Foreign Body Intrusion Detection Algorithm

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Abstract: In recent years, image processing technology has been continuously evolving. With the advent of the intelligent era, image processing technology will have a wider range of applications. This paper proposes and designs a kind of technology against the background of many problems existing in traditional railway track foreign object intrusion recognition systems Image processing-based orbit foreign body intrusion detection algorithm, and simulation verification and research analysis under Matlab working environment, can achieve the effect of accurate, fast real-time monitoring.

1. Introduction

Today, China's railway transportation industry is booming. However, with the continuous increase in the speed of trains and the increase in operating mileage, traffic accidents caused by the invasion of foreign objects (obstructions on the railway tracks that affect safe driving) have repeatedly occurred, posing a serious threat to people's lives and property[1].

Based on machine vision and digital image processing technology, this paper proposes and designs a railway track foreign object intrusion recognition system based on image processing. It is placed along the railroad where foreign objects invade frequently, and real-time remote observation is used to realize foreign object detection. Image processing mainly includes image pre-processing, track identification, advanced image processing, and foreign object detection. Image processing flowchart shown in Figure 1.

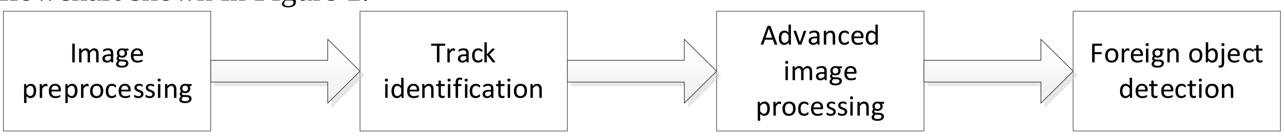


Figure 1 Image processing flowchart

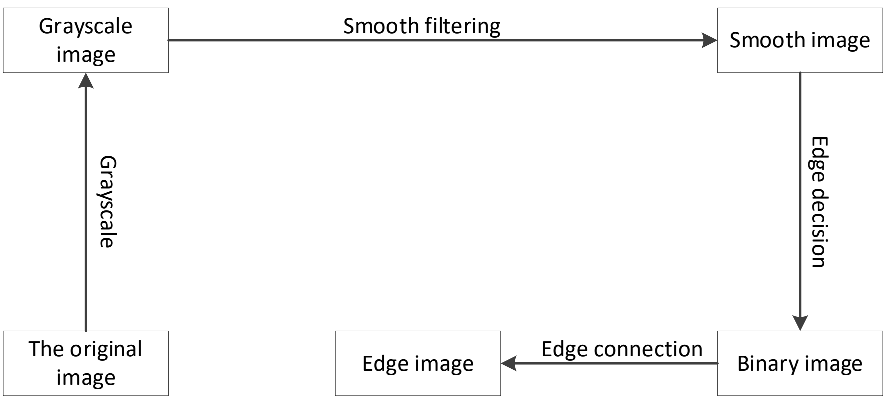


Figure 2 Image preprocessing flowchart

2. Image preprocessing

In general, the image quality is greatly reduced due to the interference of many non-artificial and uncontrollable factors during the image acquisition process[2]. To ensure the accuracy of image processing in the later period, the image quality should be improved, so image preprocessing is required. As shown in Figure 2, image preprocessing includes grayscale, smoothing filtering, sharpening filtering, and edge detection.

2.1 Image Graying

The image is grayed out to obtain a grayscale image, also called a monochrome image, where 0 is black, 255 is white, and 1 to 254 are different shades of gray. Grayscale images can better highlight the morphology and color depth of the image. The principle of graying is as follows[3]:

$$\mathrm{Gray} = 0.299 \times \mathrm{R} + 0.587 \times \mathrm{G} + 0.114 \times \mathrm{B} \tag{1}$$

Among them, R, G, and B represent the red, green, and blue components, respectively. The image graying is shown in Figure 3.

