Research on Pedestrian Tracking in Urban Rail Transit Stations Based on Adaptive Kalman Filtering

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Abstract. Traditional methods mainly use kernel-weighted feature histograms as tracking models, which are easily influenced by the similarity of tracking distributions, resulting in lower mean average precision (mAP) for tracking. In order to effectively address the issues of traditional methods, a new pedestrian tracking method based on adaptive Kalman filtering for urban rail transit stations is proposed. By combining pedestrian micro-walking state analysis with urban rail transit station pedestrian tracking features, a pedestrian tracking model is constructed. The urban rail transit station pedestrian tracking algorithm is designed using adaptive Kalman filtering, and pedestrian tracking is achieved based on the tracking model. Experimental results show that the designed pedestrian tracking method based on adaptive Kalman filtering for urban rail transit stations has a higher mAP for tracking and has certain practical value.

Keywords: Adaptive Kalman filter · City · Track · Traffic station · Pedestrian tracking

1 Introduction

Pedestrians are the main participants in the traffic system. Ensuring smooth pedestrian traffic and pedestrian safety is an important goal of urban traffic system construction [1]. However, in the current traffic system research, vehicles are often the focus of the research. In the actual urban traffic system [2], especially in a typical mixed traffic system such as China, detailed pedestrian information on urban roads is the basis for achieving urban traffic safety and efficient traffic. From the following analysis of a set of traffic data, we can understand the importance of the auxiliary driving system. Every year, more than 39000 pedestrians die in traffic accidents around the world, and more than 430000 people are injured in traffic accidents. In traffic accidents [3], the number of pedestrians injured is only second to the number of passengers injured in accidents. Therefore, people are eager to strengthen the protection of pedestrians in traffic activities and hope that some automatic detection systems can appear to protect pedestrians.

The most basic step of pedestrian research is to extract the traveller target [4] from the target. After extracting the targets in the scene, the next thing to deal with is to

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distinguish pedestrians from other targets. There are many pedestrian discrimination methods available. The basic way is to extract some pedestrian intrinsic features [5], and then compare them based on these features. These methods solve the problem of pedestrian detection in specific applications. However, in complex environments, due to the inability to solve various difficulties in human shape and appearance [6], as well as different human motion modes, existing pedestrian discrimination algorithms need to be improved in robustness and accuracy. In practical applications, it is usually necessary to collect and analyze video images in real time, which requires that the algorithm can extract the size, position, shape, contour and other information of passengers in a very short time [7], which is the real-time requirement of pedestrian detection algorithm. At present, research on pedestrian tracking has made certain progress. For example, reference [8] proposed a frame difference pedestrian tracking method, which mainly uses improved three frame difference method combined with morphological technology to detect and track pedestrian targets in surveillance videos. It can effectively fill some "voids" in pedestrian targets and ensure the quality of pedestrian tracking. Reference [9] proposes a pedestrian tracking method based on sample learning. By specifying the target to be detected in the first frame of the surveillance video, a hybrid classification model can be autonomously generated for object detection. Online progressive learning algorithms are used to learn the changes in the target's posture and update the model. Combined with color based object tracking algorithms, a high-precision object detection and tracking system is automatically constructed to ensure tracking quality.

The detection of pedestrians in complex environments is very difficult. For example, installing a camera in an application environment of a freely moving platform, such as an automobile driving aid system, due to the complexity of pedestrians, some conventional pedestrian detection methods in static background, such as the pedestrian detection method based on frame difference, are no longer applicable in complex environments. The pedestrian detection method based on sample learning has a high error rate in complex background, so pedestrian detection needs to be optimized in some ways to ensure the accuracy of detection. From the detection algorithm itself, the effect of improving detection is limited after all. In recent years, how to use some intelligent algorithms to improve the visual processing process has become a research hotspot. Under the above background, this paper analyzes the traffic characteristics of pedestrians, and uses adaptive Kalman filter to design an effective pedestrian tracking method for urban rail transit stations. The innovative points of effective pedestrian tracking methods for urban rail transit stations designed using adaptive Kalman filtering are mainly reflected in adaptability, features based on micro walking states, consideration of station environment, and evaluation of tracking effects. These innovative points enable this method to better adapt to complex station environments and provide accurate and robust pedestrian tracking results, which has practical application potential. The main contributions of this study include technological innovation, analysis of pedestrian micro walking states, application practices, and improvement of traffic safety. These research results provide important theoretical basis and practical application value for the safety management, operation optimization and Transportation planning of urban rail transit stations.

