

# Passenger Flow Detection of Video Surveillance: A Case Study of High-Speed Railway Transport Hub in China

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**Abstract**—Detect moving object from a video sequence is a fundamental and critical task in many computer vision applications. With video surveillance system of high-speed railway transport hub, one of the aims for passenger flow detection is to accurately and promptly detect potential safety hazard hidden in passenger flow. In this paper, a procedure of passenger flow detection in high-speed railway transport hub is presented. According to the key steps of procedure, a modified background model based on Dempster-Shafer theory, and a passenger flow status recognition algorithm based on features of image connected domain are proposed to improve the accuracy and real-time performance of passenger flow detection. Credit and effects of proposed methods were proved by experiment on data from high-speed railway transport hub video surveillance system.

**Index Terms**—Image analysis, image recognition, background model, passenger flow status, high-speed railway transport hub.

## I. INTRODUCTION

Any vision-based system involving tracking, interpretation and recognition of moving objects in a motion picture requires fast and reliable moving object detection method. Moving object detection aims at detecting regions corresponding to moving objects such as people and vehicles in natural scenes [1].

With rapid development of high-speed railway in China, high-speed railway transport hub has become massive passenger collection and distribution centre. High density of passenger flow generates lots of potential safety hazards. Urgent demands arise for security forewarning of passenger flow by using video surveillance which uses computer vision and artificial intelligence technology to analyze the contents of video sequence, track and detect the anomalous information. However, in surveillance scenes, the change of weather, illumination, shadow and repetitive motion of passengers make video surveillance in high-speed railway transport hub difficult to detect objects fast and reliably.

Video surveillance has been widely applied in transportation fields including:

1. Moving people and vehicles detection and tracking [2]–[4];
2. Person abnormal behaviour detection [5], [6];
3. Vehicle shape, colour and plate number recognition [7];
4. Intrusion detection of sensitive area [8];
5. Unusual event detection in crowd condition [9], [10].

According to the fields mentioned above, it is clear that most of detection focused on individual people, vehicles and goods. There are few studies on passenger flow status detection.

Moving object detection methods have been investigated in many literatures. A comprehensive survey of research on computer-vision-based human motion analysis was provided in [1]. It groups moving object detection methods into four categories: temporal differencing [11], optical flow [12], statistical methods [13] and background subtraction [14], [15]. An efficient adaptive segmentation algorithm was developed for colour video surveillance sequence in real time with non-stationary background [11]. A three step model was presented based on approach which makes use of knowledge about the human body (the relative sizes of body parts and the relations between the parts) and the motion information based on optical flow computation [12]. A trainable object detector and its instantiations for detecting faces and cars at any size, location, and pose were described. In order to find the object at any location and size, classifiers scan the image exhaustively. Each classifier is based on the statistics of localized parts. Each part is a transform from a subset of wavelet coefficients to a discrete set of values [13]. The universal process of detecting objects with background subtraction, and all typical background modelling algorithms and their merits were expounded in [14]. It summarized algorithms characteristics, and compared the performances of some algorithms. Finally, pointed out key issues and directions of future study in this area. According to comparing moving object detection methods and typical background modelling methods, a suitable method was selected for background modelling in high-speed railway transport hub

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[15].

According to the literature review above, many moving object detection methods were proposed and studied. However, there is no method can solve all problems of moving object detection. Based on the different objects and applied fields, detection method must be designed based on the specific characteristics of detection object and applied field. In this paper, we choose passenger flow of high-speed railway transport hub in China as the detecting object, and propose a background model of passenger flow detection based on Dempster-Shafer, and a passenger flow status recognition algorithm based on feature of image connected domain by the characteristics analysis of passenger flow detection area, and a procedure design of passenger flow detection.

The rest of paper is organized as follows. Section II describes the characteristics of passenger flow detection area in high-speed railway transport hub. Section III introduces procedure of passenger flow detection. Section IV proposes a background model of passenger flow detection based on Dempster-Shafer. Section V proposes a passenger flow status recognition algorithm based on feature of image connected domain. Section VI takes an experiment on data from high-speed railway transport hub to verify the method we proposed. Section VII concludes the paper and provides some directions for future work.