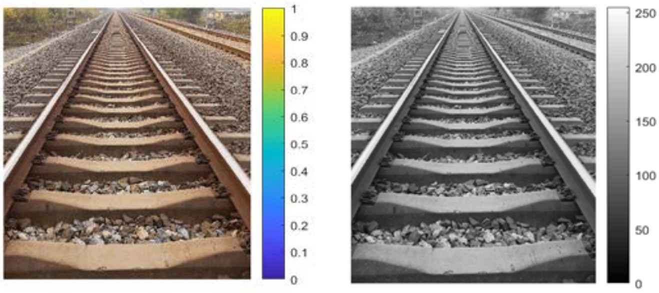
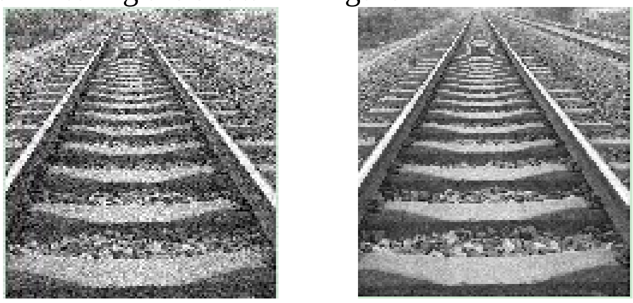


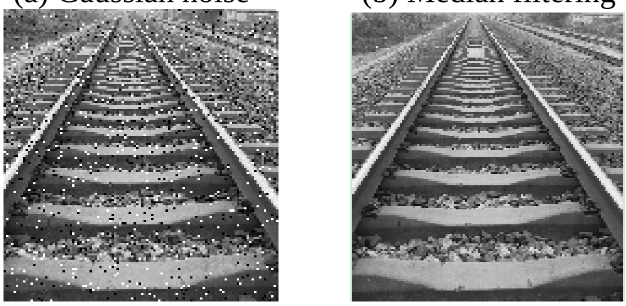
Figure 3 Image graying

2.2 Image Smoothing

In the actual railway environment, it is impossible to avoid noise interference during image acquisition and transmission[3]. In order to reduce and suppress image noise, smooth filtering is required. Median filtering has obvious effects on reducing salt and pepper noise, and small window filtering removes While protecting the edges as much as possible while noise is caused, the blur effect caused is low. The essence of median filtering is a statistical sorting filter, which uses the elements in the middle of the queue as the response of the median filtering. The simulation results of two-dimensional median filtering are shown in Figure 4



(a) Gaussian noise (b) Median filtering



(c) salt and pepper noise (d) Median filtering

Figure 4 Image smoothing filter

2.3 Image Sharpening Filtering

The smoothing filtering of the image will reduce the boundary strength of the image while suppressing noise. In order to ensure that the blurred boundary of the smoothed image becomes clearer, to avoid misdetection and omission of foreign objects in the later stage, the image should be sharpened and filtered. This paper chooses Laplace sharpening filtering.

Laplacian operator is an image enhancement based on second-order differentiation, which has a good sharpening effect on the edges of the image that is close to horizontal and close to vertical, that is, it is isotropic, and it also avoids using horizontal and vertical separately. The trouble of filtering twice, which is very beneficial for sharpening the image. The Laplacian operator of a two-dimensional function is defined as:[4]

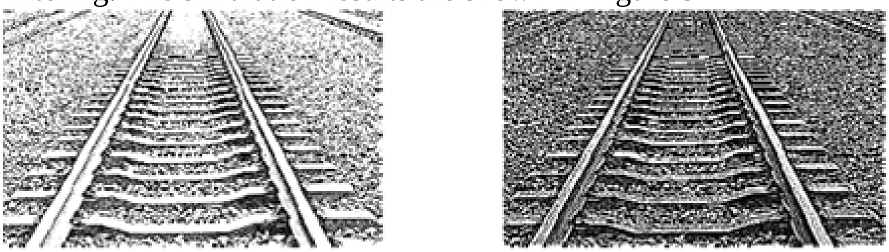
$$\nabla^2 f(x, \mathrm{y}) = \frac{\partial^2 f}{\partial x^2} + \frac{\partial^2 f}{\partial y^2} \tag{2}$$

$$f = \left[f(i+1, j) + f(i-1, j) + f(i, j+1) + f(i, j-1) \right] - 4 f(i, j) \tag{3}$$

Filter template W_1 for the four-neighbor Laplacian operator, the points around the template are assigned different weights according to the distance from the center point, and a more commonly used eight-neighbor Laplacian template W_2 can be obtained.

$$W_1 = \begin{bmatrix} 0 & -1 & 0 \\ -1 & -4 & -1 \\ 0 & -1 & 0 \end{bmatrix} \qquad W_2 = \begin{bmatrix} 0 & -1 & 0 \\ -1 & 8 & -1 \\ 0 & -1 & 0 \end{bmatrix} \tag{4}$$

The Laplacian four-neighborhood template and the eight-neighborhood template are used for sharpening and filtering. The simulation results are shown in Figure 5



(a) Four neighborhood sharpening (b) Eight neighborhood sharpening

Figure 5 Image sharpening filtering with different Laplacian operator tem

2.4 Image Edge Detection

Edges are composed of edge points that have a step change in the gray level of the pixels around the image. Significant changes in gray levels often reflect the significance and characteristics of the image, retaining important structural attributes of the image. There are currently five types of edge detection operators, namely Sobel, Prewitt, Roberts, and Log and Canny operators based on second derivatives.