2 Pedestrian Tracking Method for Urban Rail Transit Stations Based on Adaptive Kalman Filter

2.1 Analysis of Pedestrian Traffic Characteristics of Urban Rail Transit Stations

Influenced by the dynamics of urban traffic, pedestrian traffic characteristics will change dynamically, affecting the final tracking effect. Therefore, this paper first analyzes the pedestrian traffic characteristics of urban rail transit stations. Pedestrian traffic is a very important part of urban traffic. Pedestrian traffic is not as orderly as vehicle queuing. Pedestrians are affected to varying degrees by different factors such as pedestrians themselves, other pedestrians, and the environment, showing a random, complex, and changeable feature. Therefore, the study of pedestrian traffic must have a comprehensive understanding of the characteristics of pedestrian traffic. To understand the characteristics of pedestrian traffic, we can start from the micro and macro aspects.

The micro aspect is aimed at the movement of a single pedestrian. It mainly studies the space size, stride length, stride frequency, stride speed, and the role of other pedestrians and the environment when walking. The macro aspect refers to the group pedestrian movement, which mainly studies the relationship between the three important elements of pedestrian flow speed, density and flow, and pedestrian self-organization behavior. At the same time, environmental factors also have a greater impact on pedestrian walking characteristics [10]. In order to make the research more practical, it is necessary to conduct field research on the platform area of urban rail transit stations. Based on the analysis of the layout of platform facilities and pedestrian flow lines, specific research plans and locations are determined. According to the data obtained from the research and the results of observation videos, the characteristics of pedestrian walking behavior and following behavior in the platform area are analyzed to provide a basis for subsequent research. According to the characteristics of pedestrian stride, a feature map is drawn in this paper, as shown in Fig. 1 below.

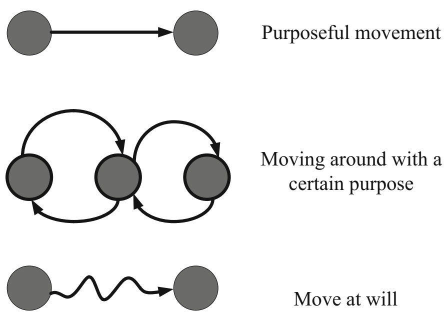

Fig. 1. Characteristic Diagram of Pedestrian Moving Stride

It can be seen from Fig. 1 that the purpose of pedestrian travel is the highest walking speed when commuting, and the walking speed when commuting can better represent the walking speed of pedestrians in urban rail transit stations.

Pedestrian static space demand refers to the space required by the body when the pedestrian is still, including the space actually occupied by the pedestrian and the safe space required by the pedestrian to maintain a certain distance from the surrounding environment psychologically. The actual occupied space depends on the shoulder width and chest thickness of pedestrians. The psychological exclusion of pedestrians should be considered for the psychological safety distance. The schematic diagram of pedestrian's static space demand is shown in Fig. 2 below.