## II. CHARACTERISTICS OF PASSENGER FLOW DETECTION AREA IN HIGH-SPEED RAILWAY TRANSPORT HUB

Passenger flow is the surveillance emphasis of high-speed railway transport hub, so the streamline of passenger flow must be taken as the core concerns. The streamline of passenger departing and arriving are shown in following figure.

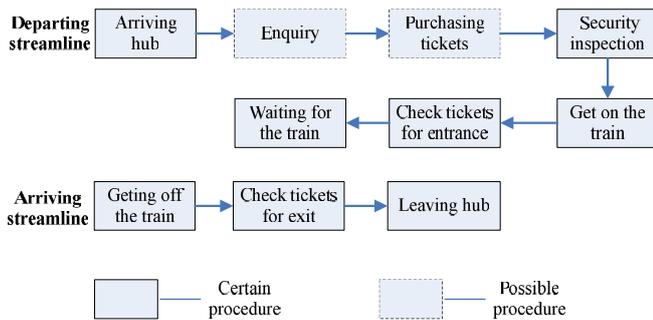


Fig. 1. Passenger departing and arriving streamline.

According to the streamline shown in Fig. 1, passing areas of passenger flow mainly include entrance, exit, ticketing area, ticket checking area, channel, waiting hall, and platform. As the main detection areas of high-speed railway transport hub, their characteristics are summarized as follows.

1. Illumination change. The main detection areas are indoor environments. Illumination in high-speed railway transport hub is stable, and cannot present gradual and sudden change;
2. Background perturbation. Facilities in high-speed railway transport hub cannot be easily changed after the hub put into service. So these areas cannot present perturbation of background;
3. Overlapping ratio. High density of passenger flow in hub leads severely overlapping among passengers. Fewer baggage of passenger increases the overlapping ratio;
4. Passenger flow change. The passenger flow in hub sharply become high density, large capacity and fast moving speed after the train arriving and before the train departing.

The characteristics mentioned above are the vital references for high-speed railway transport hub video surveillance to choose a suitable moving object detection method.

## III. PROCEDURE OF PASSENGER FLOW DETECTION

Basic procedure of passenger flow detection is shown in the Fig. 2. The inputs of procedure are initial images from the high-speed railway transport hub video surveillance. And the outputs of procedure are the passenger flow status.

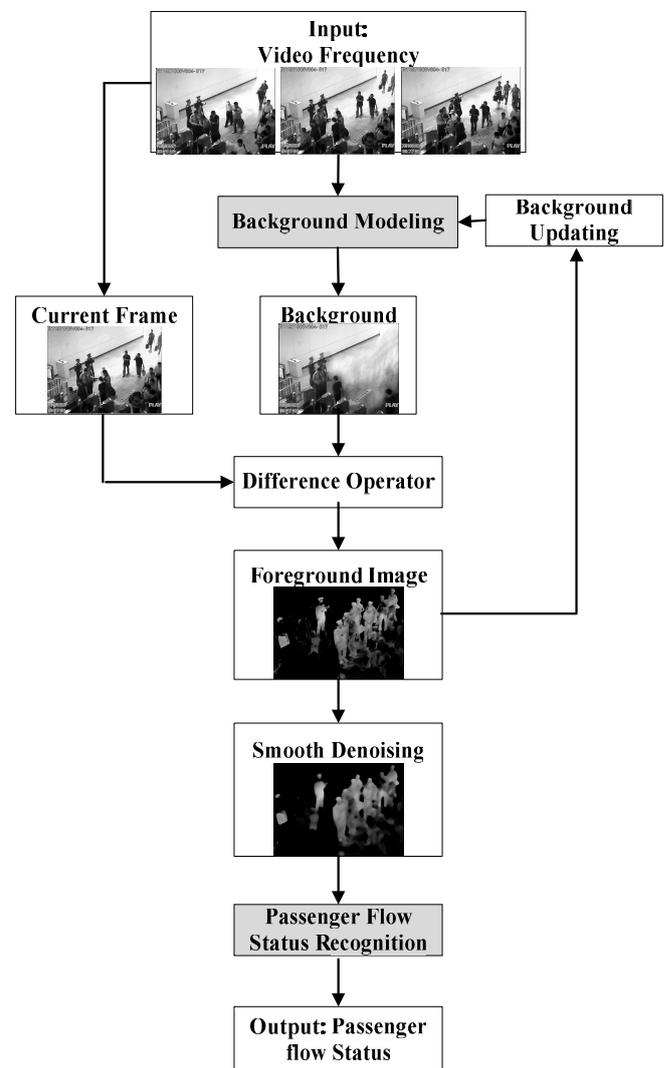


Fig. 2. Basic procedure of passenger flow detection.

