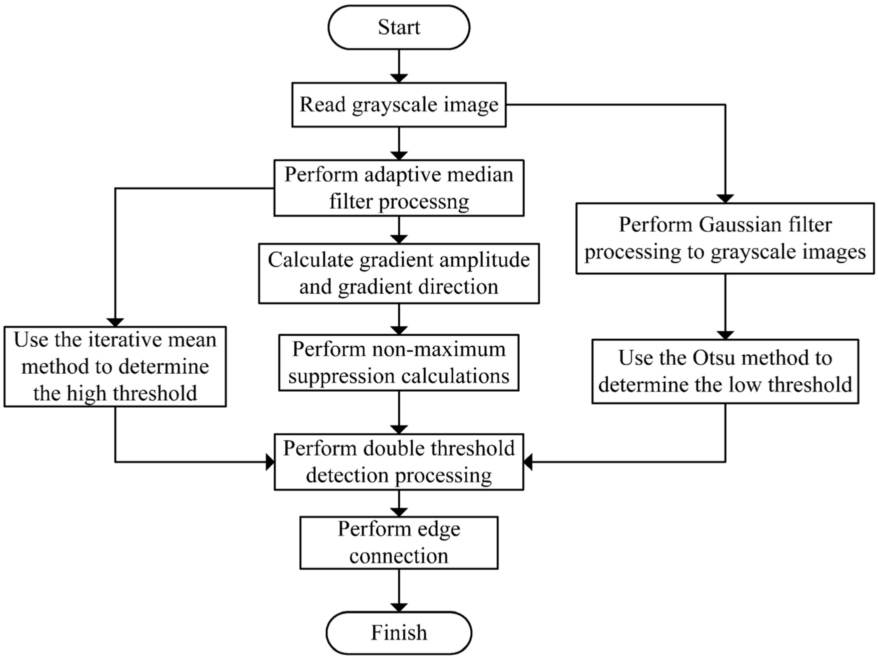

Fig. 1. The overall flow chart of the improved algorithm

Z_{med} is the median gray value in S_{xy}, Z_{xy} represents the gray value at coordinates (x, y), $S_{\max}$ is the maximum window allowed by S_{xy}.

A:

If A1>0 and A2<0, go to B; otherwise, increase the window size.

If the window size after increasing $\leq S_{\max}$, then repeat the A process; otherwise, output Z_{med}.

$$A1 = Z_{med} - Z_{\min}. \tag{1}$$

$$A2 = Z_{med} - Z_{\max}. \tag{2}$$

B:

If B1 > 0 and B2 < 0, the median value of non-noise is Z_{xy}; otherwise, the median value of non-noise is Z_{med}.

$$B1 = Z_{xy} - Z_{\min}. \tag{3}$$

$$B2 = Z_{xy} - Z_{\max}. \tag{4}$$

2.4 Calculate Image Gradient magnitude and Direction

$p(x)$, $p(y)$ are the first-order difference templates in x and y directions, respectively. $g(x)$ and $g(y)$ are the convolved images of x and y gradient maps, respectively. $\varphi(x,y)$ is the gradient intensity, and θ_φ is the gradient direction.

Define the first-order difference convolution gradient template:

$$p_x(x,y) = \begin{vmatrix} -1 & -1 \\ 1 & 1 \end{vmatrix}. \tag{5}$$

$$p_y(x,y) = \begin{vmatrix} 1 & -1 \\ 1 & -1 \end{vmatrix}. \tag{6}$$

Two-dimensional convolution processing is performed on gradient images in the x and y directions using gradient templates, respectively.

$$g(x) = f(x,y) * p_x(x,y). \tag{7}$$

$$g(y) = f(x,y) * p_y(x,y). \tag{8}$$

Further get the gradient amplitude and direction:

$$\varphi(x,y) = \sqrt{g_x^2(x,y) + g_y^2(x,y)}. \tag{9}$$

$$\theta_\varphi = \arctan(\frac{g_y}{g_x}). \tag{10}$$

2.5 Non-maximum Suppression

At each pixel point, the center point (x, y) in the eight neighborhood is compared with the coordinates of the two pixels along its corresponding gradient direction. If the center pixel is the maximum value, it is retained, otherwise it is discarded.

2.6 Iterative Mean Method to Determine High Threshold

The idea of using iterative mean as a high threshold stems from the idea that iterative nature is close to the goal [14]. For specific images with large differences in background and foreground, small data changes will result in dramatical changes in threshold selection and even in the final edge detection results. Because the iterative mean method can find the optimal threshold that converges to the minimum gray level through looping, and thus can obtain the double threshold detection condition which most approximates the difference to the maximum, so it is used for the high threshold value in double threshold detection. The iteration threshold of this algorithm iterates within the gray scale of the image, so the convergence range is the grayscale histogram range, and the minimum value of the convergence sequence is the initial value of 0. In this way, for images with interference, or images with different foreground and background differences, iterative approximation will perform very well [15-16], so based on the characteristics of closed hazardous chemical warehouses, repeated environments, and possible unexpected situations in general, iterative method to take the threshold will make the post-threshold effect outstanding. Flow chart of high threshold value obtained by adaptive iterative mean method is shown in Fig. 2.