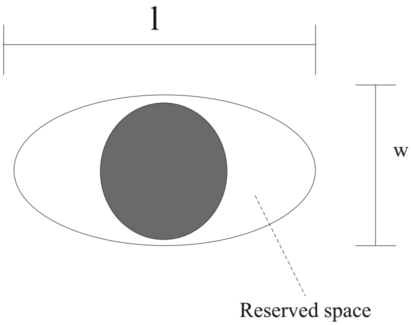

Fig. 2. Pedestrian Static Space Demand

It can be seen from Fig. 2 that the safe space of pedestrians is mainly related to their own gender, customs, personality, status, interpersonal relationships, environment and other factors. The safety space between acquaintances is smaller than that between strangers. When the environment is comfortable, women will generally reserve 0.37 square meters of safety space, while men will reserve 0.74 m^2 of safety space, and the safety zone is vulnerable to environmental impact. The safety space required by pedestrians will be greatly reduced when the surrounding pedestrian density is high. Pedestrian speed refers to the average speed of pedestrians in the study area in a certain period of time, which is related to the walking speed of each person $v(t)$ as shown in (1) below.

$$v(t) = \frac{\sum_{i=1}^{N} v_i(t)}{N} \tag{1}$$

In formula (1), $v_i(t)$ represents the instantaneous speed at which pedestrians pass, N represents the total number of people passing through, and the formula for calculating the average speed of pedestrians in the space at this time v as shown in (2) below.

$$v = \frac{L}{\sum_{i=1}^{N} \frac{t_i}{N}} \tag{2}$$

In formula (2), L represents the walking distance, t_i it represents the time consumed by pedestrians to complete the walking distance. Pedestrian density refers to the average number of pedestrians per unit area, which is calculated by k as shown in (3) below.

$$k = \frac{N}{L \times W} \tag{3}$$

In formula (3), W it represents the width of sidewalk. According to the above pedestrian density characteristics, the traffic class relationship can be set to generate the pedestrian speed, density, and flow tracking characteristic formula, as shown in (4) below.

$$q = v \times k \tag{4}$$

In formula (4), q represents pedestrian flow, v represents pedestrian speed, k represent pedestrian density. According to the above pedestrian tracking characteristics, pedestrian tracking parameters can be effectively calculated, which is the basis for subsequent tracking model construction.

2.2 Build Pedestrian Tracking Model of Urban Rail Transit Station

In order to solve the problem that the average tracking accuracy mAP is low due to the tracking distribution similarity when the kernel weighted feature histogram is used as the target tracking model, this paper constructs a pedestrian tracking social model for urban rail transit stations based on the pedestrian tracking feature parameters of (1)–(4).The social force model is a microscopic simulation mechanical model, which describes the movement of pedestrians under the action of social forces according to the principle of Newtonian mechanics. The social force in the model is based on the interaction results between pedestrians themselves, between pedestrians, and between pedestrians and the environment. It emphasizes more on the subjective initiative of pedestrians and can more realistically display the characteristics of pedestrian traffic. The social force pedestrian tracking model is shown in Fig. 3 below.

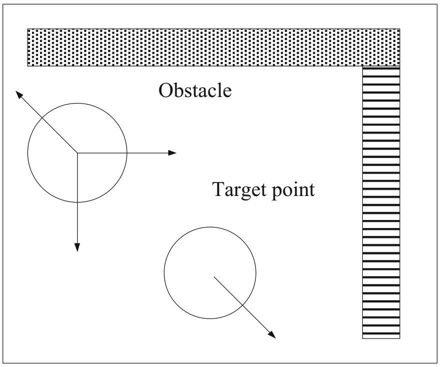

Fig. 3. Pedestrian tracking model of traffic social forces

It can be seen from Fig. 3 that in the traditional social force model, pedestrians are mainly affected by three forces: pedestrian self driving force refers to the power from the target point, and the direction points to the target point; Interaction between pedestrians. The force surface of the environment on the pedestrian is the force from the obstacle that the pedestrian receives, and the direction is perpendicular to the obstacle and points to the pedestrian. At this time, the final force on the pedestrian F As shown in (5) below.

$$F = m_i \frac{dv(t)}{dt} \tag{5}$$

In formula (5), m_i represents the mass of pedestrians, $dv(t)$ represents the force exerted by the environment on pedestrians, dt represents equivalent reaction. The moving acceleration of pedestrians can be calculated according to the force relationship of pedestrians $v_i(t)$, as shown in (6) below.

$$v_i(t) = at + v_0(t) \tag{6}$$

In formula (6), at represents the actual speed of pedestrians, $v_0(t)$ it represents the repulsive force of pedestrians against obstacles.