There are four key steps in the detection procedure:

1. Background modelling is to build a good background in order to adapt the characteristics of detection areas in hub;
2. Background updating is to update the background to adapt the dynamic change of hub circumstance;
3. Smooth denoising is to decrease noises and keep details of foreground image;

4. Passenger flow status recognition is to extract the corresponding shapes of foreground image and recognize the passenger flow status.

#### IV. BACKGROUND MODELLING OF PASSENGER FLOW DETECTION BASED ON DEMPSTER-SHAFER

According to the characteristics of detection areas in high-speed railway transport hub, average background model is selected as the basic method to build background. And grey division and Dempster-Shafer theory are used to improve processing speed and accuracy of background modelling.

##### A. Grey Division

As influences of moving objects and system noises (illumination change, camera displacement, etc.), grey values of point in background is fluctuated in grey region. A video sequence of high-speed railway transport hub is taken to experiment. We choose one hundred frames of video, and extract grey value of one point (yellow point in Fig. 3) frame by frame. The statistics of grey value distribution in the point is shown in Fig. 4.

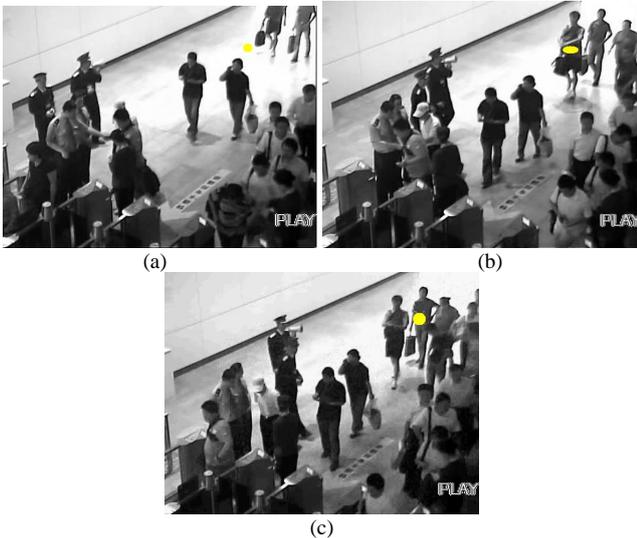


Fig. 3. Frame images extracted from video sequence.

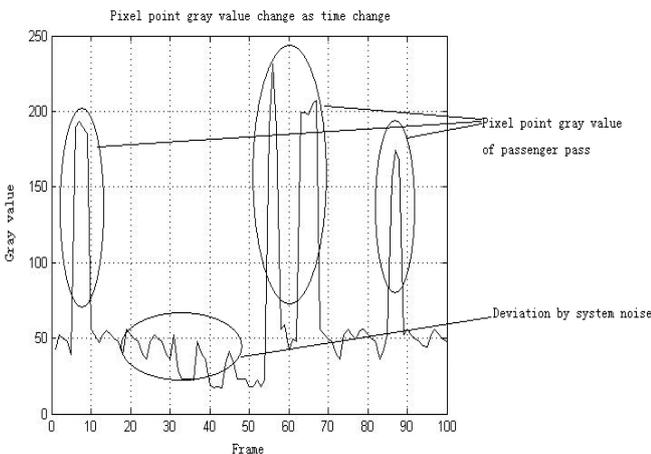


Fig. 4. Statistics of grey value distribution in the point.

According to the statistics of grey value distribution, we can find that most of the time grey value of points in background are fluctuated in a small region by system noise, and fluctuated sharply when the point has passenger flow

passing. So we divide grey region and select high probability of occurrence region to improve speed and accuracy of background modelling.