(1) Initialize the threshold to T_0;

(2) Use T_i to divide all pixel values into two parts, the value less than or equal to T_0 is G_1 and the value greater than T_0 is G_2, calculate the average of the two parts is m_1 and m_2, respectively.

(3) Use m_1 and m_2 to calculate the new threshold $T_i = \frac{m_1 + m_2}{2}$;

(4) Compare T_0 and T_i, if $|T_i - T_{i-1}| < \Delta T$, then return T_i, which is the iteration threshold; otherwise $T_0 = T_i$, repeat steps 1-3;

The convergence condition is that the threshold change after iteration is less than a convergence control condition. This condition determines the convergence accuracy of the threshold and affects the final threshold. When this condition (denoted as ΔT) is set too large, the number of iterations decreases and the speed becomes faster, and the accuracy decreases; if ΔT is too small, the number of iterations increases and the accuracy increases. For the selection of the initialization threshold T_0, the average values m_1 and m_2 of G_1 and G_2 are calculated respectively, and then the average values of m_1 and m_2 are made, the selection of T_0 is as close to the middle pixel as possible, which can effectively reduce the number of iterations.

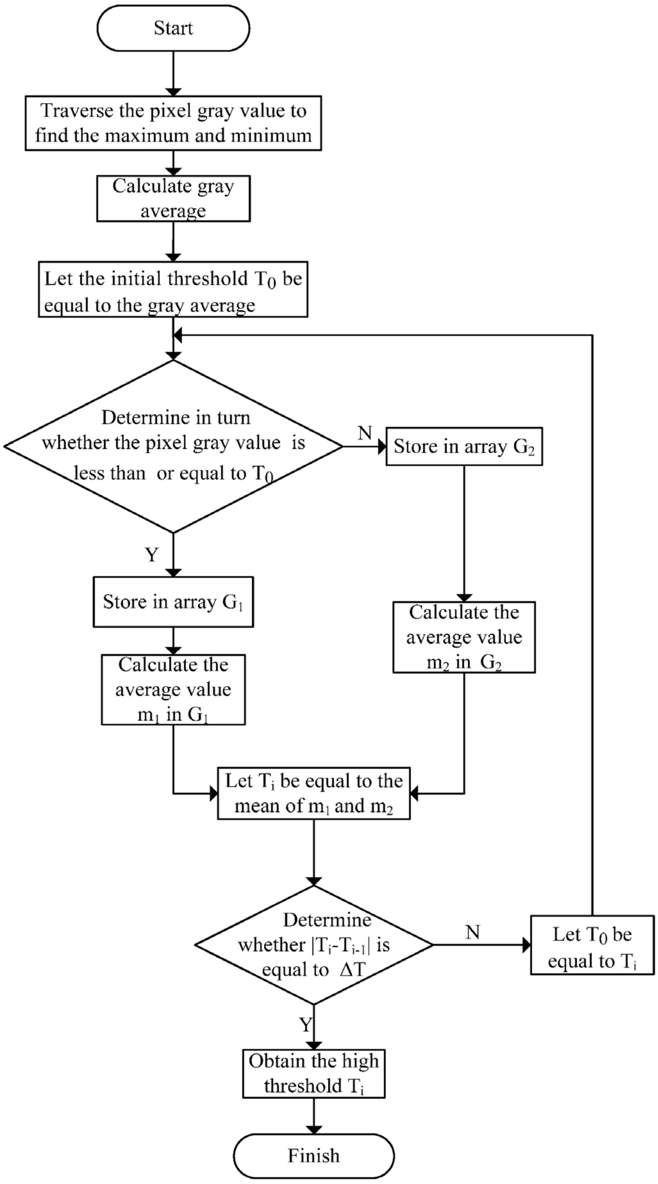

Fig. 2. Flow chart of high threshold value obtained by adaptive iterative mean method

2.7 Otsu Method Determines Low Threshold

The Otsu method is also known as the maximum inter-class variance method. As the name implies, it is a method of segmenting the image with a global adaptive threshold [17]. The algorithm assumes that the image contains two types of pixels, foreground pixels and background pixels, based on the dual-mode histogram. According to the grayscale characteristics of the image, if the calculation makes their intra-class variance minimum, that is, the inter-class variance is maximum, and the optimal threshold for the separation of the two parts is obtained, the image can be divided into two parts, foreground and background. The larger the variance between the background and the foreground, the greater the difference between the two parts that make up the image. When part of the foreground is wrongly divided into the background or part of the background is wrongly divided into the foreground, the difference between the two parts becomes smaller, that is, the segmentation with the largest variance between the classes means the smallest error rate. According to the judgment criterion of double threshold detection, the purpose of the low threshold is to smooth the edge contour, ensure that the edges after strong edge segmentation are continuous and increase the strong segmentation effect, so this paper uses the Otsu method with a small error rate as the low threshold in double threshold detection. Otsu method to obtain adaptive low threshold flow chart is shown in Fig. 3.