Self driving force is the force generated by pedestrians to reach the target point as soon as possible, maintain the desired speed, and select the shortest path subjectively without external environmental interference. When pedestrians are disturbed and the actual speed does not reach the expected speed, self driving force will be generated to accelerate pedestrians. The direction of self driving force is determined by the pedestrian pointing to the target point, and the size is determined by the pedestrian's expected speed and actual speed F_{ID} the calculation formula is as follows (7).

$$F_{ID} = m_i \frac{1}{\tau_i}(ve - v_i) \tag{7}$$

In formula (7), τ_i represents pedestrian response time, ve represents the actual speed of pedestrians, v_i represents the expected speed of pedestrians.

Pedestrians are affected by four forces when walking, including pedestrian self driving force, pedestrian force, pedestrian and obstacle force, and pedestrian gravity. When walking, pedestrians will select the following condition 4 in the field of vision.

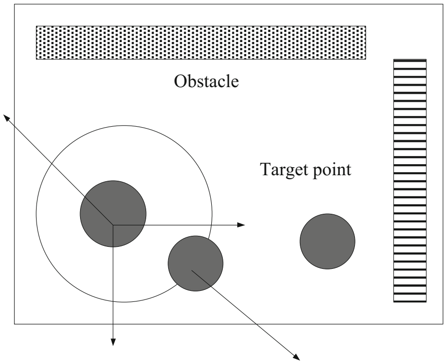

Fig. 4. Follow force of pedestrians in the model

It can be seen from Fig. 4 that, combined with the influence of various directional factors, this paper optimizes the pedestrian tracking model above, and constructs the pedestrian tracking optimization model for traffic stations $f_{\max}$ as shown in (8) below.

$$f_{\max} = \varphi m_i \frac{v_i}{\tau_i} \tag{8}$$

The above model studies the relationship between the following behavior revision coefficient and pedestrian traffic efficiency. Through research, it is found that pedestrian traffic efficiency increases with the increase of the following behavior revision coefficient. This shows that pedestrians follow the same direction of movement. The stronger the willingness of other pedestrians on the bus, the faster the pedestrians adjust their speed in the direction of movement, the faster the pedestrian flow will be formed, and the traffic efficiency will be improved. By studying the relationship between pedestrian speed and pedestrian density, it is found that when the revision factor is 0.2, the simulation results are more realistic, so the revision factor of the model is set to 0.2.

2.3 Design of Pedestrian Tracking Algorithm for Traffic Stations Based on Adaptive Kalman Filter

Only using the pedestrian tracking model of the traffic station built above for tracking may lead to the problem of limited tracking efficiency. Therefore, this paper designs the pedestrian tracking algorithm of the traffic station based on adaptive Kalman filter. Adaptive Kalman filter means that while filtering with measured data, the filter itself constantly judges whether there is any change in the system dynamics, estimates and modifies the model parameters and noise statistical characteristics of the above design, so as to improve the filter design and reduce the actual error of the filter. Therefore, foreground extraction is needed first, which can be realized by background subtraction, frame subtraction, optical flow and other methods. Considering the application environment and real-time nature of the algorithm, this paper uses the Gaussian mixture model with high adaptability to the background and moderate operating efficiency to extract foreground.

The Gaussian mixture model uses K Gaussian distributions to represent the characteristics of each pixel in the image, and matches each pixel in the current image with the Gaussian mixture model. If the matching is successful, the point is determined as the background point; otherwise, the point is the front spot, and at this time, each pixel X becomes the probability of tracking the background point $P(X_i)$ as shown in (9) below.

$$P(X_i) = \sum_{k=1}^{k} w \times \eta \tag{9}$$

In formula (9), w represents the high-speed distribution weight at different times, η represents the mean variance of Gaussian distribution, and the probability density function can be generated according to the tracking probability calculated above $\eta(x)$, as shown in (10) below.

$$\eta(x) = \frac{1}{(2\pi)\sigma} e \tag{10}$$

In formula (10), σ represents the matching coefficient, e representing the pixel matching value, the Gaussian mixture model can accurately evaluate the background model and carry out multi-target detection. In this paper, the EM algorithm is used to train the Gaussian mixture distribution. Through recursive calculation, a pedestrian tracking image with good adaptability can be obtained.