Through dividing the grey range into  $m$  regions including  $[0, n]$ ,  $[n, 2n]$ ,  $[(m-1)n, 255]$ , count the probability of grey value in each region for one point of background, and calculate grey value of this point as in (1), (2):

$$B = \sum_{i=1}^N r_i S_i, \quad (1)$$

$$S_i = \frac{(2i-1)n}{2}, \quad (2)$$

where  $i \in [1, m]$ ,  $B$  is grey value of one point in background image.  $r_i$  is probability of grey value in each region.  $S_i$  is mean value of each grey region.

##### B. Dempster-Shafer Theory

Dempster-Shafer theory (D-S theory) originated from the concept of lower and upper probability induced by Dempster in 1967. Glenn Shafer extended the theory in his book-A Mathematical Theory of Evidence in 1976. D-S theory can handle the uncertainty caused by hypotheses, and restrains events probability by building belief function instead of accurate probability. An important advantage of the D-S theory is its ability to express degree of ignorance [16].

As foundation of evidence combination and key content of D-S theory, mass function represents supporting degree of events happening. In this paper, we build a mass function to decrease weight of irrelevant background grey regions which are caused by moving object moving, increase confidences of grey regions which have high probability.

In the mass function, there are  $N$  objective types,  $M$  evidence bodies.  $A_j$  is the  $j$  objective.  $E_i$  is the  $i$  evidence body.  $C_i(A_j)$  is correlation coefficient between  $A_j$  and  $E_i$ .  $r_i$  is the uncertainty of  $E_i$ .  $m_i(A_j)$  is calculated as in (3)

$$m_i(A_j) = \frac{C_i(A_j)}{\sum_{j=1}^N C_i(A_j) + r_i}. \quad (3)$$

##### C. Modelling Process

The modelling process of background image is shown in the following:

Step 1: Sample selection.  $S$  is an observed value set of every image pixel.  $S = \{x_i\}, i = 1, 2, \dots, n$ , variable  $x_i$  is a sampling value of pixel following time domain,  $n$  is the number of sample.

Step 2: Grey range division. After binary image processing, we get the grey value  $I, I \in [0, 255]$ . We divide the grey value into  $m$  regions,

$\left[0, \frac{255}{m}\right], \left[\frac{255}{m}, 2 \times \frac{255}{m}\right], \dots, \left[(m-1) \times \frac{255}{m}, 255\right]$ .  $P_i$  is the probability of  $x_i$  grey value in every section,  $\sum P_i = 1, 1 \leq i \leq m$ .

Step 3: Grey section probability calculation. We select two grey sections  $G_1$ ,  $G_2$  which have high frequency of occurrence from the probability value of xi grey value. Merge the rest sections as  $G_3$ .

Step 4: Mass function build. Set  $\mu = \{F_1, F_2, F_3\}$ ,  $F_1$  means  $x_i$  grey value is in  $G_1$ ,  $F_2$  means  $x_i$  grey value is in  $G_2$ ,  $F_3$  means  $x_i$  grey value is in  $G_3$ . We select two same length videos as independent evidence bodies to fuse. In one video, count the probabilities of  $F_1$ ,  $F_2$  and  $F_3$ , and get the  $P_{F_1}$ ,  $P_{F_2}$ ,  $P_{F_3}$  as the expert  $A$ . In another video, count the probabilities of  $F_1$ ,  $F_2$  and  $F_3$ , and get the  $P_{F_1}'$ ,  $P_{F_2}'$ ,  $P_{F_3}'$  as the expert  $B$ . Calculate  $m_A(G_j)$  and  $m_B(G_j)$  as in (4), (5):

$$m_A(G_j) = \frac{P_{F_i}}{1 + r_A}, \quad (4)$$

$$m_B(G_j) = \frac{P_{F_i}'}{1 + r_B}. \quad (5)$$

Calculate mass function of  $G_j$  as follows

$$m_{AB}(G_j) = m_A(G_j) \oplus m_B(G_j). \quad (6)$$

Step 5: Background image build. The grey value of a pixel in background image is calculated by  $B = \sum_{j=1}^3 r_j G_j$ ,

$$r_j = \frac{m_{AB}(G_j)}{\sum_{j=1}^3 m_{AB}(G_j)}. \text{ Integrating the grey value of every pixel,}$$

build the background image.

