Comparative Study on Perimeter Intrusion Detection System of High-speed Railway

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Abstract: The perimeter intrusion detection system is critical to China's railway safety. An efficient intrusion detection system can effectively avoid human casualties and property damage. This article makes a comprehensive comparison of popular detection systems in recent years. It first outlines the characteristics and classification of intrusion detection systems, and then introduces the relevant literature of contact and non-contact systems according to different types, and also introduces the principles and architecture of the models they use in detail. Finally, the detection performance and suitable environment under different system models are analyzed by comparison.

Key words: Intrusion Detection, Contact System, Non-contact System, Machine Vision

1 Introduction

With the rapid development of China's high-speed railways and urban rail transit, the safety of railway transportation has received increasing attention. Foreign matter invasion of the railway is very dangerous to the normal operation of the railway. For example, the collapse of tunnel entrances and landslides pose a huge threat to railway safety. During the construction of highways interlaced with railways, construction machinery, materials and workers may invade the gaps of the railways and cause great damage to passing trains. As an important part of the railway disaster prevention system, the foreign body intrusion detection system is used to detect any object that invades the railway gap along the railway area. It can detect the intrusion of foreign objects on the railway in real time, and warn the foreign objects that have a tendency to invade, so as to avoid fatal accidents.

There are various ways of intrusion detection systems for manual investigation and equipment detection. Due to the length of high-speed railway lines, manual inspections are only used to assist and verify information from equipment inspections. There are currently two types of popular device detection: contact and non-contact. Fences with test lines or fiber Bragg gratings (FBG) are typical contact detection methods[1]. It can well detect human intrusion to protect the surroundings. Moreover, the optical fiber sensor has the ability to resist electromagnetic interference, and has high sensitivity, compactness, remote sensing capability, and stability in harsh environments. It also has the disadvantages of not being able to accurately detect small objects and the installation of fences is complicated and expensive. Infrared, microwave, laser and machine vision are typical solutions of non-contact methods[2]. Infrared is often used in the design of low-cost security surveillance systems. But it cannot determine the exact size and location of the object. Microwaves and lasers are widely used in autonomous positions of robots, which can give precise object positions and sizes, but equipment is usually more expensive[3]. Target recognition systems with video surveillance are widely used in banks, hotels, markets, and roads. Compared with other non-contact methods, machine vision has the advantages of wider range, simple and intuitive installation. Therefore, we have conducted extensive research on machine vision-based intrusion detection systems.

The rest of the paper is organized as follows: Section 2 reports contact detection methods. Section 3 reports non-contact detection methods. Section 4, we compared two common detection systems from different perspectives. Finally, the paper is concluded in Section 5.

2 Contact Detection Method

References [4] and [5] have proposed railway perimeter intrusion detection systems based on fiber Bragg grating (FBG) sensors. This system uses FBG strain sensors to convert strain into Bragg wavelength displacement to sense load-related strain. Deploying an appropriate FBG network in the perimeter of the railway can detect intruders by monitoring their respective Bragg wavelengths.

The two literatures mainly differ in the size of the study area, and the literature [4] mainly studied the use of the system in the outer area of the railway. First, by applying a static load at different distances from the FBG, the influence area of each sensor (that is, the sensing area of a single FBG) is obtained. Then, increase the size of the sensing area of a single FBG (detection area) by using a "rigid" plate superimposed on the rubber pad, thereby improving the possibility of sensor pad performance. Finally, a management software package (SW) was developed and installed on a personal computer to enable real-time monitoring of intrusion events.

Reference [5] divided the area to be detected into the outer area of the rail and the area near the rail. As far as the outer area of the railroad track is concerned, it is treated in the same way as in [4]. The experimental results in [5] show that a network with four equidistant FBGs per square meter can detect people walking on the mat in real time. For the area near the rail, two FBG-based accelerometers are placed under the rail to detect intruders walking on the rail. The experimental results in [5] show that intruders can be accurately detected at a distance of 5m from the installed sensors and a distance of about 0.8m from the railway area.