After the above steps are completed, this paper uses Faster RCNN network as the pedestrian detection network, which is divided into two processes: training and testing. The two processes are similar. Before the image sequence is input into the network, the data set is first preprocessed. Therefore, it is necessary to manually calibrate the Bounding Box for pedestrians in the training data set, obtain the minimum coordinates surrounding pedestrians, and save the coordinate information as an xml file for Faster RCNN to read. Since the Faster RCNN network has no fixed requirements for the size of the input image, it does not need to normalize the image sequence. When the image is input into the network for feature extraction, it will unify the image normalization scale according to the set scale.

Input the whole image into CNN for feature extraction. CNN has 13 relu layers and 4 pooling layers. The convolution core of each convolution layer is 3, and all convolutions are expanded outward for one circle. At the same time, the convolution core of each pooling layer is 2, and the step is 2, to obtain the feature map of the image. Think of the extracted feature as a 51 * 39 256 channel image, and input it into the RPN network to generate the region proposal. Essentially, the sliding window is made on the feature map finally extracted by CNN to obtain the multi-scale aspect ratio of the region proposal, that is, for each position of the feature image, three kinds of scale and aspect ratio are considered, and a total of nine possible candidate windows (anchors) are considered.

The anchors with the largest overlap ratio with the ground truth in these candidate regions are recorded as foreground samples, and then those with the overlap ratio with the bounding box greater than 0.7 are selected from these foreground anchors as foreground samples, and those with the overlap ratio less than 0.3 are recorded as background samples. Finally, the probability belonging to foreground and background is output from these 256 dimensional features. The proposed feature maps will be calculated and extracted at the ROI pooling layer, sent to the full connection layer to determine the target category, and the bounding box region will be used to obtain the target position detection box with the final accurate position.

The research of pedestrian re recognition began with multi vision tracking. In the re recognition algorithm, there are two very important parts: image description and distance measurement. A good distance measurement is very important because when the sample variances are consistent, high-dimensional visual features usually do not extract invariants. Among them, distance measurement methods are classified into supervised learning and unsupervised learning, global learning and local learning. In the re recognition algorithm, most of the work is mainly supervised global distance measurement learning. The general idea of global metric learning is to make vectors of the same class closer and those not belonging to the same class farther. The most commonly used is Markov distance, which is an extension of Euclidean distance using linear scale and rotation methods in the feature space. The algorithm designed in this paper tracks pedestrians based on Euclidean distance, so as to quickly obtain the tracking distribution relationship of pedestrians and maximize the tracking accuracy of pedestrians at stations.

3 Experiment

In order to verify the tracking performance of the designed pedestrian tracking method for urban rail transit stations based on adaptive Kalman filter, this paper selects a research area and compiles a simulation experiment program to compare it with the conventional frame difference pedestrian tracking method and the pedestrian tracking method based on sample learning. Experiments are carried out as follows.

3.1 Experiment Preparation

This chapter takes the platform investigation area of a subway station line 2 as the research background, applies the pedestrian following behavior simulation model program compiled by MATLAB software, selects reasonable parameters, and conducts simulation experiments on pedestrian tracking behavior in the platform area of urban rail transit stations. First, we need to build the functional structure of the experimental platform according to the characteristics of MATLAB software, as shown in Fig. 5 below.

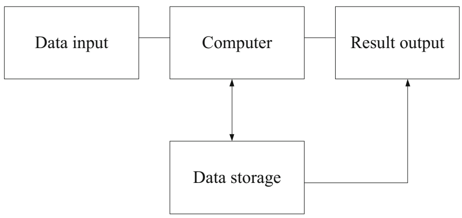

Fig. 5. Functional structure of the experimental platform

It can be seen from Fig. 5 that this experiment will divide the simulation experiment platform into four parts: data input part, data operation part, data storage part and result output part. The experimental platform built in this paper is divided into two parts: local computer side configuration and remote server side configuration. The specific configuration of the local side and server side is shown in Table 1.