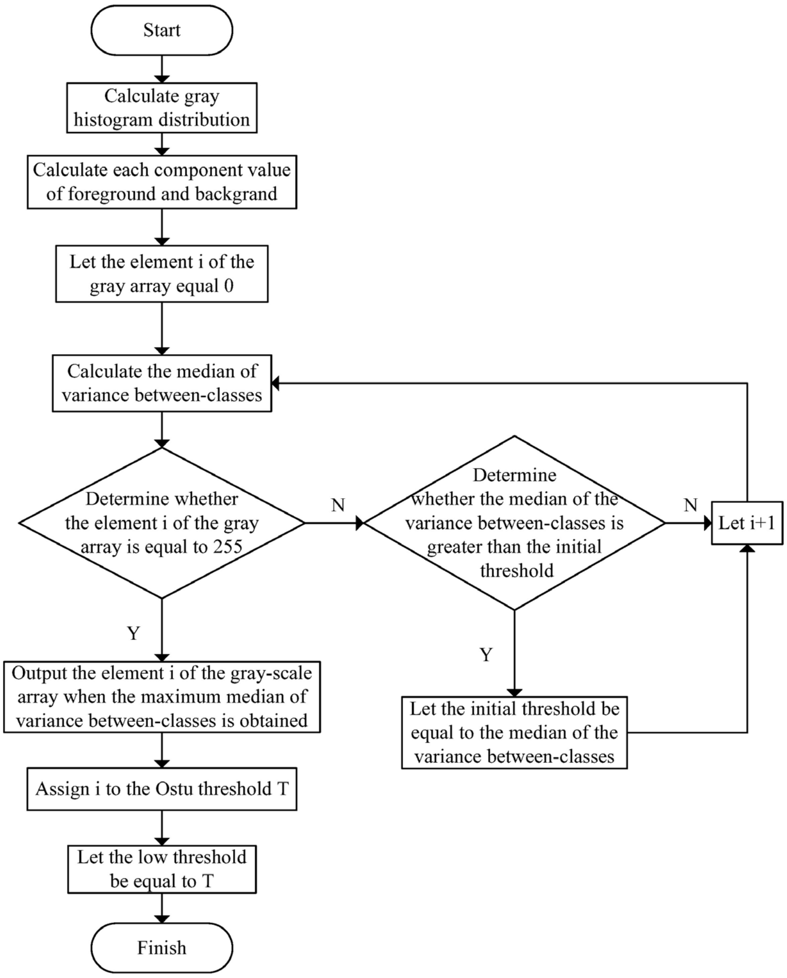

Fig. 3. Flow chart of Otsu method for obtaining adaptive low threshold

First, save the image as a grayscale histogram, divide the grayscale histogram into the foreground and background, use the Otsu method to traverse the histogram in sequence, and perform iterative segmentation operations. When there is a value that maximizes the variance between the foreground and background pixels, the value is the optimal segmentation threshold.

Let *T* be the grayscale threshold, set the pixels in the image whose gray value is higher than T as the foreground, the pixels lower than T as the background. Let g be the inter-class variance of the image, w_0 be the proportion of foreground pixels to image pixels after segmentation, u be the weighted total grayscale of the image, u_0 be the average grayscale of foreground pixels after segmentation, w_1 be the proportion of background pixels to the image pixels after segmentation, and u_1 be the average grayscale of background pixels after segmentation, then the expressions of u and g are shown in formulas (11) and (12).

$$u = w_0 * u_0 + w_1 * u_1. \tag{11}$$

$$g = w_0 * (u_0 - u) * (u_0 - u) + w_1 * (u_1 - u) * (u_1 - u). \tag{12}$$

Because

$$w_0 + w_1 = 1. \tag{13}$$

Then formula **(12)** can be simplify as

$$g = w_0 * w_1 * (u_0 - u_1) * (u_0 - u_1). \tag{14}$$

Traverse t with L gray levels to maximize g, and finally get a low threshold of 0.4 * Otsu threshold.

2.8 Gaussian Filtering

The Otsu method is theoretically not affected by the brightness and contrast of the image, and is not affected by noise. However, it has been found through experiments that the thresholds of the front and back scenes of the simulation of the hazardous chemicals warehouse using the Otsu method will be affected by light. Therefore, before the Otsu process, Gaussian filtering is added. Gaussian filtering is to do preprocessing for the Otsu method. Gaussian filtering is a linear smoothing filter, which is the process of weighted averaging the entire image [18]. The value of each pixel is obtained by weighted average of itself and the values of other pixels in the neighborhood. In this way, the smoothness of the image can be achieved while retaining the distribution characteristics of the overall grayscale of the image.

The image is convolved with a two-dimensional Gaussian function, where $G(x,y)$ is the Gaussian function and $H(x,y)$ is the image after convolution.

$$G(x,y)=\frac{1}{\sqrt{2\pi\sigma}}\exp(-\frac{x^2+y^2}{2\sigma^2}). \quad \textbf{(15)}$$

$$H(x,y)=f(x,y)\cdot H(x,y). \quad \textbf{(16)}$$

Where σ is the standard deviation of the Gaussian function and $f(x,y)$ is the gray value of the input image.

