Research on Real-time Monitoring of Video Images of Traffic Vehicles and Pedestrian Flow using Intelligent Algorithms

Xiujuan Dong*, Jianping Lan, Wenhuan Wu
School of Electrical & Information Engineering
Hubei University of Automotive Technology
Shiyan, Hubei 442002, China

Abstract—**The development of urbanization has brought many traffic problems, among which the delayed feedback of traffic flow and people flow has led to traffic congestion. In order to effectively analyze the traffic flow and people flow on the traffic road, this research proposes a traffic surveillance video image object detection model based on the improved Vibe algorithm, and uses the moving historical image to track the traffic flow and people flow. Finally, the performance analysis of the algorithm shows that the loss rate of the improved Vibe algorithm proposed in the study is only 0.25%, and its detection accuracy reaches 91.25%. The above results show that the use of Vibe intelligent algorithm can significantly improve the detection effect of traffic flow and pedestrian flow in traffic monitoring video, help to improve urban traffic management ability and promote the development of urban modernization.**

Keywords—Urban development; object detection; traffic video; Vibe algorithm; visitors flowrate; image filtering

I. Introduction

Rapid economic development promotes urban development. However, in urban development, the increase in the number of motor vehicles and long-term residents increases the difficulty of traffic control. Therefore, a large number of studies have put forward the concept of intelligent transportation on the existing urban traffic problems. In intelligent transportation, it is believed that the processing of traffic data can be realized by using intelligent algorithms, and the traffic pressure can be relieved by understanding the traffic conditions [1, 2]. In the current research, the emphasis is on the systematic and real-time nature of intelligent transportation, which realizes the traffic management of multiple road sections through its system planning, makes timely traffic diversion through real-time nature, and ensures the convenience of people's travel [3]. With the development of computer technology, intelligent algorithms have been continuously introduced in the monitoring and monitoring of traffic flow and people flow. The purpose is to use the moving target tracking algorithm to grasp the changes of vehicle and people flow in the traffic section in real time, and provide a planning scheme for subsequent sections [4]. However, it has to be admitted that my country's traffic video image traffic flow and people flow monitoring technology started later than foreign countries, and the existing detection schemes are difficult to deal with the increasing traffic problems. In this study, a video image target recognition model based on the improved Vibe algorithm is proposed, and the tracking of vehicles and human bodies is realized with the help of motion history images, and the real-time monitoring of traffic flow and people flow is realized, in order to relieve urban traffic pressure and speed up China's Urbanization.

The main structure of the article is divided into four parts. In the second part, the development status of urban traffic monitoring technology and image processing technology is analyzed. In the third part, the intelligent algorithm design for traffic vehicle and pedestrian flow monitoring is proposed. In the fourth part, the algorithm performance analysis and monitoring effect test are conducted.

There are two innovations in this paper. First, image processing is carried out for traffic flow and pedestrian flow monitoring videos; the second is to study the further processing of the surveillance video image and target tracking with the aid of only algorithms, which improves the real-time detection capability of the surveillance video.

II. Related Works

With the continuous progress of urban traffic, the monitoring technology for the detection of urban traffic vehicles and people flow has also become increasingly prominent. In the same way, aiming at the existing urban traffic flow management problems, the research proposes to introduce intelligent algorithms to realize the monitoring and control of vehicle flow and pedestrian flow. In order to further understand the monitoring status of traffic flow, the research status in this field is analyzed. In order to promote the development of urban modernization, Pan S et al. used network tomography to realize the optimization of urban traffic monitoring, and used FIM and multi-agent reinforcement learning methods to help monitors improve the processing capacity and performance of surveillance video. The simulation experiment proves that the proposed scheme can effectively reduce the error of monitoring video processing compared with the traditional scheme [5]. In order to improve the traffic monitoring ability, Rogowski M gained experience from the traffic monitoring of tourists in national parks. In this study, Rogowski M proposed a comprehensive monitoring method. It has been proved by practice that the proposed method can effectively monitor and evaluate tourists [6]. In

*Corresponding Author.