This experiment selects two data sets, namely Crowd Human pedestrian data set and the traffic hub pedestrian data set collected and produced in this paper. Crowd Human pedestrian data set is a benchmark data set for pedestrian detection in the crowd, and the data set collected and produced in this paper is the pedestrian data set under various environmental conditions in each traffic hub.

There are 15000 training pictures, 4370 verification pictures and 5000 test pictures in Crowd Human pedestrian data set. The pedestrian individuals in each picture use three kinds of label frames, namely head frame, body frame and visible area frame. In order to intuitively display each label frame in the data set, draw a rectangular box for the pedestrian in the picture with the cv2.rectangle function at the end of the data set, The

Table 1. Configuration of Experimental Platform

Experimental platform		detailed parameters
Local end	CPU	i5-6500 CPU
	operating system	64 bit window7 operating system
	Memory	8G
	operating system	Linux centos7-1
Server side	CPU	40*Intel(R) Xeon(R) Silver 4210 CPU @ 2.20 GHz
	GPU	TITAN RTX (24G VRAM)
	Memory	8* 16 GB TruDDR4 2933 MHz
	other	CUDA10.2, cuDNN7

pedestrian individuals in each picture use three kinds of annotation frames, namely head frame, body frame and visible area frame. The annotation status of different annotation frames is shown in Fig. 6 below.

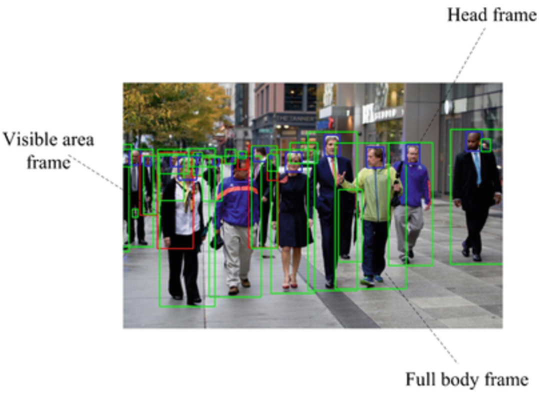

Fig. 6. Experimental image annotation frame

The data structure of this dataset is shown in Fig. 7 below.

As shown in Fig. 7, first use python programming to process the odgt annotation file of Crowd Human pedestrian dataset. Each ID of the odgt file is a picture. Divide it according to the ID, and extract the information under each ID. The targets tested in this paper are bbox and hbox. Therefore, the overall length and width of the picture, the coordinate information of the bbox box, and the coordinate information of the hbox box are extracted, Each image extraction information is saved as a separate xml file, and the xml file is named with the corresponding image name, which corresponds to the images stored in the JPEGImages folder one by one, and all are stored under the Annotations folder. Combining the above dataset data structure, this paper has produced an effective experimental dataset image, as shown in Fig. 8 below.

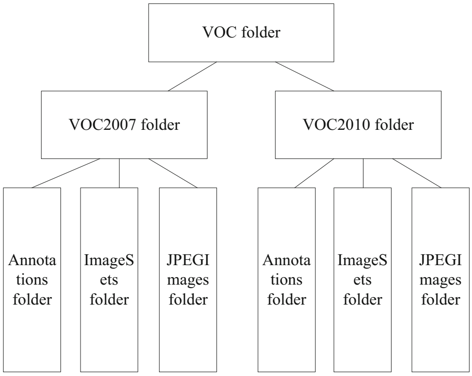

Fig. 7. Dataset Data Structure Diagram

It can be seen from Fig. 8 that this experiment detects pedestrians in the traffic hub. Due to the large number of detected targets, the target features are seriously lost in the case of serious occlusion. Therefore, this paper adopts the idea of head and shoulder detection to collect and produce the pedestrian head and shoulder data set of the traffic hub. There are 6196 pictures in total, with a total of 83072 effective numbers marked. The pictures are mainly from the two ways of photography and network, including the train exit Traffic intersection, station square and other scenes.