(1) Roberts[5] operator uses the method of oblique deviation to find the edge, which is more sensitive to noise, the template is small, and some edges are easily lost. Roberts operator template is:

$$W_1 = \begin{bmatrix} -1 & 0 \\ 0 & 1 \end{bmatrix} W_2 = \begin{bmatrix} 0 & -1 \\ 1 & 0 \end{bmatrix} \tag{5}$$

(2) Sobel and Prewitt[6] operators consider neighborhood information, which can suppress some noise, but cannot exclude all false edges. Where G_x is a horizontal Sobel template, G_y is a vertical Sobel template, W_y is a horizontal Prewitt template, W_y is a vertical Prewitt template.

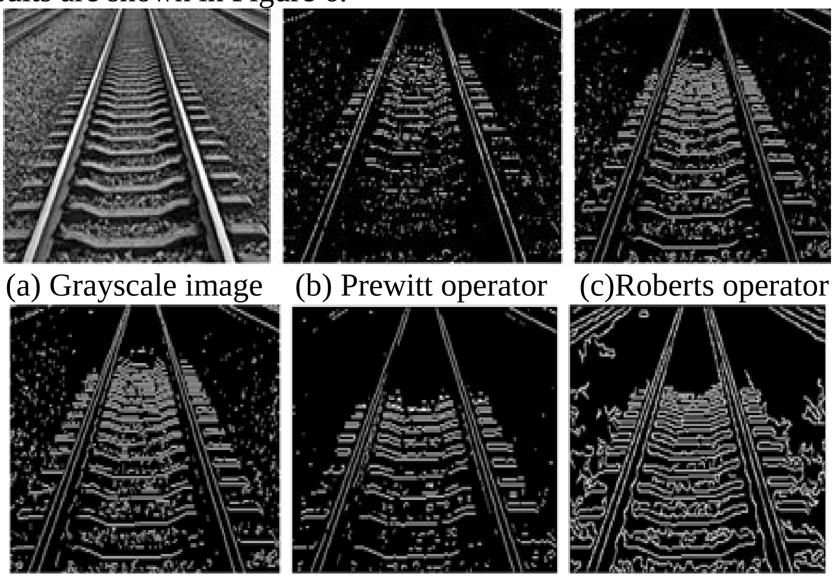
$$G_x = \begin{bmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{bmatrix} G_y = \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix} \tag{6}$$

$$W_x = \begin{bmatrix} -1 & -1 & -1 \\ 0 & 0 & 0 \\ 1 & 1 & 1 \end{bmatrix} W_y = \begin{bmatrix} -1 & 0 & 1 \\ -1 & 0 & 1 \\ -1 & 0 & 1 \end{bmatrix} \tag{7}$$

(3) The Log[7] operator can suppress noise by smoothing, but cannot detect sharp edges that are smoothed out. The commonly used Log operator is a 5 × 5 template:

$$W = \begin{bmatrix} 0 & 0 & -1 & 0 & 0 \\ 0 & -1 & -2 & -1 & 0 \\ -1 & -2 & 16 & -2 & -1 \\ 0 & -1 & -2 & -1 & 0 \\ 0 & 0 & -1 & 0 & 0 \end{bmatrix} \tag{8}$$

(4) The Canny[8] operator tries to find the best compromise between anti-noise interference and accurate positioning. Based on the finite difference convolution of the first-order partial derivative, the gradient amplitude and direction are calculated, while retaining the point with the largest local gradient. Finally, a dual-threshold algorithm is set to detect and connect edges. The five types of edge detection results are shown in Figure 6.



(a) Grayscale image (b) Prewitt operator (c)Roberts operator

(d)Sobel operator (e)Log operator (f)Canny operator

Figure 6 Detection results of different edge detection operators

3. Identify tracks

The track is the main feature of railway video images. The comparison of the invading foreign body and the track position determines whether the invading foreign body will pose a threat to safe driving. Therefore, the identification of the track is the premise of the early warning of the foreign body. The edge of is regarded as the dividing line between the safe area and the alert area of the foreign body invasion[9].