order to monitor the traffic flow, Zhu L et al. proposed a self-organized flow monitoring measure, and finally proved the feasibility of the measure through safety analysis and experimental verification. However, although this research can achieve traffic flow monitoring, it is difficult to extract effective targets from the monitoring video [7]. In order to obtain traffic conditions in low-light environments such as nighttime, Cai X et al. explored light control strategies in traffic monitoring, aiming to use threshold increments to evaluate disability glare, and showed in the final results, research. The proposed light control strategy can reduce the interference caused by glare in traffic monitoring and improve the effect of traffic monitoring [8]. Almeida TD et al. believe that most of the current traffic monitoring systems require high maintenance costs, so in order to improve the effect of traffic monitoring and reduce costs, a community-based decentralized traffic monitoring system is proposed. The traffic conditions of the road sections are analyzed, and the comparative analysis finally confirms that the accuracy of the system proposed by this study can be higher than 90% in multiple scenarios. However, this research is difficult to monitor the rapid growth of traffic flow and people flow in real time [9].

The processing of traffic monitoring is to process the detected video images. In the research of video image processing, a large number of scholars have proposed effective methods. In order to increase the sensitivity and specificity of medical video image processing, Obukhova N et al. proposed a personalized processing method, which uses artificial intelligence technology to realize the visualization of video image data, which is displayed in the result classification. The proposed video image processing method has high accuracy and improves the diagnostic efficiency of medical images [10]. Long C proposed an edge computing framework to optimally group mobile devices into video processing groups, and at the same time proposed an efficient collaborative video processing scheme that can achieve sub-optimal performance with existing detection accuracy. Each parameter is evaluated, and the effectiveness of the method proposed in the study is confirmed in the simulation experiment, and its superiority compared with the baseline scheme is proved [11]. Ragan-Kelley J et al. believed that there was too little work in different stages in image processing to load the results into the corresponding memory and would add extra cost, so the team wrote a high-performance image processing code that implements The simplification of image processing and the ability to use a dedicated image processor to generate effective results finally confirmed the efficiency of the image processing code through experiments. However, the image processing code proposed in the study has some limitations in application, and is difficult to deal with the environment with huge data [12]. In order to detect acephate, Osman MJ et al. proposed an image processing technology combined with an aptamer sensor, using the sensor to obtain the relevant information of the aptamer, and using the image processing technology to achieve colorimetric detection, and finally proved in the experiment the effectiveness of the current method. Although this research can effectively achieve image detection, it uses sensor technology, which is vulnerable to environmental interference [13]. In order to reduce the mite infection in bee farming, Sevin S et al. proposed an image capture device that can automatically focus detection. The device is compatible with cloud storage and 5G technology, and can distinguish bees from Varroa mites through images, and finally train on samples. The method proposed in the research shows that the method can effectively distinguish between honeybees and Varroa mites [14].

To sum up, with the continuous development of intelligent technology, the research on video image processing in modern technology research is increasing, but in traffic monitoring, there are still few effective processing solutions for monitoring video. For the real-time monitoring of traffic flow and people flow, a monitoring video image processing algorithm based on Vibe intelligent algorithm is proposed to detect the traffic flow and people flow. See Fig. 1 for the structure and flow of research contents.

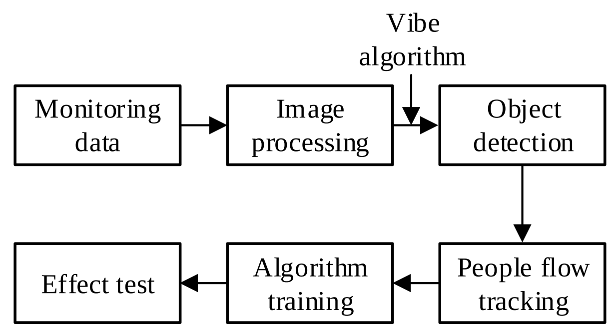


Fig. 1. Workflow diagram.

III. Design of Target Detection Algorithm for Traffic Surveillance Video Image

A. Traffic Flow and People Flow Detection

In urban traffic video detection, affected by the traffic environment and the natural environment, the monitoring video has significant interference noise. Therefore, in order to accurately monitor the real-time traffic flow and people flow, the video image needs to be preprocessed first [15, 16]. In the research, for image denoising in surveillance video, the method of image filtering is used to extract the target features in the image, and the median filtering method is used to suppress the noise in the image. The basic principle of median filtering is to replace the value in the image with the median value of the region where it is located. One-dimensional median filtering is shown in equation (1) [17].

$$y = med(f_0, f_1, ..., f_k) \tag{1}$$

In formula (1), it $(f_0, f_1, ..., f_k)$ represents the sequence value in the one-dimensional sequence; k it represents the sequence length. After filtering, the image needs to be enhanced. In the image enhancement, the research adopts Laplacian sharpening to achieve it. The Laplace calculation method is shown in formula (2).