The Crowd Human pedestrian data set is made into a standard VOC data set format to prepare for algorithm training and testing. After the experimental data set is selected, the experimental indicators can be selected. According to the requirements of pedestrian tracking at the station, this paper selects the average accuracy rate mAP as the evaluation indicator, and its accuracy rate P and recall rate R as shown in (11) and (12) below.

$$P = \frac{TP}{TP + FP} \tag{11}$$

$$R = \frac{TP}{TP + FN} \tag{12}$$

In formula (11)–(12), TP in order to correctly detect the quantity, FP is the number of false checks, FN The number of pedestrians detected as the background is the number of pedestrians detected as the background by mistake. At this time, take the pedestrian detection at the traffic hub as an example, take the recall rate as the abscissa, and the accuracy rate as the ordinate, draw the P-R curve, and use the integral to calculate the value of mAP, as shown in (13) and (14) below.

$$F1 = \frac{2TP}{2TP + FN + FN} \tag{13}$$

$$mAP = \int_0^1 P(R)d(R) \tag{14}$$

At this time, F1 can be used as a comprehensive measure of accuracy and recall. The closer to 1, the better the effect will be.

Pictures of pedestrians at the exit

Pictures of pedestrians at the entrance

Bus stop pedestrian map

Pictures of pedestrians in station square

Pedestrian map at traffic intersections

Pedestrian Map at Intersection

Fig. 8. Picture of experimental data set

In the simulation in this paper, the pedestrian is represented by a circle, and the K-means algorithm is used in Crowd Human dataset and transportation_hub_The experimental clustering parameters obtained by clustering on the Human dataset are shown in Table 2 below.

Table 2. Experimental clustering parameters

data set	Input size	Anchor Box
Crowd Human(fbox)	608	(4,10), (7,19), (10,35), (14,53), (20,27), (20,76), (28,114)
	416	(3, 8) (5,17) (8, 29)
	320	(2, 8) (3, 15) (6, 19)
Crowd Human(hbox)	608	(2, 3) (4, 5) (5, 8)
	416	(3, 8) (5, 17) (8, 29)
	320	(1, 2) (2, 3) (5, 8)
Transportation_ hub_Human	608	(1, 1) (1, 2)
	416	(6, 11) (9, 15) (12, 19)
	320	(5, 9) (12,19)

Table 2 shows that K-means++ can be used in Crowd Human dataset and transportation_hub_The clustering effect on the Human dataset can determine the number of experimental samples and effectively carry out subsequent pedestrian tracking experiments.

3.2 Experimental Results and Discussion

Combined with the above experimental preparations, pedestrian tracking experiments at urban rail transit stations can be carried out in the selected experimental data set, that is, five experimental samples are preset, and the pedestrian tracking methods at urban rail transit stations designed in this paper based on adaptive Kalman filter, conventional frame difference pedestrian tracking methods, and pedestrian tracking methods based on sample learning are used for tracking, Use formula (11)–(14) to calculate the average accuracy mAP of the three methods in different samples. The experimental results are shown in Table 3 below.

Table 3 shows that the average accuracy mAP of the pedestrian tracking method for urban rail transit stations designed in this paper based on adaptive Kalman filtering in different samples is close to 1.0, while the average accuracy mAP of the conventional frame difference pedestrian tracking method and the pedestrian tracking method based on sample learning is quite different from 1.0.The above results prove that the pedestrian tracking method of urban rail transit station designed in this paper based on adaptive Kalman filter has good tracking effect, accuracy and certain application value.