In actual railway scenes, due to factors such as noise interference and uneven light intensity, the track edge points obtained in most cases are discontinuous. Intermittent edge points must be converted into meaningful ones through edge connections. Edge. As shown in Figure 7, the most commonly used Hough transform is based on the principle of point and line duality. Complete straight line extraction[10].

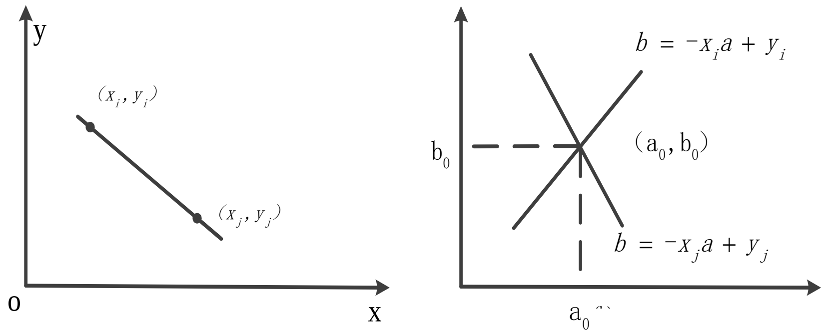


Figure 7 Hough transform in rectangular coordinate system

In particular, when the straight line is perpendicular to the x-axis, the slope is infinite, so to avoid this problem, the Hough change can be transformed into a polar coordinate system, as shown in Figure 8, where ρ is the distance from the origin to the straight line, θ The vector angle from the origin to the straight vertical line.

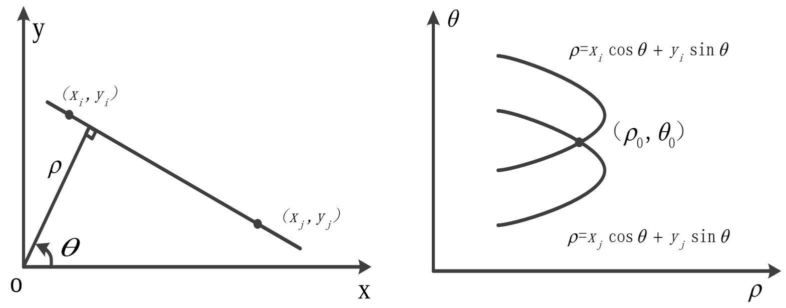


Figure 8 Hough transform in polar coordinate system

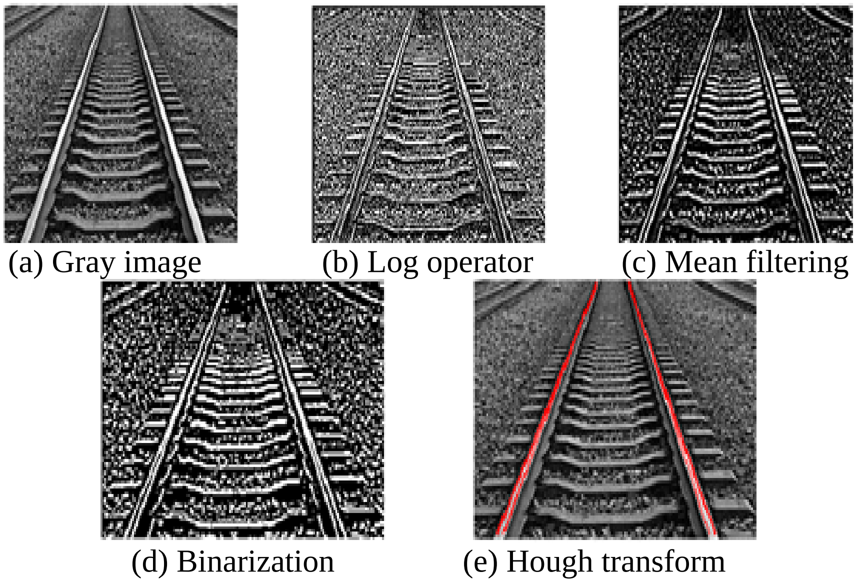


Figure 9 Hough transform for track identification

This paper is based on the background of Matlab, combined with edge detection and Hough transform, to complete the automatic identification of the track. The simulation results are shown in Figure 9. The edge of the track determines the boundary of the warning area for foreign body intrusion identification. The basics. In addition, in order to reduce and suppress the influence of noise on the track image, smooth filtering is performed on the track image.