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

In formula (2), it (x, y) represents the coordinates of a certain point in the image.

The detection of traffic flow and people flow in video images is to find out the moving vehicles and people from the video. The target detection algorithm is used to realize the target selection of continuous video. In the research, the background difference method is used to find the appropriate target. The background difference method is often used in the detection of moving objects such as human bodies and vehicles, which can strip the background area in the video image to obtain moving objects [18, 19]. In the application of the background difference method, the Vibe algorithm is widely used, and its calculation is divided into three steps. The first is background initialization. In the background initialization, the video is initialized through the first frame image, that is, to establish the current video. For the background model, see equation (3).

$$BK_m^0 = f^0(x^i, y^i) \mid (x^i, y^i) \in N_G(x, y) \tag{3}$$

In formula (3), it $N_G(x, y)$ represents the neighborhood point. After the background is initialized, the foreground image is detected, and the background model established by the background initialization is used to judge whether the subsequent image sequence belongs to the foreground, and the foreground part is separated. The judgment formula is shown in formula (4).

$$f^k(x, y) = \begin{cases} fore & BK > T \\ back & BK \le T \end{cases} \tag{4}$$

In formula (4), T represents the threshold set according to the experimental environment. When the value of the background model is greater than T that, it is judged as the foreground, and when it is less than, it is judged as the background. In addition, as shown in formula (4), in the selection of the foreground part, the pixel is the selection of points in random. The last step is to update the background model of the image, in order to reduce the error effect of the light intensity on the image [20, 21]. In the process of updating the background model, for any background point, it has a certain probability to update the background model, and randomly selects samples in the updated sample set. After a certain period of time, the probability that the sample value is retained can be expressed as (5).

$$P(t, t+dt) = \left(\frac{N-1}{N}\right)^{(t+dt)} \tag{5}$$

In formula (5), it N represents the number of background models; dt represents the update time; $\frac{N-1}{N}$ represents the probability of not updating at time t. However, the traditional Vibe algorithm is based on the background model. Under the premise of efficient image processing, there is still ghosting phenomenon. The reason is that the algorithm is difficult to accurately detect the slow moving stage. For this reason, in order to solve the ghosting of the Vibe algorithm, the research introduces the frame difference image of adjacent frames to optimize the effect of foreground detection, as shown in Fig. 2.

As shown in Fig. 2, for the calculation of the frame difference image of adjacent frames will judge the selected first frame image after the background initialization. When the selected image is not the first frame image, the pixel points selected multiple times are filtered out by calculating the adjacent frame difference, and they are eliminated to ensure that no background points appear in the foreground part and reduce the appearance of ghosts. In addition, in the actual traffic situation, when there is sufficient light, pedestrians and vehicles on the road will produce obvious shadows during the movement, and the existence of shadows will be judged as the foreground part during detection, resulting in the failure of foreground detection. To achieve better results, a shadow removal algorithm is proposed in this research. First, the brightness in the video image is modeled, see equation (6).

$$s_k(m, n) = E_k(m, n)\rho_k(m, n) \tag{6}$$

In formula (6), $E_k(m, n)$ represents (m, n) the radiance of the pixel point, and $\rho_k(m, n)$ represents the reflection coefficient of the vehicle or pedestrian to the light. On the basis of brightness modeling, HSV is used to eliminate shadows, and the discriminant function of shadow detection is shown in formula (7).

$$HSV(x, y) = \begin{cases} 1 & \partial \le \dfrac{I_k^V(x, y)}{B_k^V(x, y)} \le \beta \cap (I_k^S(x, y) - B_k^S(x, y)) \le T_s \cap \\ & \left| I_k^H(x, y) - B_k^H(x, y) \right| \le T_B \\ 0 & other \end{cases} \tag{7}$$