2.9 Double Threshold Detection and Edge Connection

Traditional Canny algorithm chooses the maximum gradient amplitude in the image after non-maximum suppression to define the high and low thresholds [19]. Pixels with gradient amplitudes less than the low threshold are defined as weak edges; Pixels with gradient amplitudes greater than the high threshold are defined as strong edges; and Pixels with gradient amplitudes between strong and weak edges use eight-connected regions, and their gradient amplitudes are the average of the gradient values of the pixels in the connected eight area, so as to achieve a smooth effect.

3 Experimental Simulation Verification and Analysis

The experimental hardware platform is an Intel Core i7-8565 computer, 8G running memory, and the operating system is Windows10. Use Opencv 2.4.11 + Visual Studio2013 for programming. A POE camera is used to collect images of a simulated dangerous goods warehouse. It consists of a number of 80 * 80 * 80mm, 100 * 100 * 100mm boxes and painted cylinders, which are used to simulate different sizes and shapes of dangerous goods in the dangerous goods warehouse. Chemical goods constitute 35 combinations. In the experimental environment, the pixels of the collected pictures are 640 * 480 and 640*360.Under ordinary illumination, night vision environment, night vision and lighting interference conditions, 10 groups of pictures were collected for the experiment.

3.1 Experimental Data

In normal lighting, night vision environment, night vision and light interference three environments were randomly selected three groups of experimental pictures. The experimental pictures of the comparison between the traditional algorithm and the improved algorithm in the three cases are shown in Fig. 4 to Fig. 12. Among them, Fig. 4 to Fig. 6 are comparative experiments of two algorithms under ordinary lighting, Fig. 7 to Fig. 9 are comparative experiments of two algorithms under night vision environment, and Fig. 10 to Fig. 12 are comparative experiments of two algorithms under night vision and light interference. The following circled characters are the picture numbers; a, b, and c represent the original picture, the traditional Canny algorithm to process the picture, and the improved Canny algorithm to process the picture, respectively.

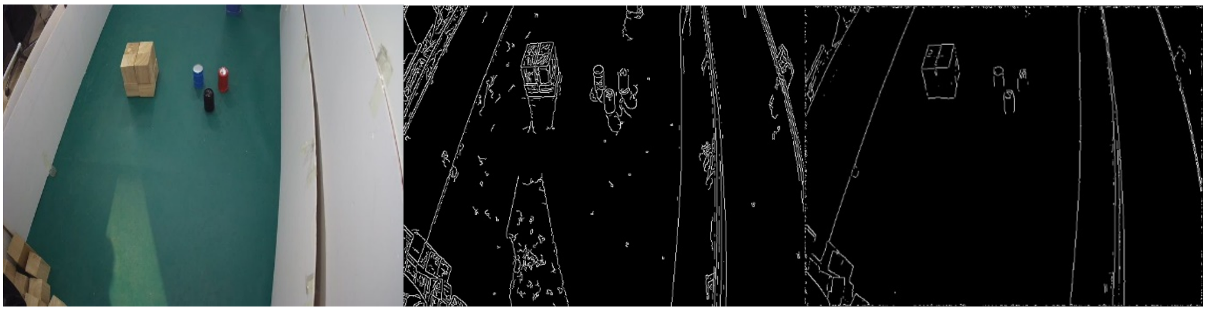

Fig. 4. Comparison under ordinary illumination (*a(1), b(1), c(1)*)

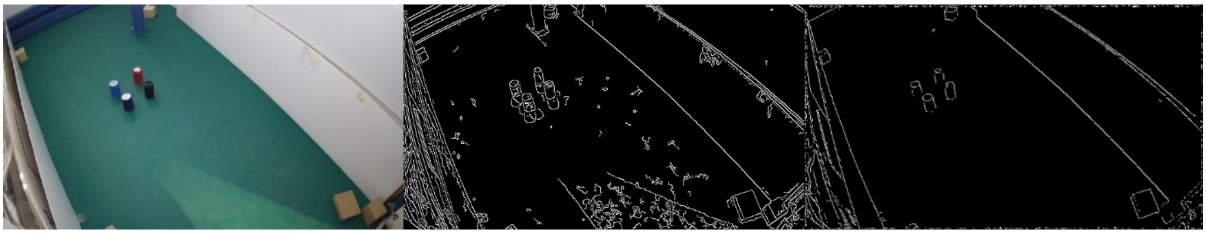

Fig. 5. Comparison under ordinary illumination (*a(4), b(4), c(4)*)

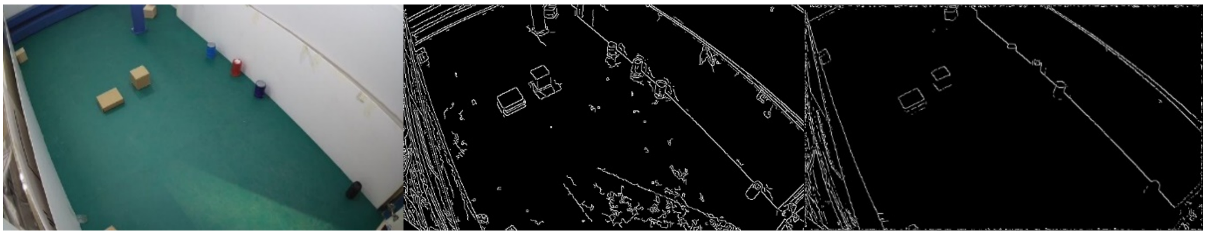

Fig. 6. Comparison under ordinary illumination (*a(6), b(6), c(6)*)