3 Non-contact Detection Method

3.1 Detection Method Based on Machine Vision

Reference [6] proposed a high-speed railway intrusion clearance detection system based on binocular stereo vision, including the following three parts: an image acquisition module, an image processing module and a remote monitoring module. The image acquisition module uses a binocular camera to collect images, and at the same time uses an image acquisition card to convert analog image data into digital image data, which is stored for processing. The image processing module processes the acquired image data, including image noise reduction, image enhancement, camera calibration, and detection and identification of intruders. Finally, the communication module is used to transmit the image data containing the intrusion to the remote monitoring module. The algorithm of intrusion monitoring area has the following steps: First, the image data is collected through an image acquisition card. Considering the influence of the external environment on the image, [6] used wavelet threshold to perform image denoising. Then using histogram equalization to improve the visual effect of the image. Finally, after background extraction, difference algorithm, automatic 3D matching, and 3D reconstruction, it can determine whether there is foreign body intrusion.

Reference [7] designed a dynamic intruder detection and tracking method for railways, which can detect and track dynamic intruders appearing near railway tracks. The theoretical framework of the detection system is shown in Fig.1.

In the first stage, reference [7] proposed a new algorithm to extract the orbit trajectory. A set of structural elements was first designed, as shown in formula (1).

$$S_1=\begin{bmatrix}0&0&0&1&0&0&0\\0&0&0&1&0&0&0\\0&0&0&1&0&0&0\\0&0&0&1&0&0&0\\1&1&1&1&1&1&1\\0&0&0&1&0&0&0\\0&0&0&1&0&0&0\\0&0&0&1&0&0&0\\0&0&0&1&0&0&0\end{bmatrix}\ S_2=\begin{bmatrix}0&0&1&0&0\\0&0&1&0&0\\0&0&1&0&0\\0&0&1&0&0\\1&1&1&1&1\\0&0&1&0&0\\0&0&1&0&0\\0&0&1&0&0\\0&0&1&0&0\end{bmatrix}$$

$$S_3=\begin{bmatrix}0&1&0\\0&1&0\\0&1&0\\1&1&1\\0&1&0\\0&1&0\\0&1&0\end{bmatrix}\ S_4=\begin{bmatrix}0&1&0\\1&1&1\\0&1&0\end{bmatrix} \tag{1}$$

The image is then morphologically processed as shown in formula (2). Finally, the orbit trajectory was successfully extracted with the progressive probability Hough transform.

$$\begin{aligned}OP_1&=\left(f\circ S_2\right)\oplus S_4-\left(f\bullet S_4\right)\Theta S_4\\OP_2&=f\circ S_3\\OP_3&=\left[\left(f\bullet S_3\right)\Theta S_3\right]\bullet S_1-\left(f\circ S_1\right)\oplus S_1\end{aligned} \tag{2}$$

Where, $\oplus$ is an expansion operation, Θ is an etching operation, $\circ$ is an open circuit operation, and $\bullet$ is a closing operation.

In the second stage, reference [7] uses a visual background extractor (ViBe) to detect moving objects. In the final stage, a Kernel Correlation Filter (KCF) is used to track intruders.

Reference [8] proposed a railway foreign body intrusion detection method based on multi-background modeling, black-and-white pixel difference and ratio method. The theoretical framework of the detection system is shown in Fig.2.