#### D. Background Updating

In order to correct the background error which is result from slow moving of passenger flow, a background updating method is applied after  $T$  period of background modelling. The updating procedure is shown as follows:

Step 1: select a pixel point  $P_i$  of background,  $g$  is the grey value of the current background,  $g_1$  is the grey value of the previous background,  $\alpha$  is the threshold of updating,  $N$  is the amount of pixel point in background.

Step 2: compare  $g$  to  $g_1$ , if  $|g - g_1| \leq \alpha$ , the grey value of this point do not need to correct, set  $i = i + 1$ , if  $i \leq N$ , go to Step1, otherwise go to step5. If  $|g - g_1| > \alpha$ , go to step 3.

Step 3:  $g_2$  is the grey value of the background 24 hour ago. As the stability and regularity of high-speed railway timetable, the grey value of the background 24 hour ago is also a remarkable reference value for background updating. Compare  $g$  to  $g_2$ , if  $|g - g_2| \leq \alpha$ , set  $i = i + 1$ , if  $i \leq N$ , go to Step 1, otherwise go to step5. If  $|g - g_2| > \alpha$ , set  $g = g_2$ , go to Step 4.

Step 4: set  $g_i = g$ ,  $g_i$  is the grey value of point  $P_i$  in the current background. Set  $i = i + 1$ , if  $i \leq N$ , go to Step 1, otherwise go to Step 5.

Step 5: gather the grey value of all points in the current background, and get the background.

#### V. PASSENGER FLOW STATUS RECOGNITION ALGORITHM BASED ON FEATURE OF IMAGE CONNECTED DOMAIN

After the stable background built in Section IV, a current frame is taken to difference operate on background for obtaining foreground image. Through the smooth denoising to decrease noise and keep details of foreground, a passenger flow status recognition algorithm is proposed in this section.

##### A. Analysis of Passenger Flow Image Connected Domain

In ideal conditions, the amount of passenger flow can be counted by statistics of image connected domains. But for practical application in high-speed railway transport hub video surveillance, the disturbances result from errors of difference operator, system noise and overlap caused by crowded passengers can make large error of passenger flow status recognition.

In order to reduce the disturbances, passenger flow image connected domains are divided into two types.

1. Diminutive area connected domains independent of passenger flow connected domains which are mainly caused by independent passenger, errors of difference operator and system noise.
2. Large area and non-circular connected domains which are mainly caused by overlap which is result from crowded and slow-moving passengers flow.

##### B. Recognition Algorithm Based on Feature of Image Connected Domain

Firstly, sequential algorithm is used to mark all connected domains. Secondly, select the first type connected domains to recognize and count the amount of passengers. Thirdly, select the second type connected domains to recognize and count the amount of passengers. Finally, add the passenger amount of two types connected domains, compare to safety status level of passenger flow, and obtain the current passenger flow status. The detailed procedure of recognition algorithm based on feature of passenger image connected domain is shown in the Fig. 5.

The notations of algorithm are defined as follow:

- $n$  – amount of connected domains
- $i$  – the number of connected domains.
- $S_i$  – area of the  $i$  connected domain.
- $L_i$  – circumference of the  $i$  connected domain
- $M_i$  – measurement of the  $i$  connected domain,
- $M_i = 4f \cdot S_i / L_i^2$ .
- $D_s, D_l, D_m$  – thresholds,  $D_s > D_l$
- $n_{i1}, n_{i2}$  – passenger amount of two types connected domains.
- $n_i$  – passenger amount of the  $i$  connected domain.
- $n_1$  – amount of quasi-circulars.
- $N$  – passenger amount in the image.