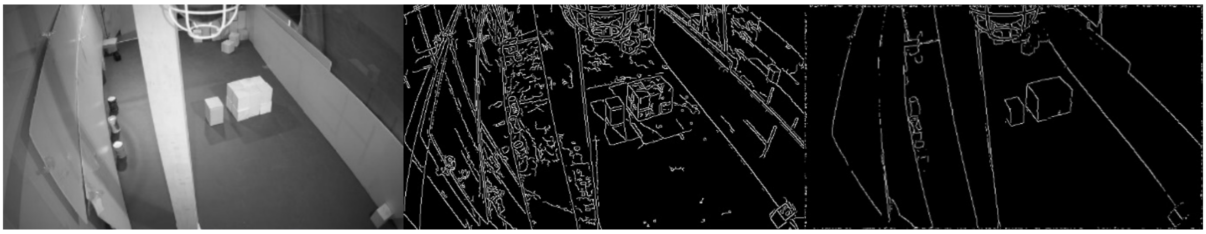

Fig. 7. Comparison under night vision (*a(12), b(12), c(12)*)

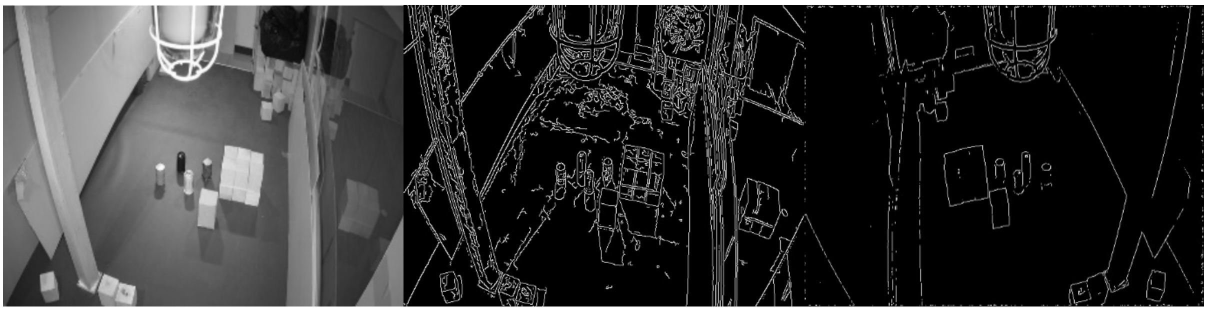

Fig. 8. Comparison under night vision (*a(18), b(18), c(18)*)

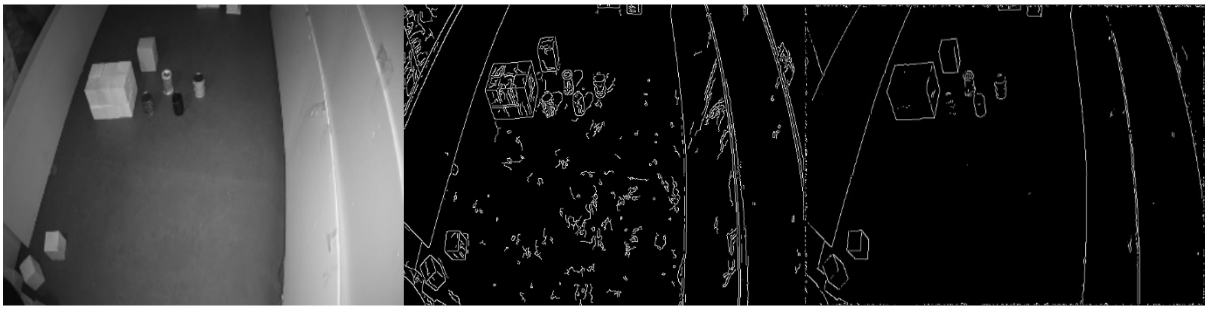

Fig. 9. Comparison under night vision (*a(20), b(20), c(20)*)

Fig. 10. Comparison under night vision and light interference (*a(23), b(23), c(23)*)

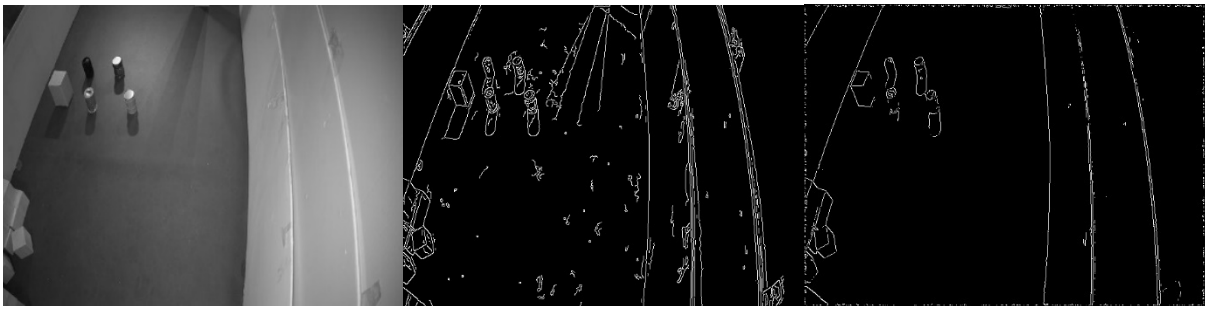

Fig. 11. Comparison under night vision and light interference (*a(24), b(24), c(24)*)