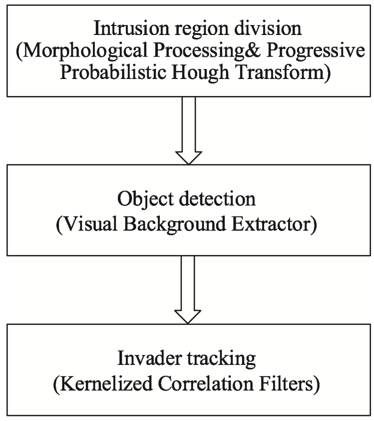

Fig.1 The theoretical framework of the proposed method

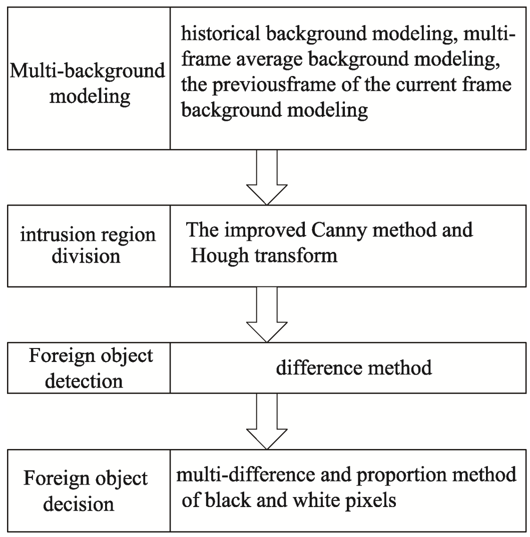

Fig.2 Theoretical framework of detection systems in [8]

Multi-background modeling is a model of three methods: integrated historical background modeling, multi-frame average background modeling and continuous frame background modeling. The multi-background model is shown in formula (3),

$$\begin{aligned}&\text{Background image 1:}\\&p_1(x,y)=f_m(x,y)\\&\text{Background image 2:}\\&p_2(x,y)=\frac{1}{n}\sum_{i=m+1}^{m+n}f_i(x,y)\\&\text{Background image 3:}\\&p_3(x,y)=f_w(x,y)\end{aligned} \tag{3}$$

Where $f_i(x, y)$ is the gray value of the image, $f_m(x,$

y) is the gray value of the historical frame, $f_w(x, y)$ is the gray value of the previous frame of the current frame, and $p_1(x, y)$ is the historical background modeled image, $p_2(x, y)$ is a multi-frame average background modeling image, and $p_3(x, y)$ is a continuous frame modeling image. n, m and k are sequences of frames.

In order to extract the orbit trajectory, the literature [8] combined the Hough transform to optimize the Canny operator, thereby obtaining the orbit image with low noise.

Finally, based on the above-mentioned multi-background model and trajectory detection, a foreign object is detected using a difference method. By comparing the current frame with the multi-background model image. The formula is as follows,

$$\begin{aligned} d_i(x, y) &= \left| f_{w+1}(x, y) - p_i(x, y) \right| \\ d_4(x, y) &= \frac{1}{3}\sum_{i=1}^{3}\left| f_{w+1}(x, y) - p_i(x, y) \right| \end{aligned} \tag{4}$$

Where, $f_{w+1}(x, y)$ is the current frame, and $d_i(x, y)(i$=1,2,3) represents the difference image between the current frame and the background image in the three background models. $d_4(x, y)$ is the average image of these three difference images.

Then, it is determined whether there is a foreign object by comparing d4 with a preset threshold. Finally, the quantitative ratio of the black and white pixels of the obtained image is used to determine the size of the foreign matter, so as to determine whether it poses a danger to the operation of the train.

Reference [9] proposed a railway headroom intrusion detection algorithm based on convolutional neural network. The working flowchart of the algorithm is shown in Fig.3.

In the first stage, all lines in the image are marked by a line segment detector (LSD). In order to obtain a complete orbital area, reference [9] proposed a line segment merging method. The merging of two line segments mainly depends on three parameters: the horizontal distance threshold dx and the vertical distance threshold dy between the two closest endpoints of the two line segments, and the slope threshold kt between the two line segments.

Finally, according to the railway, it must be a long straight line to select the merged line segments, and thus determine the track area.

In the second stage, an improved convolutional neural network model is used to detect and classify the image of the orbital region in a single frame of image. Aiming at the problem of the slow convergence speed of the VGG19 model, reference [9] added a packet loss layer between each set of convolutional layers to stabilize the training and speed up the convergence speed. At the same time, the ReLU function is replaced by the LeakyReLU function to correct the data distribution and improve the detection performance of the model. Finally, in order to prevent the classification network from becoming too large, a new classification network is proposed. The classification network consists of four convolutional layers and an average pooling layer, instead of the original classification network that consisting of fully connected layers. This reduces the number of parameters, improves training speed and prevents overfitting.