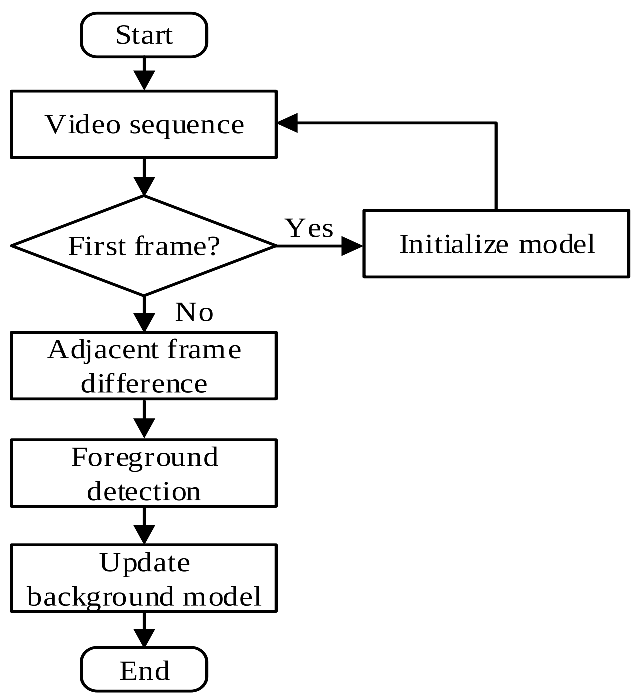


Fig. 2. Image foreground detection.

In formula (7), $I_k^V(x,y)$, $I_k^S(x,y)$, $I_k^H(x,y)$ represent the component of the kth frame image pixel in HSV space; $B_k^V(x,y)$, $B_k^S(x,y)$, $B_k^H(x,y)$ represent the component of the kth frame background pixel in HSV space; ∂, β represent the judgment parameter; T_s, T_B represent the threshold; when the discriminant function When the value is 1, the position is (x,y) defined as the shadow, and the rest are the target. The improved Vibe algorithm and shadow elimination algorithm are combined to realize the detection of traffic flow and human flow. The detection process is shown in Fig. 3.

As shown in Fig. 3, in the moving target detection, the traffic surveillance video is firstly used as the input for detection, and the HSV shadow removal algorithm is used to eliminate the ghost in the target detection. Image denoising is used to remove noise in video images after target detection. Finally, the contours of moving objects in the video images are extracted to analyze the foreground objects of vehicles and human bodies in the images.

B. *Traffic Flow and People Flow Tracking and Early Warning*

In actual traffic conditions, different traffic conditions have significant differences in the impact of urban traffic flow and people flow, so after solving the problem of vehicle flow and people flow detection, it is necessary to track the moving target. In moving target tracking, it is necessary to perform feature matching on each frame image in the video, that is, mark each moving target, so as to establish the correspondence between adjacent frame images [22, 23]. In the research, in order to track and identify the moving target, the motion history image is used for module tracking, and H is the pixel intensity in the motion history image. The calculation method is shown in formula (8).

$$H(x,y,t)=\begin{cases}\tau & \psi(x,y,t)=1\\ \max(0,H_\tau(x,y,t-1)-\delta) & other\end{cases} \tag{8}$$

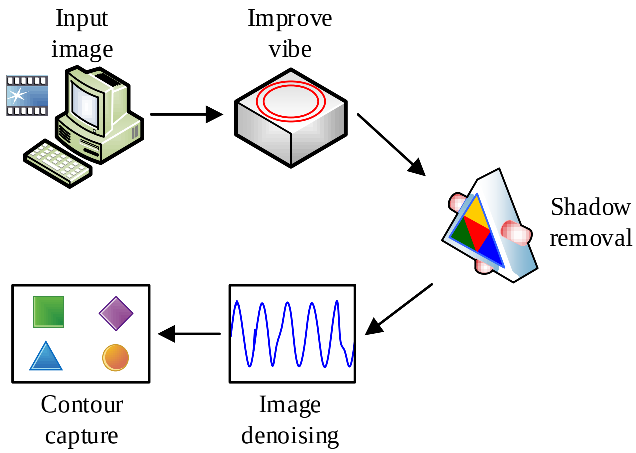


Fig. 3. Detection process of vehicle flow and passenger flow.