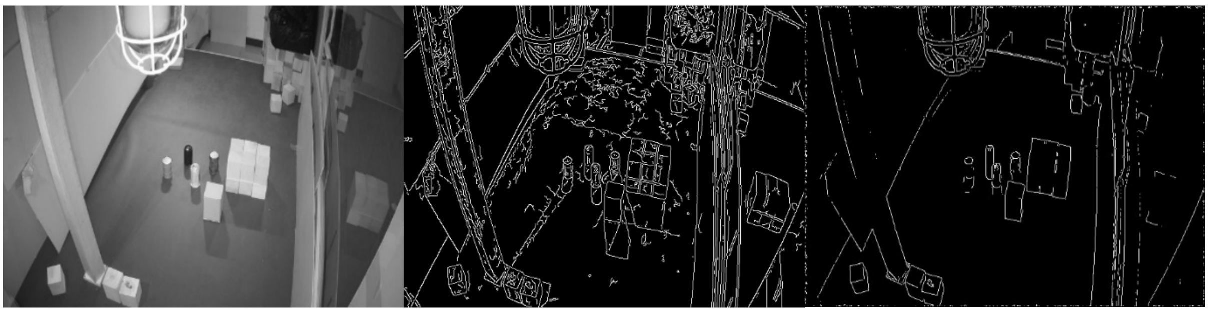

Fig. 12. Comparison under night vision and light interference (*a(28), b(28), c(28)*)

It can be seen from the experimental pictures that under ordinary illumination, the traditional Canny algorithm mixes more pepper and salt noise points, and at the same time, there are more pseudo-edge, which is difficult to distinguish the edges of objects. The edge of the improved algorithm removes more pepper and salt noise points and retains a more complete edge of objects. Under the conditions of night vision and light interference under night vision, the traditional algorithm is difficult to distinguish the edges of objects, the noise interference is serious, and the edge connection is incomplete. The improved algorithm effectively removes noise through adaptive median filtering, and the Otsu threshold has obvious effects on image protection and processing on pseudo-edge.

3.2 Evaluation Index

According to the research plan described in this article, the peak signal-to-noise ratio (Peak signal-to-noise ratio, PSNR) and information entropy are used as evaluation indicators for the obtained experimental data to verify the feasibility and effectiveness of the improved Canny algorithm.

3.2.1 Peak Signal-to-noise Ratio

The peak signal-to-noise ratio is the ratio of the maximum possible power of a signal to the destructive noise power that affects its representation accuracy. The peak signal-to-noise ratio is usually expressed in decibels. The edge detection pictures obtained by the two algorithms after compression are respectively calculated by PSRN to obtain image distortion and noise levels, thereby comparing the advantages and disadvantages of image edge detection. The higher the PSNR of the image is, the better picture is. PSNR is defined as:

$$PSNR = 10 \cdot \log_{10}\left(\frac{MAX_I^2}{MSE}\right) = 20 \cdot \log_{10}\left(\frac{MAX_I}{\sqrt{MSE}}\right). \quad \textbf{(17)}$$

MSE is the mean square deviation:

$$MSE = \frac{1}{mn}\sum_{i=0}^{m-1}\sum_{j=0}^{n-1} \| I(i,j) - K(i,j) \|^2 . \quad \textbf{(18)}$$

MAX represents the maximum gray scale of the image pixels, I is the image to be detected, K is the reduced image, and the image size is m * n.

Calculate and compare the peak signal-to-noise ratio of ten groups of images based on traditional Canny algorithm and improved algorithm under one environment.

3.2.2 Information Entropy

Information entropy refers to a mathematically abstract concept, which can be understood as the occurrence probability of certain information and can be used to judge the degree of confusion of the image. Its unit is bits / pixel. The smaller the information entropy is, the more accurate the edge information is, and the better the edge detection effect the algorithm has.

Use H to represent the information entropy, traverse the distribution of pixel gray values, and select the average gray value of the neighborhood of the image as the spatial feature quantity of the gray distribution. It forms a feature dual with the pixel gray of the image, and is denoted as (i, j), where i represents the pixel gray value ($0 \le i \le 255$), j represents the neighborhood gray ($0 \le i \le 255$), N represents the image scale (m * n), P_{ij} is one-dimensional entropy, and $f(i,j)$ is the frequency of (i,j) .

$$P_{ij} = f(i,j)/N^2. \quad \textbf{(19)}$$

$$H = \sum_{i=0}^{255} p_{ij} \log p_{ij}. \quad \textbf{(20)}$$

Calculate and compare the information entropy of ten groups of images based on traditional Canny algorithm and improved algorithm in one environment.