4. Advanced image processing

Advanced image processing is to extract detection targets based on background images. The main methods are background difference method[11], frame difference method and optical flow method. The background difference method can ignore the complexity of the background for foreground extraction, and the recognition is accurate and fast, which can meet the requirements of real-time railway operation and site complexity. This paper uses background difference method to detect targets.

4.1 Background Modeling and Updating

Images can be divided into foreground and background based on whether they contain detection targets. In this paper, the track without detection target is taken as the background image. In order to reduce the image error caused by external temperature, weather changes, and sensor jitter, the background image needs to be modeled. Taking into account the leaves shaking, the small changes caused by changes in light intensity will affect the accuracy of target recognition, and the background image needs to be updated in real time.

This paper uses mean value modeling to implement background modeling, that is, to take the average gray value of each pixel of consecutive N multi-frame images as the gray value of the pixel corresponding to each point of the background image. The specific method of background update is to integrate the gray value of the pixel of the current frame image into the corresponding pixel of the background image according to a certain proportion of weight, and update the gray value of the corresponding pixel of the current frame image and the background image passed by the background pixel gray value The gray value of the corresponding pixel is represented linearly[12].

$$\begin{cases} F_b^{*}(x,y,t) = \alpha F_b(x,y,t) + \beta F_d(x,y,t) \\ \alpha + \beta = 1 \end{cases} \tag{9}$$

Among them, α and β background update coefficients are reasonably selected according to theoretical experience, actual needs, and site environment, F_b^* is the updated background image, F_b is the background image, and F_d is the current frame image[13].

The specific implementation is: Subtract the corresponding pixels of the current frame image and the background model image one by one to obtain a differential image. For each pixel of the differential image, compared with the preset experience threshold, when the pixel is greater than the experience threshold, the pixel The point is the front spot, otherwise it is the background point. Thus, a binary image of the detection target is obtained. This paper uses the background difference method.

Among them, T is the set threshold, F_b is the background image, $F_q(t)$ is the current frame image, m is the background binary image after the difference, and the threshold is calculated according to the graythresh function[14].

$$F_q(t) = \begin{cases} 1, \left| F_d(x,y,t) - F_b(x,y,t) \right| \geq T \\ 0, \quad \text{others} \end{cases} \tag{10}$$

The adaptive method for determining the threshold is also called the Otsu method[15]. Extract the gray histogram characteristic parameters of the image and determine the initial threshold T',The gray histogram is a two-dimensional image describing the statistical characteristics of each gray level of the image, including gray histogram and gray normalized histogram. The abscissa is the gray level of each pixel of the image, and the ordinate represents the number and probability of each gray level of the image. For a normalized histogram[16]:

$$P(r_k) = \frac{n_k}{N} \qquad (k = 0,1,2,...,L-1) \tag{11}$$

Among them, the total pixel value of the track image is N, the pixel value of the gray level is n_k, the first gray level is r_k, and the relative frequency of the gray level is $P(r_k)$.

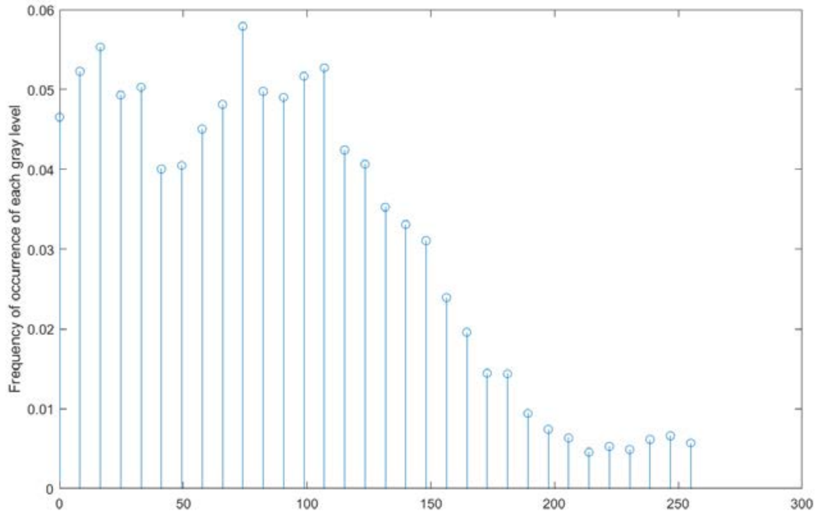
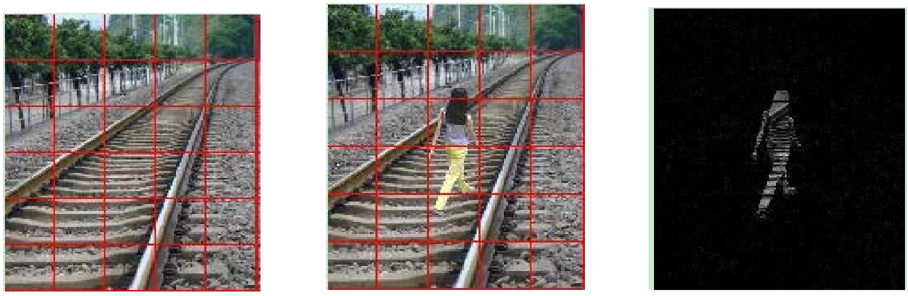