In formula (8), τ represents the duration between two frames in the video scene; t represents the time of the target pixel point; δ represents the decay parameter; $\psi(x,y,t)$ represents the inter-frame difference method. In addition, in the tracking process, the size of the weight of the pixel will affect the stability and reliability of the target detection, and the weight calculation is shown in formula (9).

$$k(x)C=\frac{1}{\sum k(\frac{x_i-x_0}{h})},\quad \sum_{n=1}^{m} q_n \tag{9}$$

In formula (9), C represents the normalization coefficient; q_n represents the color distribution probability; h represents the area radius; m represents the total number of pixel points. The normalization coefficient is expressed as formula (10).

$$C=\frac{1}{\sum(\frac{y-x}{h})} \tag{10}$$

Secondly, similarity is used to measure the matching degree between moving target templates, see equation (11).

$$p=\sum_{n=1}^{m}\sqrt{q_n(y)q_n(x)} \tag{11}$$

In Equation (11), $q_n(x)$, $q_n(y)$ represent the image x axis and y the color distribution probability on the axis, respectively. According to the pixel points in the motion history image proposed by the research, the tracking of traffic flow and people flow is realized, and the method flow is shown in Fig. 4.

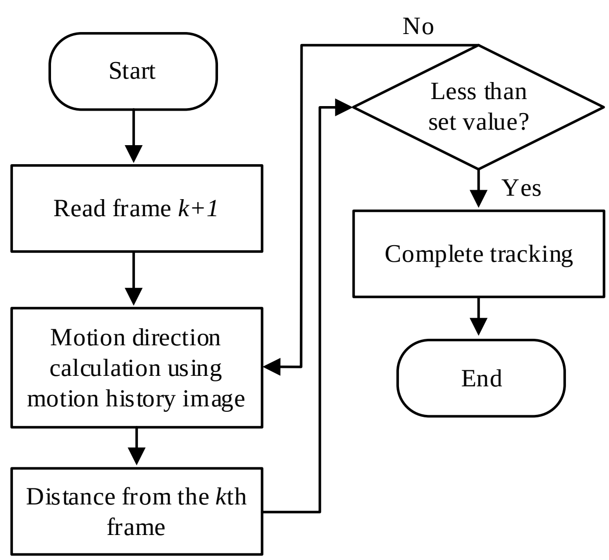


Fig. 4. Tracking process of traffic flow and people flow.

Finally, it is necessary to make a certain early warning in the monitoring of traffic flow and human flow, so as to reduce the incidence of traffic accidents. In the early warning, it is mainly aimed at identifying the distance between the age of the vehicle and the vehicle and between people. A neural network is used for distance monitoring. The distance between cars and cars and between people Z has been expressed since, and its calculation method is shown in formula (12).

$$Z = f * H / y \tag{12}$$

In formula (12), f represents the focal length of the monitoring equipment; H represents the distance from the ground to the particle; y represents the distance from the horizontal contact point of the previous moving target to the vertical distance of the video image. To set parameters for the rear vehicle under monitoring, the distance formula can be updated to formula (13).

$$Z = f * H / y = F * H / Y \tag{13}$$

Formula (13), F represents the equivalent vertical focal length of the rear vehicle in the video image; Y represents the number of pixels at the bottom of the front vehicle and the key position of the image. Through traffic monitoring, it is judged whether there is a possibility of collision between two vehicles, and the time of the vehicles that may collide is estimated. Equation (14) is used to calculate the transformation of vehicles in the image.

$$h = Z_0 / Z_t \tag{14}$$

Equation (14), Z_0 the position of the vehicle detected at the initial time in the image is Z_t expressed, and the position of the vehicle detected at time *t in the image is expressed.* Considering the speed difference between v vehicles, calculating the collision time between vehicles is shown in Equation (15).

$$G = \frac{Z_0 * a}{v_0^2} \tag{15}$$

In formula (15), a represents the braking parameter. Through the motion detection of vehicle information and people flow information in traffic monitoring video images, the monitoring of traffic flow and people flow and accident warning are realized.

IV. Algorithm Performance and Application Test

A. *Algorithm Performance Analysis*

In the research, the performance of the proposed monitoring video image target detection algorithm for traffic flow and people flow is analyzed. The experiment is set up in Intel Core i5-5300, its main frequency is 2.3GHz, the memory is 4GB, and the operation is performed in Windows7. The data set used in the research is the road surveillance video data of a certain urban area on sunny days, cloudy and rainy days and at night. The data is divided into three data sets, which are 70% training set, 20% test set and 10% application set. , select the training set and test set for calculation training. First, evaluate the loss value of the algorithm through comparative analysis, as shown in Fig. 5.