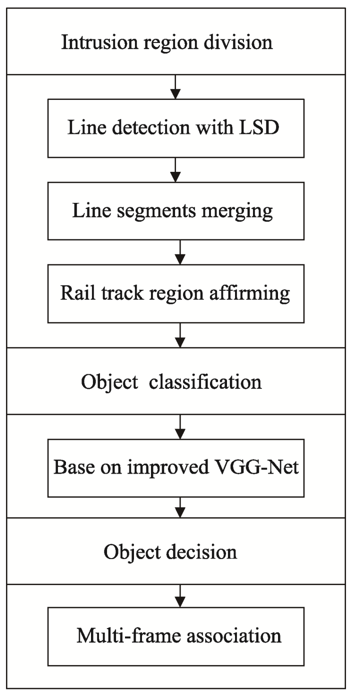

Fig.3 The main flow chart of the algorithm in [9]

In the final stage, the inter-frame correlation is used to optimize the detection result of a single frame to obtain the final detection result.

Reference [10] designed an automatic detection system for foreign object intrusion based on machine vision and embedded technology. The system includes a monocular camera, an ARM-based embedded detection hardware platform, a router, and a remote monitoring terminal. The embedded foreign object intrusion detection platform is the core of the system, which mainly completes the automatic identification and alarm of foreign objects in the detection area. Reference [10] proposed an embedded foreign body intrusion detection algorithm combining foreign object classification and motion behavior analysis. The algorithm flowchart is shown in Fig.4.

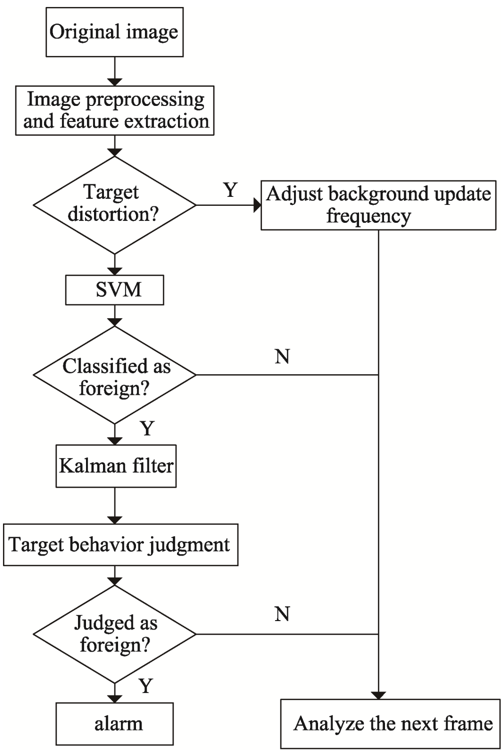

Fig.4 The main flow chart of the algorithm in [10]

The algorithm uses a two-level discriminant structure. First, a support vector machine (SVM) and a set of feature vectors are used to classify the foreign object targets obtained from the background difference image, and most of the traveling train targets are filtered according to the classification results. Then use Kalman filter to design the target tracking algorithm, analyze the behavior and movement trend of the remaining targets, filter out the non-invasion interference information to improve the alarm accuracy rate, and give early warning to the foreign objects with invasion trend.

Reference [11] proposed a real-time detection algorithm for foreign body intrusion based on deep learning, which is used to solve the high reliability problem of the detection system. First, due to the problems of large memory consumption and long detection time in deep convolutional neural networks, reference [11] proposed a recursive cropping algorithm based on the feature map L1 norm. The algorithm uses the L1 norm of the feature map F of each convolution kernel as the basis for evaluating the importance of the convolution kernel. Calculate the mean value of the feature map L1 norm output by each convolution kernel in a convolutional layer under the target training sample set. The convolution kernels are sorted according to the size of the results, and a certain number of convolution kernels are removed to achieve the purpose of identification and cropping. The mean value of the L1 norm of the characteristic map of each channel is as formula (5),

$$\overline{F}_{L1} = \frac{1}{N}\sum_{i=1}^{N}\left\|F_{xi}\right\|_1 \tag{5}$$

Where, $\overline{F}_{L1}$ represents the average L1 norm of the feature map of each channel; $\left\|F_{xi}\right\|_1$ is the L1 norm of the output feature map of the convolution kernel K after the i-th picture xi is input into the network.