The analysis of the data in Fig. 13 to Fig. 18 shows that the improved Canny algorithm has higher PSNR and lower information entropy than the traditional Canny algorithm, which is consistent with the reduction of the experimental picture's distortion rate and the improvement of image quality. By improving the algorithm and the traditional algorithm under different environments, the PSNR mean and information entropy show that the improvement under night vision and lighting interference is the most obvious, followed by the night vision environment, then ordinary illumination. Since the traditional Canny algorithm uses Gaussian filtering for smoothing, and in the case where the existing pepper and salt noise is also affected by illumination interference, the improved algorithm uses adaptive median filtering that is better than the Gaussian filtering of the traditional Canny algorithm, and the threshold is more appropriate. It is difficult to judge the threshold when the night vision environment and ordinary lighting are similar in the foreground and background environment. Using an iteration threshold to select a high threshold can effectively protect the integrity of the edge and ensure the authenticity of the edge effect.

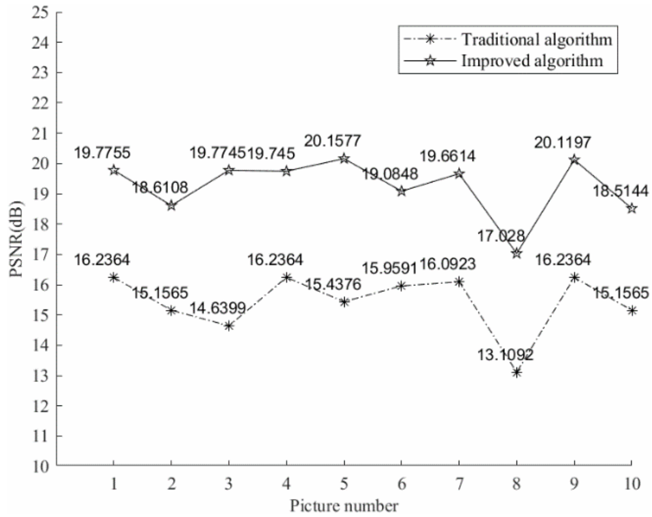

Fig. 13. Comparison of PSNR of two algorithms under ordinary illumination

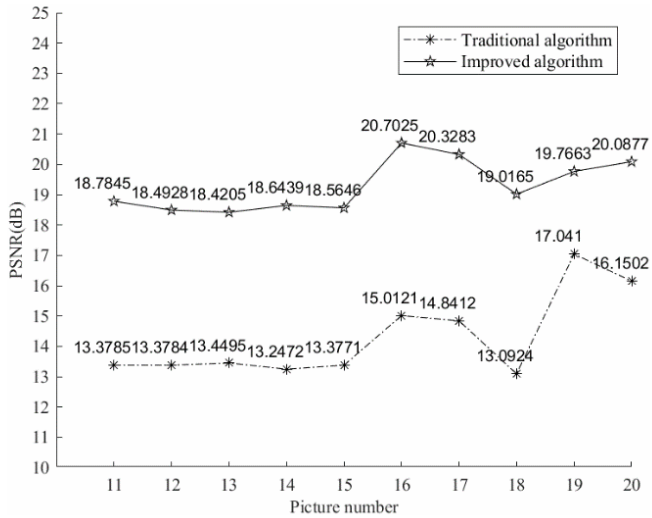

Fig. 14. Comparison of PSNR of two algorithms under night vision

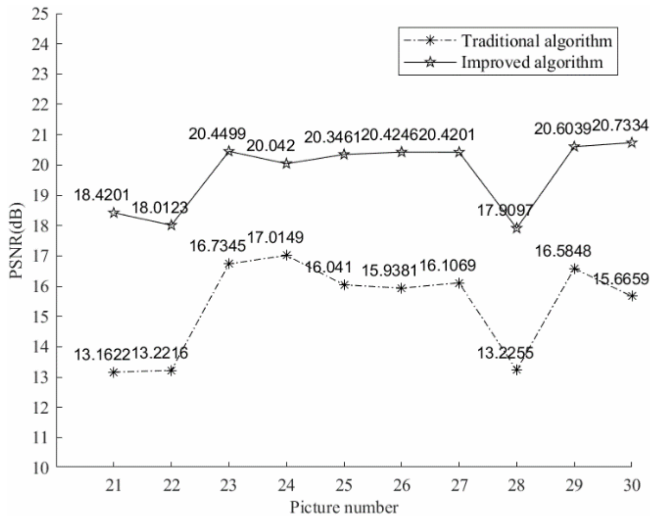

Fig. 15. Comparison of PSNR of two algorithms under night vision and light interference