As can be seen from Fig. 5, the research compares the detection loss rate of the improved Vibe algorithm with the traditional convolutional neural network and A* algorithm. As shown in Fig. 5(a), in the training set, the loss rate of the traditional convolutional neural network during the training process shows a decreasing trend, and after the number of iterations reaches 50, it decreases to near the minimum value. The minimum value of the loss rate is 0.43%. In the training process of the A* algorithm, when the number of iterations reaches 70, the changes of the algorithm begin to gradually stabilize, and finally the loss rate is stabilized at 0.51%. However, the improved Vibe algorithm proposed by the study begins to stabilize after the number of iterations reaches 30, and its loss rate is reduced to 0.25%, which is significantly lower than the other two algorithms. Fig. 5(b) is the test effect in the test set, where the three algorithm changes are consistent with the training set. Secondly, the missed detection rate and the false negative rate index of the three algorithms are analyzed to judge the accuracy of different algorithms in target recognition, as shown in Fig. 6.

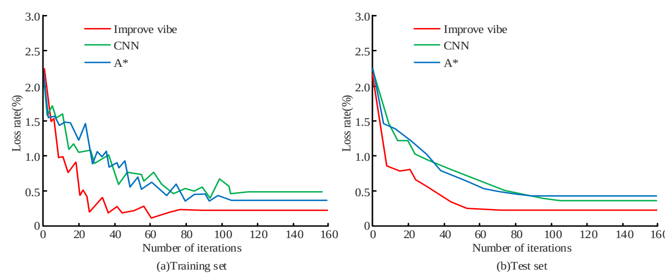


Fig. 5. Training and testing of loss rate.

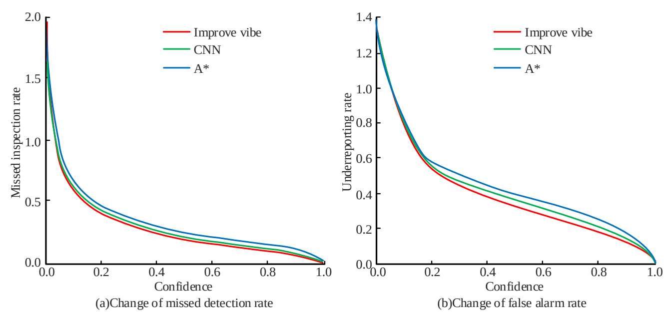


Fig. 6. Test results of missed detection rate and missed report rate.

As can be seen from Fig. 6, with the continuous increase of the confidence, the missed detection rate and the false negative rate of the three algorithms show a decreasing trend. It can be clearly seen that during the training process of the improved Vibe algorithm proposed by the study, the missed detection rate and the false negative rate indicators show a decreasing trend, and show a rapid decline before the confidence level of 0.2, and then gradually show downward trend. It can be seen from the changes of the missed detection rate and the false negative rate indicators of the improved Vibe algorithm that compared with the changes of the FPPI indicators of the traditional convolutional neural network and the A* algorithm, the improved Vibe algorithm can reduce it to a lower level, and its reduction speed is also significantly higher than the rest of the object detection algorithms. After that, the precision and recall rates of all algorithms in target detection training are analyzed, and the PR curve is used to describe them, as shown in Fig. 7.

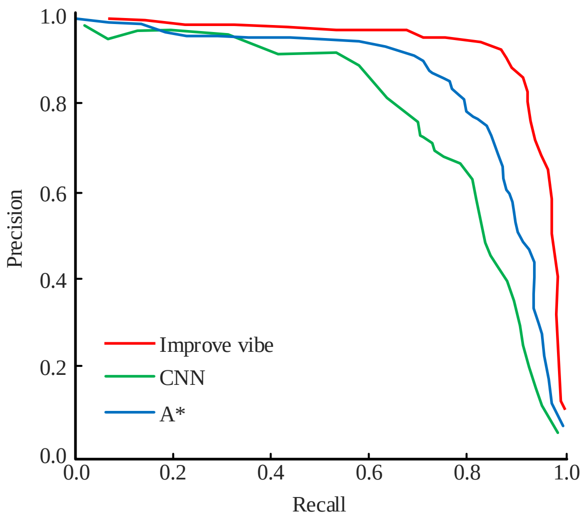


Fig. 7. PR curve comparison.

As can be seen from Fig. 7, in the change of the PR curve, the traditional convolutional neural network is closer to the lower left corner, indicating that the traditional convolutional neural network has a lower detection accuracy than the A* algorithm and the improved Vibe algorithm. . In addition, the precision rate and recall rate of the A* algorithm are in the middle position, and the calculated precision rate and recall rate are 87.62% and 89.17%, respectively. The improved Vibe algorithm proposed in the study is closer to the upper right corner, and its precision and recall rates are 91.25% and 93.33%, respectively. Comparing the PR curves of the three algorithms, it can be seen that the improved Vibe algorithm proposed in the study has higher precision and recall rates, and the target recognition and detection effects reflected in data training are more significant.

