Multi Target Tracking Method for Rail Transit Crossing Based on Transient Electromagnetic Radar

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Abstract. Conventional multi-target tracking methods for rail transit crossings mainly use the Deep SORT tracking detector to measure the tracking Mahalanobis distance, which is vulnerable to the dynamic change of target tracking state, resulting in low accuracy of multi-target tracking. Therefore, a new multi-target tracking method for rail transit crossings needs to be designed based on transient electromagnetic radar. That is to say, the transient electromagnetic radar is used to collect the multi-target tracking data of rail transit crossings, build the multi-target tracking model of rail transit crossings, and design the multi-target tracking algorithm of rail transit crossings, thus realizing the multi-target tracking of rail transit crossings. The experimental results show that the designed multi-target tracking method based on transient electromagnetic radar has high accuracy, which proves that the designed multi-target tracking method for rail transit crossings has good tracking effect, accuracy, and certain application value, and has made certain contributions to improving the safety of rail transit crossings.

Keywords: Transient electromagnetic radar · Track · Traffic lane · Fork · Multi target tracking

1 Introduction

In today's society, rail transit system, as one of the important urban transportation modes, its safety and operating efficiency are crucial to ensure passenger travel and smooth urban traffic. As a key component of the rail transit system, the crossing is responsible for scheduling the direction of train travel, and its safe and smooth operation plays a vital role in the operation of the whole system [1, 2]. Therefore, the research on multi-target tracking of rail transit crossings has important background and significance. Through this research, the safety, operating efficiency and intelligent level of rail transit system can be improved, providing better security and services for urban traffic development and passenger travel [3].

The commonly used multi-objective tracking methods for rail transit intersections include traditional computer vision based multi-objective tracking methods, deep

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learning based multi-objective tracking methods, and multi-sensor fusion based multi-objective tracking methods. The multi object tracking method based on traditional computer vision methods utilizes traditional computer vision algorithms to track target objects at intersections, and detects and tracks targets based on their appearance, motion features, and trajectory information. The deep learning based multi-objective tracking method uses a deep neural network model to achieve target detection and tracking by learning a large amount of data, which to some extent improves the robustness of tracking. The multi target tracking method based on multi-sensor fusion can capture the information of target objects more comprehensively by integrating and fusing data from multiple sensors. Although the above methods can achieve target tracking, they usually require a large amount of annotated data for training, and for efficient target detection and tracking, they require huge computational resources to support, which limits the feasibility and scalability of these methods in practical applications, and the tracking accuracy is low [4–6].

In response to the above issues, this article proposes a multi target tracking method for rail transit intersections based on transient electromagnetic radar. Transient electromagnetic radar can detect and track targets from interference clutter, which can be converted into the precise distance between the radar and the target, which is beneficial for improving the accuracy of target tracking. A multi-objective tracking model for rail transit intersections has been constructed, which utilizes a state transition mechanism to handle the common phenomenon of random appearance and disappearance of targets in multi-objective tracking. At the same time, it can also utilize the performance advantages of existing single target tracking methods, which is beneficial for improving target tracking performance. By using Markov decision processes to model multi-objective tracking problems, the entire tracking process can be represented as a decision sequence. In modeling, it is necessary to define the state of the system, including information such as target position and speed, as well as other environmental states related to tracking tasks. Then, define the set of actions, which are selectable tracking operations in each state. Next, the reward function is defined to evaluate the pros and cons of each state and action to guide the decision-making process. Finally, using MDP solving algorithms such as value iteration or policy iteration, find the optimal strategy to maximize long-term cumulative rewards and achieve effective tracking of multiple objectives. This modeling method can provide systematic decision support and help optimize the performance and effectiveness of multi-objective tracking algorithms.