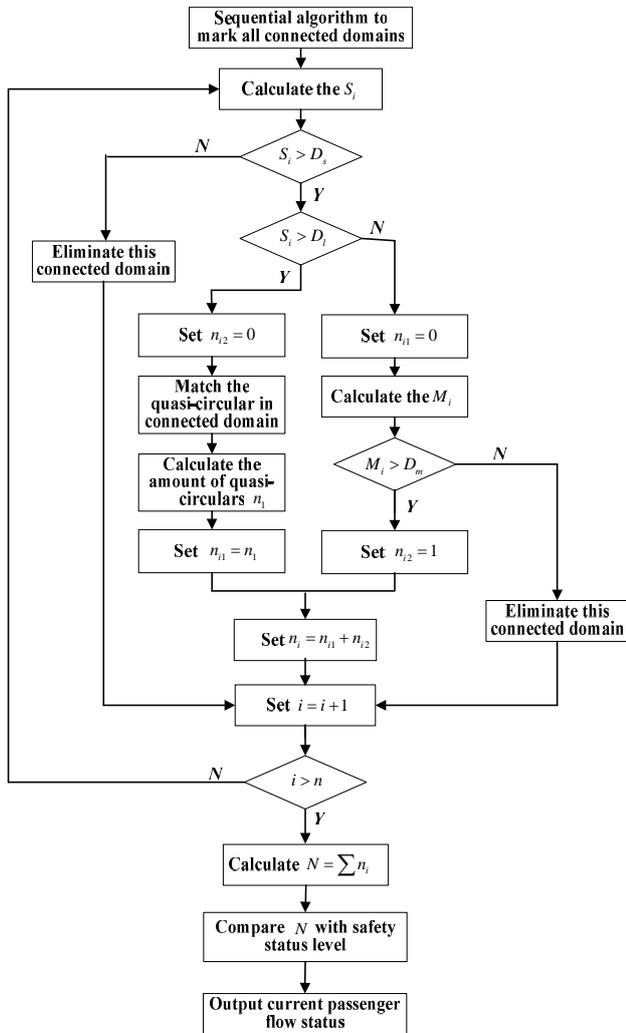


Fig. 5. Procedure of recognition algorithm based on feature of passenger image connected domain.

## VI. EXPERIMENT ON HIGH-SPEED RAILWAY TRANSPORT HUB

A high-speed railway transport hub surveillance video sequence is taken as an example to experiment on our method. Fig. 6(a), Fig. 6(b) and Fig. 6(c) are the first, 60th and 120th frame of surveillance video sequence.

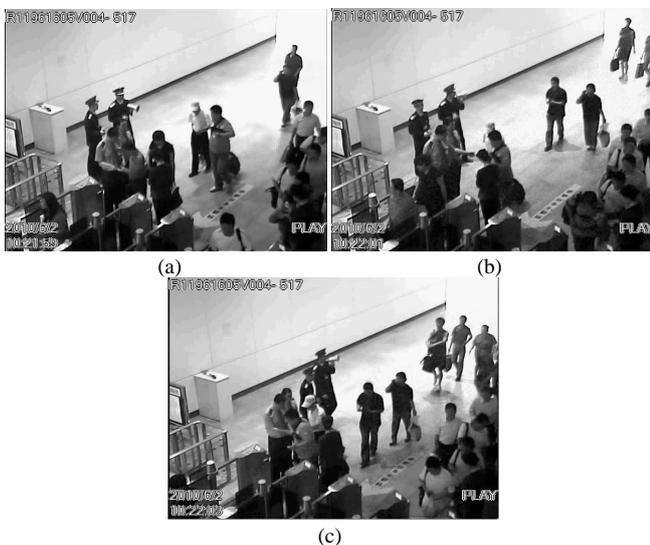


Fig. 6. Video sequences of passengers waiting for entrance: (a) the 1st frame image, (b) the 60th frame image, (c) the 120th frame image.

A background was built by the method proposed in Section IV. The effect of background is shown in Fig. 7(c). The other backgrounds shown in Fig. 7(a) and Fig. 7(b) were built by common average model and codebook model. From the comparison of background built by different methods, we can find the background built by our method is better in the filled of image quality, definition and moving object removing.