Table 3. Experimental Results

The pedestrian tracking method designed in this article for urban rail transit stations based on adaptive Kalman filtering	
Sample number	mAP
CA01	0.954
CA02	0.957
CA03	0.986
CA04	0.974
CA05	0.936
Frame difference pedestrian tracking method	
CA01	0.654
CA02	0.639
CA03	0.665
CA04	0.659
CA05	0.598
Pedestrian tracking method based on sample learning	
CA01	0.745
CA02	0.569
CA03	0.623
CA04	0.558
CA05	0.628

4 Conclusion

Accurate detection of pedestrians is fundamental to ensuring the safety of transportation hubs. With the rapid development of urbanization, cities are facing increasing traffic pressure, congestion, and frequent traffic accidents. In this context, effective positioning and tracking of pedestrians are necessary to improve traffic safety. Therefore, this paper determines the characteristics of pedestrian tracking in urban rail transit stations based on micro-walking states. A pedestrian tracking model is constructed, and an adaptive Kalman filtering algorithm is designed for urban rail transit station pedestrian tracking. The traditional Kalman filtering method is usually based on static models to estimate the position of pedestrians, but in practical situations, the motion state of pedestrians may change. This method introduces self-adaptability and adjusts the parameters of the filter based on real-time observation data to adapt to changes in pedestrian motion status, thereby improving the accuracy and robustness of tracking. The experimental results demonstrate that the designed method for pedestrian tracking in urban rail transit stations has good tracking performance, accuracy, and practical value. Pedestrian tracking in urban rail transit stations has wide application prospects, as it can enhance safety, operational management efficiency, and urban planning levels. As technology continues to advance and be applied, pedestrian tracking will play an increasingly important role in the future. By integrating technologies such as artificial intelligence, computer vision, and deep learning, the accuracy and efficiency of pedestrian tracking can be improved. It is also important to integrate pedestrian tracking technology with urban planning to provide scientific and accurate data support for city design and transportation planning. Through proper pedestrian flow guidance and planning, the urban traffic conditions and living environment can be improved.

References

1. Yang, S., Chen, Z., Ma, X., et al.: Real-time high-precision pedestrian tracking: a detection-tracking-correction strategy based on improved SSD and Cascade R-CNN. J. Real-Time Image Proc. **2**, 19 (2022)
2. Xu, Y., Chan, H.Y., Chen, A., et al.: Walk this way: Visualizing accessibility and mobility in metro station areas on a 3D pedestrian network. Environ. Plan. B Urban Anal. City Sci. **49**(4), 1331–1335 (2022)
3. Xu, X., Li, X., Zhao, H., et al.: A real-time, continuous pedestrian tracking and positioning method with multiple coordinated overhead-view cameras. Measurement **178**, 109386 (2021)
4. Xu, Y., Shmaliy, Y.S., Hua, L., et al.: Decision tree-extended finite impulse response filtering for pedestrian tracking over tightly integrated inertial navigation system/ultra wide band data. Meas. Sci. Technol. **3**, 32 (2021)
5. Zhou, Y., Yang, W., Shen, Y.: Scale-adaptive KCF mixed with deep feature for pedestrian tracking. Electronics **10**(5), 536 (2021)
6. Zhang, X., Wang, X., Gu, C.: Online multi-object tracking with pedestrian re-identification and occlusion processing. Vis. Comput. **5**, 37 (2021)
7. Wong, K.Y., Luo, H., Wang, M., et al.: Recognition of pedestrian trajectories and attributes with computer vision and deep learning techniques. Adv. Eng. Inform. **49**, 101356 (2021)
8. Huang, Y., Li, D., Cheng, J.: Simulation of pedestrian-vehicle interference in railway station drop-off area based on cellular automata. Phys. A **579**(4), 126142 (2021)
9. Mo, D.L., Yang, R.H., Wu, W., et al.: Pedestrian target detection in surveillance video based on improved three-frame difference method. Sci. Technol. Innov. Guide **18**(6), 138–142 (2021)
10. Shao, W., Zhao, F., Luo, H., et al.: Particle filter reinforcement via context-sensing for smartphone-based pedestrian dead reckoning. IEEE Commun. Let. PP(99), 1–1 (2021)