In order to verify the performance of the algorithm, reference [11] compares it with a cropping criterion based on the L1 norm of the convolution kernel. In the tests based on the ImageNet database and the railway scene database, the algorithm can compress the VGG16 model by about 660 times and accelerate the calculation by 4.4 times, while the loss detection accuracy is only 1.2% and 0.25%, respectively. This result is far superior to the existing clipping criterion based on the L1 norm of the convolution kernel.

3.2 Detection Method Based on Wireless Network

There are many kinds of non-contact intrusion detection. In the above work, we introduced intrusion detection based on machine vision. Below we introduce a novel non-contact detection method based on wireless network detection method.

Reference [12] proposed a detection scheme based on channel state information (CSI), using the MUSIC algorithm to process the collected signals, thereby realizing the intrusion detection of obstacles. First, the CSI information of the physical layer is obtained through OFDM technology [Reference]. For narrow-bandwidth flat fading channels, the OFDM system can be expressed as formula (6),

$$y_i = Hx_i + N_i \tag{6}$$

Where, xi and yi represent the signal vectors of the transmitting end and the receiving end, Ni is the additive white Gaussian noise in the channel, and H is the CSI matrix reflecting the channel state information.

Secondly, the MUSIC algorithm can calculate the propagation path of WiFi signals with smooth CSI. Reference [13] has proved that, by moving a fixed sensor subset which can be written as a linear combination of the same vectors, the CSI values on different sensor subarrays are obtained. In fact, the steering vector entries of the fixed sensor subsets of different paths now form the steering matrix A, and by combining the steering matrix vectors with different weights, the CSI values of different sensor subarrays are obtained.

Therefore, if the measurement matrix X is constructed using the CSI values of different sensor sub-arrays that are similar in structure but offset from each other, MUSIC can be successfully applied using this new measurement matrix X. Reference [12] smoothed the CSI matrix collected by Intel 5300 network card according to the following steps,

$$\begin{bmatrix} csi_{1,1} \\ \vdots \\ csi_{1,30} \\ csi_{2,1} \\ \vdots \\ csi_{2,30} \\ csi_{3,1} \\ \vdots \\ csi_{3,30} \end{bmatrix} \Rightarrow \begin{bmatrix} csi1,1 & csi1,5 & \cdots & csi1,16 & csi2,1 & \cdots & csi2,16 \\ csi1,2 & csi1,3 & \cdots & csi1,17 & csi2,2 & \cdots & csi2,17 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ csi1,15 & csi1,16 & \cdots & csi1,30 & csi2,15 & \cdots & csi2,30 \\ csi2,1 & csi2,2 & \cdots & csi2,16 & csi3,1 & \cdots & csi3,16 \\ csi2,2 & csi2,3 & \cdots & csi2,17 & csi3,2 & \cdots & csi3,17 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ csi2,15 & csi2,16 & \cdots & csi2,30 & csi3,15 & \cdots & csi3,30 \end{bmatrix} \tag{7}$$

Finally, using the MUSIC algorithm to process the smoothed CSI matrix, a matrix of AOA multipath signals can be obtained. Each AOA value corresponds to a multipath signal. By counting the AOA value of each antenna, the number on each antenna can be known. From this, the position and size of obstacles on the propagation path can be known.

4 Comparison of Intrusion Detection Systems

4.1 Comparison of Non-contact Systems

As a common detection method for intrusion systems, contactless detection methods have been widely studied. We summarize the relevant literature as shown in Table 1.

References [7], [8], and [14], these methods do not use matrix operations and convolutional neural networks, so their processing speed is fast. On the basis of ensuring a certain accuracy, the method using the background difference can improve the adaptability of the environment, effectively suppress the noise interference, and have better real-time performance. And the literature [7] adopted KCF tracking algorithm can play the function of early warning. Literatures [9] and [11] used convolutional neural networks to classify and identify images, which greatly improved the accuracy of recognition. At the same time, in order to improve the calculation speed of the system, the literature [11] improves the VGG16 network by recursively cutting on the basis of maintaining a recognition rate of 99.55%. As the image processing is more refined, the detection system performs better in environmental adaptability and noise interference. Reference [10] based on the support vector machine and Kalman filtering target classification and tracking algorithm, integrates the behavior of the target into the foreign object recognition, and can still maintain high accuracy without using a convolutional neural network. At the same time, the tracking algorithm is used to make the system have early warning function. Reference [12] is a bold attempt to use the signal multipath effect detection system. Although this method does not have high anti-interference and accuracy, it is also feasible.