B. Application Test of Target Detection Algorithm

The monitoring video traffic flow and people flow detection algorithm proposed by the research is applied and practiced, and 10% of the collected traffic data in an urban area is used as a sample for application testing. Firstly, the detection results of traffic flow and people flow under different algorithm models are analyzed, and the real rate is used as the detection index, as shown in Fig. 8.

From Fig. 8, in the detection of traffic condition data, the true rate of the detection model proposed in the study can finally reach 0.98, and it can be known from the changes of its true rate and false positive rate that its highest false positive rate is only is 0.06. From the change of the true rate of the detection model under the convolutional neural network, it can be seen that its true rate is only 0.96 at the highest, and its false positive rate reaches 0.11. In addition, the application of the A* algorithm detection model shows that the changes of its true rate and false positive rate are significantly different from those of the detection model proposed in the study and the convolutional neural network detection model. The highest value of the true rate is only 0.85, while the false positive rate reached 0.26. The reason for the analysis is that the detection performance of the A* algorithm in the detection of traffic data is interfered by many factors, which leads to the suppression of its true rate. Secondly, the detection time required by different models in the detection of traffic flow and people flow is analyzed, as shown in Fig. 9.

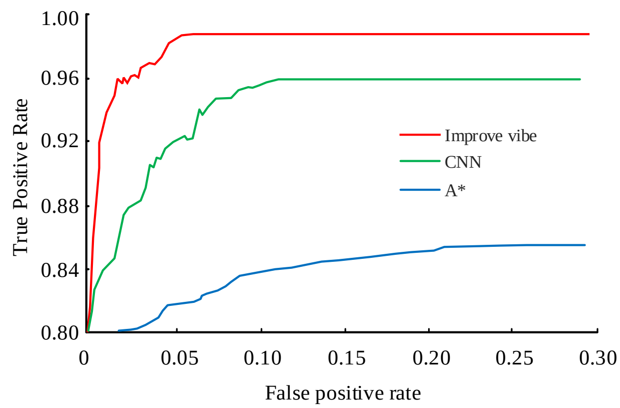


Fig. 8. Real rate test results.

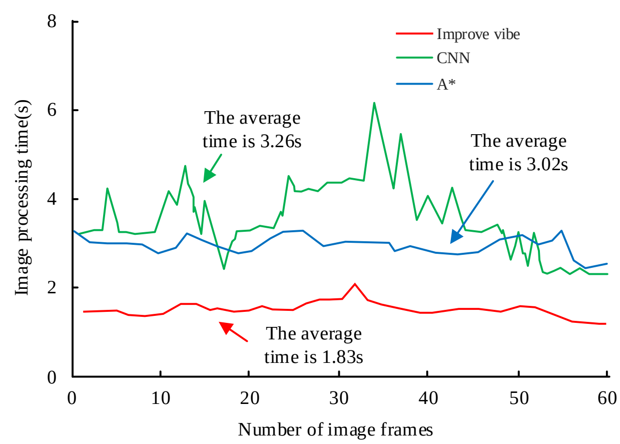
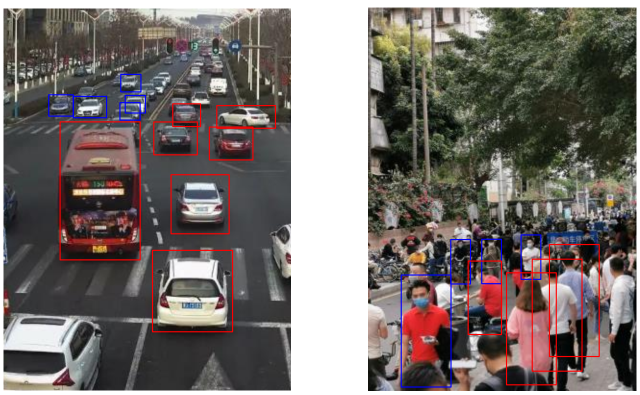


Fig. 9. Comparison of detection time.