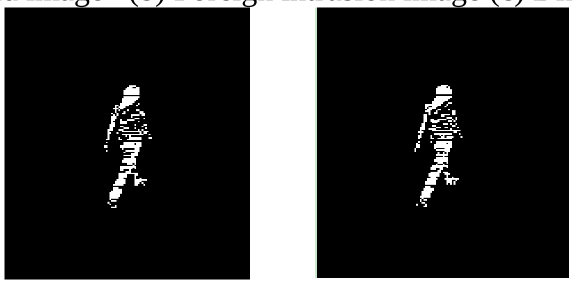
Figure 10 Normalized histogram of gray image

The (normalized) grayscale histogram of the track image can intuitively reflect the brightness and contrast characteristics of the image. As shown in Figures 10, the peak value of the grayscale histogram is on the right side, indicating that the image is dark and the dark part of the image Features and details are easier to distinguish. The non-zero distribution of the histogram is wider and more uniform, indicating that the contrast of the image is higher[17].

The image is divided into a background image and a target image portion. The larger the inter-class variance between the background image and the target image, the greater the difference between the two parts that make up the image[18]. the segmentation that maximizes the variance between classes means the smallest probability of misclassification, and the threshold T is the threshold when the variance is minimized[19].



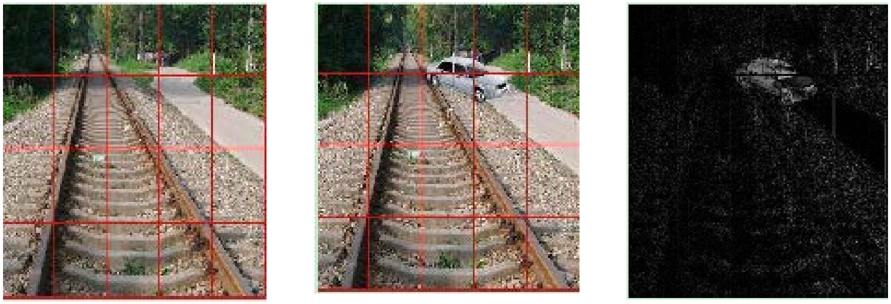
(a) Background image (b) Foreign intrusion image (c) Difference image



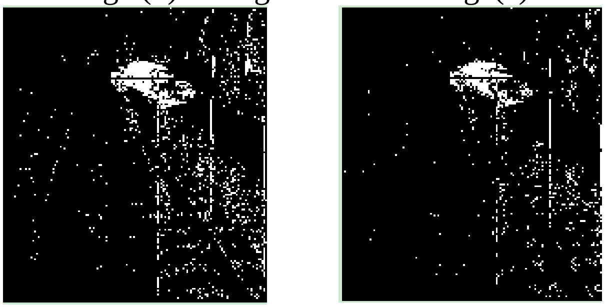
(d) Graythresh image (e) Background difference image

Figure 11 Pedestrian intrusion foreign object recognition

As shown in Figure 11 and Figure 12, this article has completed the simulation recognition of pedestrians and vehicles invading foreign objects based on Matlab.



(a) Background image (b) Foreign intrusion image(c) Difference image



(d) Graythresh image (e) Background difference image

Figure 12 Vehicle Intrusion Foreign Object Identification

5. Conclusions

With the rapid development of China's railway industry, the safety problems caused by the intrusion of foreign objects in rails have become increasingly prominent. The traditional intrusion identification system of rails has the problems of poor real-time recognition, low accuracy, and high system failure rate[20]. Aiming at these problems, this paper proposes and designs an orbital foreign body intrusion detection algorithm based on image processing. The overall algorithm was simulated and verified under Matlab's working environment, and the recognition of pedestrians and vehicles' track invasion of foreign objects was realized and the expected goal was achieved.

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