4.2 Comparison of Contact and Non-contact Systems

Here we compare two different types of detection methods. The environmental impact, false alarm rate, concealment, maintainability, installation requirements, damage resistance, and recoverability were analyzed. As shown in table 2.

Each test method has its own characteristics and applicable working environment. As a typical contact detection method, FBG has excellent performance in severe weather (such as snow, rain, fog, hard or dark light). However, its sensitive detection sensor may cause some false positives, and it cannot detect the type and accurate location of the surrounding intrusions. The installation process is cumbersome, and the sensor is easily damaged. In contrast, the non-contact detection method has great advantages in detecting the type and accurate location of the surrounding intrusions, and the staff can watch real-time or stored video at any point in time. In addition, the target detection combined with convolutional neural network greatly reduces the false alarm rate of the system. Since this solution requires the use of a camera to acquire images, it is easily affected by the environment such as weather, light and visibility. However, drones are a flexible method that can quickly appear at alert locations and track moving objects. In recent years, drone technology has developed rapidly, and the drone detection system proposed in [9]. Utilizing the

Table 1 Comparison of non-contact detection systems.

Author	Data sources	Image processing / Signal processing			Accuracy
		Region division	Object detection	Invader tracking	
Niu et al. [8]	Machine vision	Improved Canny & Hough transform	Black and white pixel quantitative ratio & difference method	-	-
Wang et al. [7]	Machine vision	Morphology & Pro-gressive Probability Hough Transform	Visual Background Extractor (ViBe)	KCF	-
Zhou el at.[14]	Machine vision	Hough transform	Background difference	-	
Huang el at.[9]	Machine vision	Improved VGG19-Net & Multi-frame Association		-	97.62%
Wang el at.[11]	Machine vision	Improved VGG16-Net		-	99.55%
Shi el at.[10]	Machine vision	SVM & Background difference		Kalman filter	97.11%
Xie el at.[12]	wireless network	MUSIC algorithm			-

Table 2 Comparison of contact detection system and non-contact detection system.

Author	System type	Environmental impact	False alarm rate	Installation conditions	Damage resistance	Maintainability
Niu el at.[8]	Non-contact	Medium	Medium	Easy	High	Easy
Wang el at.[7]	Non-contact	High	High	Easy	High	Easy
Shi el at.[10]	Non-contact	Low	Low	Easy	High	Easy
Huang el at.[9]	Non-contact	High	Low	Medium	Low	Medium
Xie el at.[12]	Non-contact	High	Medium	Medium	Medium	Easy
Catalano el at.[4]	Contact	Low	Low	Hard	Medium	Easy
Catalano el at.[5]	Contact	Low	Low	Hard	Medium	Easy

flexibility of drones, it can quickly reach an alert location for eviction. At the same time, UAVs have great advantages in long-distance railway inspections.

5 Conclusions

Efficient perimeter intrusion detection methods are critical to the safety management of China's high-speed railways. This paper studied the characteristics of the perimeter intrusion detection system under different models, and analyzed and compared the models proposed in related literature. In this paper, we draw the similarities between the different literatures in the research process according to the type detection, and also explained their differences. The models of some non-contact systems were compared, the performances of the respective models were compared and the shortcomings between them were pointed out. Finally, the appropriate application scenarios of each model were pointed out by comparing the non-contact and contact systems. In the subsequent research, we can consider the combination of two different types of systems to achieve a system that maintains good detection performance in various environments. This provides a reference meaning for subsequent research.

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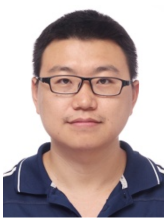

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