It can be seen from Fig. 9 that the average detection time of multiple models in the detection of traffic flow and people flow is within 5s. Among them, the detection time fluctuation of the traditional convolutional neural network detection model is the most significant, and its average time is 3.26s. From the detection time change of this model, it can be seen that with the continuous increase of the number of image frames, its fluctuation frequency continues to increase. The application of the A* algorithm detection model shows that the average detection time of this model is 3.02s, which is a certain reduction compared to the convolutional neural network detection model, and the model has less fluctuation in detection , which is not significantly changed by changes in the number of image frames. Finally, it can be seen from the application results of the detection model proposed in the study that the average detection time of this model is only 1.83s, and with the continuous increase of the number of image frames, the model detection time has no significant change, which is more efficient than the A* detection model for gentle changes. Then, in order to fully understand the application effect of the human flow and traffic flow detection model proposed by the research, we conduct in-depth exploration by analyzing the renderings of its traffic flow and human flow, as shown in Fig. 10.

As can be seen from Fig. 10, the vehicle flow and people flow detection model proposed by the study can count the flow of vehicles and people, and can distinguish between vehicles and people in detail. At the end of the study, a vehicle collision warning model based on convolutional neural network is proposed, which aims to judge the accident rate during the calculation of traffic flow, and use the receiver operating characteristic curve (ROC) curve to evaluate its warning effect, as shown in Fig. 11.



(a)Traffic flow detection (b)Pedestrian flow detection

Fig. 10. Detection effect of traffic flow and pedestrian flow.

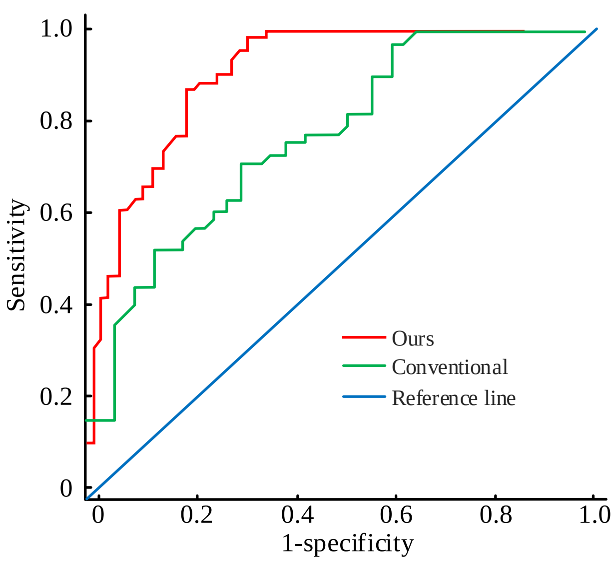


Fig. 11. ROC curve comparison.

As can be seen from Fig. 11, the area under the curve of the early warning model proposed by the study is 0.802, which is significantly higher than the standard value of 0.5, and compared with the traditional early warning model, the area under the curve increases by 0.038. The above results show that the proposed accident early warning model can effectively predict the upcoming traffic accident and provide early warning, and is more efficient than the traditional early warning scheme.

V. Conclusion

Urban development makes urban traffic show a trend of continuous development. Under this trend, how to monitor and monitor the traffic flow and people flow in the city is very important. In the research, a detection model based on Vibe algorithm is proposed for the traffic flow and people flow information in the traffic monitoring video images, and an algorithm for eliminating vehicle shadows is proposed for the traffic conditions in the video images. Finally, the motion history images are used to detect motion. The target is tracked. The algorithm performance simulation shows that the minimum loss rate of the improved Vibe algorithm proposed by the study reaches 0.25%, and the missed detection rate and the false negative rate are also low. Finally, the application test shows that the detection time of the detection model proposed in the study is only 1.83s, and it can count and distinguish the traffic flow and people flow in the traffic situation. In addition, the ROC of the detection model proposed in the study is in traffic accident warning. The offline area reached 0.802. The above results show that the improved Vibe algorithm is effective in detecting traffic flow and people flow in traffic videos, and the lower detection time indicates that it can realize real-time monitoring of traffic vehicles and people flow. However, the improved Vibe algorithm used in the study does not consider the image quality in different weather conditions. Therefore, in the follow-up work, it is necessary to improve the algorithm's ability to deal with complex environments to ensure that the vehicle flow and pedestrian flow can be monitored in various weather conditions

Acknowledgment

This study was supported by Guiding project of Hubei Provincial Department of Education Science Research Plan in 2022 (B2022397).

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