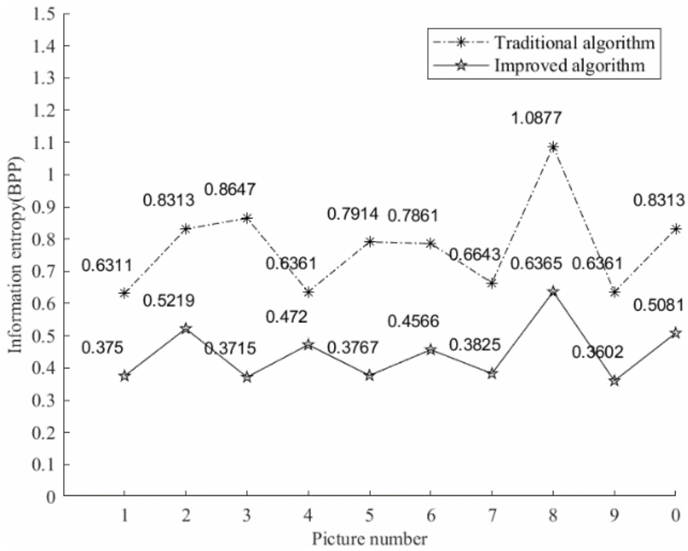

Fig. 16. Information entropy comparison of two algorithms under ordinary illumination

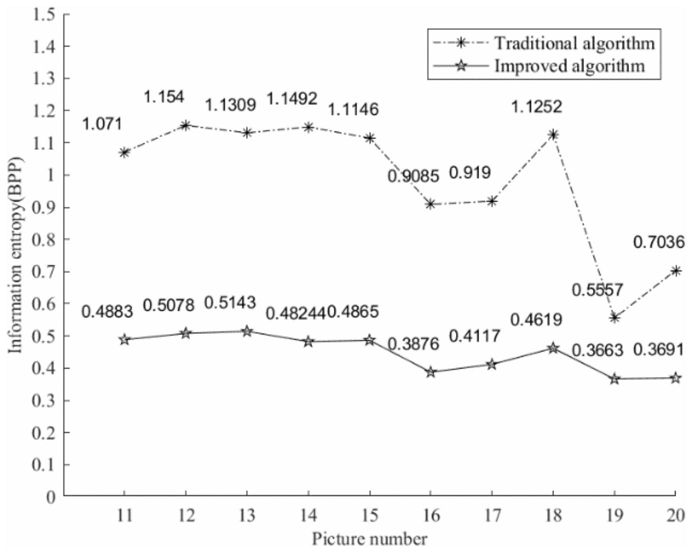

Fig. 17. Information entropy comparison of two algorithms under night vision

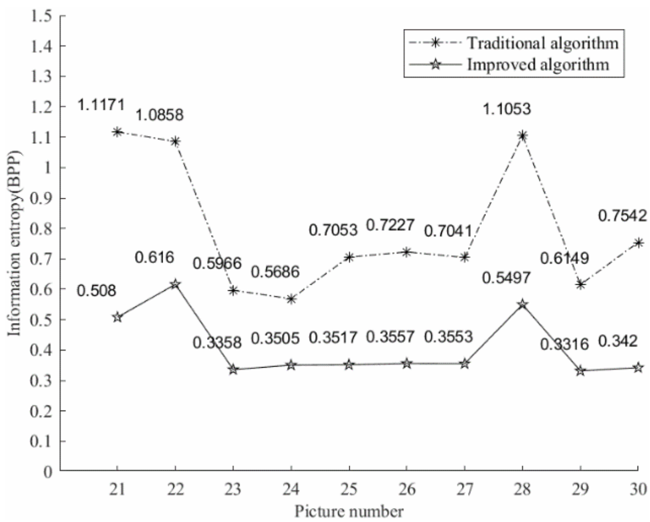

Fig. 18. Information entropy comparison of two algorithms under night vision and light interference

It can be seen from the comparison between Fig. 5 and Fig. 6, that the fourth picture is more complicated than the sixth picture under ordinary illumination. Through the analysis of the evaluation index PSNR and information entropy, it is found that the two parameters of the complex picture are slightly better than the evaluation index of the simple picture. This shows that the improved algorithm edge detection effect is still better under the condition that the average image information is large.

The reason why the effect of individual pictures differs greatly from the pictures in the same group is not due to improved algorithms, but other factors. For example, the PSNR of the 28th picture is too low, it can be seen that the influence of lighting interference in this case is too serious, beyond the range of the selectable segmentation threshold, and is not a problem of adaptive median filtering and adaptive threshold.

From the six curve pictures in three cases, it can be seen that the improved algorithm is steadier than the ordinary algorithm, indicating that the improved algorithm can adapt well to a variety of environments and is suitable for the edge detection of hazardous chemical warehouses.

4 Conclusion

The edge information of the hazardous chemicals warehouse goods will be greatly affected by the environment, especially the light, salt and pepper noise, which affects the operation effect of the edge detection algorithm. This paper proposes the Canny algorithm improved by adaptive median filtering, Otsu method and iterative mean method. The results under different experimental environments show that the improved algorithm reduces the interference of salt and pepper noise, removes false edges, improves the peak signal-to-noise ratio, and effect of edge detection is significantly increased. In the next step, we will continue to improve and explore problems such as incomplete edge connections and broken corners.

Acknowledgements

Fund Project: Cross-cultivation of high-level talents in Beijing high school, the “Practical Training Project” Deepening Project of University Student Research and Training Program (2019) (144): Research on Stereo Matching Algorithm in 3D Reconstruction System of Binocular Vision Ranging; Beijing University Student Research and Training Program Fund Project (2020J00186): Fire monitoring and early warning in hazardous chemicals warehouse based on multiple features.

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