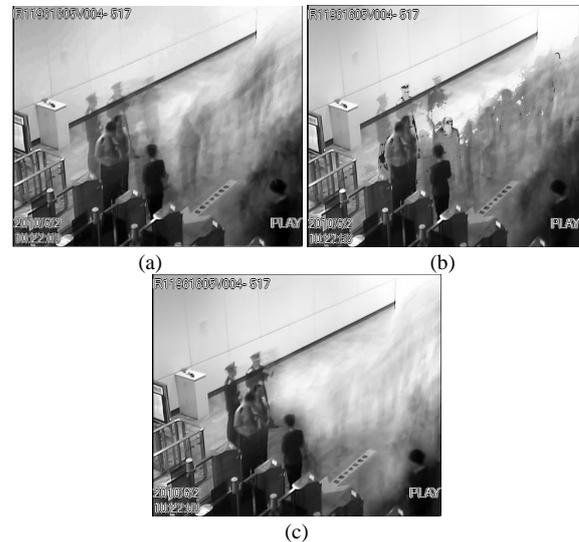


Fig. 7. Background built by different models: (a) Background built by common average model; (b) Background built by codebook model; (c) Background image built by our method.

Two hundred frames of video sequence are taken to experiment for determining the appropriate sample size to build the background. The backgrounds built by different sample size ( $n = 50, 80, 100$ ) are shown in Fig. 8. Moving objects were almost removed from the background when the sample size is 80. The background became more distinct when the sample size is increased to 100. Although continuously increasing sample size can improve the definition of background, background generated time is simultaneously increased. So the definition of background will not be further improved under the premise of satisfying passenger flow detection demands.

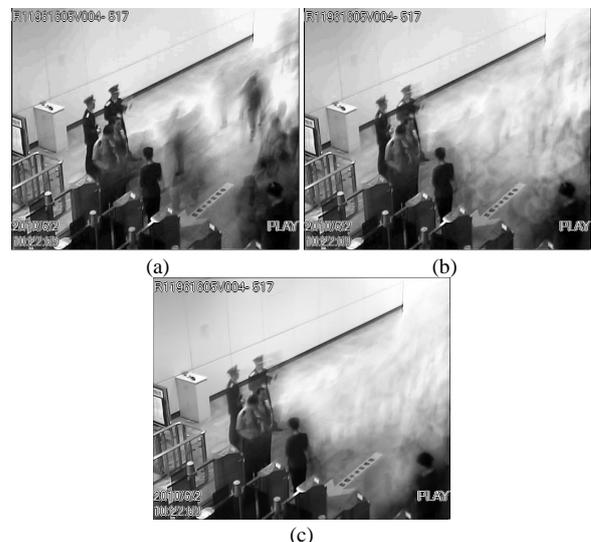


Fig. 8. Background built by different sample size: (a)  $n = 50$ ; (b)  $n = 80$ ; (c)  $n = 100$ .

The result of difference operator between current frame and background is shown in the Fig. 9(a). The foreground after morphological processing is shown in the Fig. 9(b).

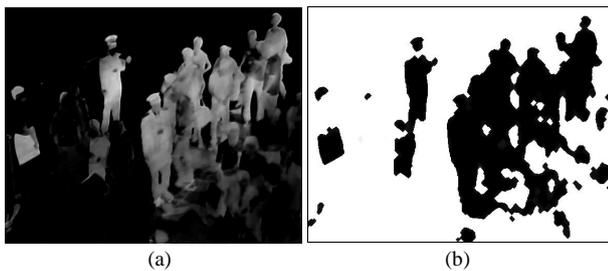


Fig. 9. Result of difference operator and morphological processing.



Fig. 10. Screenshots of passenger flow detection system based on the methods proposed in this paper.

Figure 10(a)–Fig. 10(d) are screenshots of passenger flow detection system based on the methods proposed in this paper. After a great deal of experiments, the average accuracy of passenger flow detection based on our method can reach 85 %.

## VII. CONCLUSIONS

In this paper, we considered the passenger flow detection problem of video surveillance in China high-speed railway transport hub. Through the analysis on characteristics of passenger flow detection areas in hub and procedure design of passenger flow detection, a modified background model based on Dempster-Shafer, and a passenger flow status recognition algorithm based on feature of image connected domain were proposed to improve the veracity and time-validity of passenger flow detection in high-speed railway transport hub video surveillance. Computational experiment on data from high-speed railway transport hub video surveillance system shows that the proposed model and

algorithm are effective and efficient in solving the problem.

There are two possibilities for future research. One is the adaptability analysis of detection method for different passenger density. Another is adaptive updating method of background for disturbance from temporarily motionless passenger flow.

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