2 Design of Multi-target Tracking Method for Rail Transit Crossing Based on Transient Electromagnetic Radar

2.1 Acquisition of Multi-target Tracking Data of Rail Transit Crossings Based on Transient Electromagnetic Radar

Transient electromagnetic radar (TEM) is a kind of wireless detection device, which can detect targets and determine their spatial positions by radio. When there is relative movement between targets, frequency Doppler effect will be generated. Transient electromagnetic radar can detect and track targets from interference clutter and convert them into accurate distance between radar and target [7]. According to the principle of multi-target tracking at rail transit crossings, this paper selects 24GHz transient electromagnetic radar to transmit modulated signals of specific frequencies. The distance and speed of the target can be obtained by comparing the frequency difference between the transmitted signal at the moment and the echo signal at any moment. The composition block diagram of the radar is shown in Fig. 1 below.

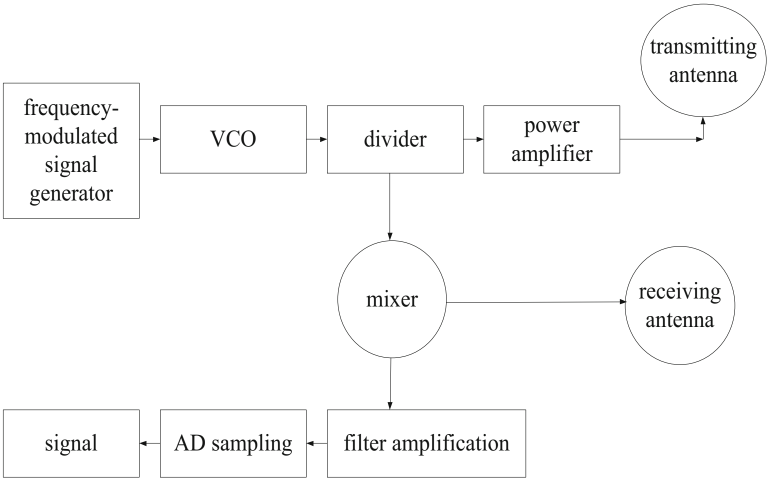

Fig. 1. Composition block diagram of 24GHz transient electromagnetic radar

It can be seen from Fig. 1 that the radar is mainly composed of three parts: antenna part, RF front-end and signal processing back-end. The antenna part is divided into two parts: transmitting antenna and receiving antenna; RF front-end mainly includes: power divider and mixer; The rest of the modulation signal generators and AD sampling constitute the back-end of signal processing. The modulation signal generator provides the modulation signal required by the radar, and generates a continuous signal [8] of a specific frequency through the VCO control of the voltage controlled oscillator. One part is transmitted from the transmitting antenna end through the power amplifier, and the other part is used as the local oscillator signal. In the process of outward transmission of the emitted electromagnetic wave, once encountering the measured target, it will return to the receiving antenna. At this time, the frequency difference between the echo signal and the non transmitted LO signal will occur. After passing through the mixer, the beat signal [9] will be obtained. The frequency of beat signal determines the distance and speed of the target. After the signal processing system calculates, the real distance and speed of the target can be obtained.

The innovative points of collecting multi target tracking data at rail transit intersections based on transient electromagnetic radar are as follows:

(1) Non visual perception: Traditional multi target tracking methods mainly rely on image or video data collected by visual sensors (such as cameras). The innovation based on transient electromagnetic radar lies in the use of non visual perception

to obtain information about the target object. Transient electromagnetic radar can detect and track target objects by measuring the propagation characteristics of electromagnetic waves between the target object and the radar, without being affected by factors such as lighting and occlusion.

(2) Distance and velocity information acquisition: Transient electromagnetic radar can provide relevant information such as distance and velocity of target objects, which is crucial for target tracking. By collecting and processing data from transient electromagnetic radar, real-time information such as the position, velocity, and motion trajectory of the target object can be obtained, thereby achieving accurate tracking of multiple target objects at intersections.

(3) Strong robustness: Transient electromagnetic radar has strong robustness in complex environments, unaffected by weather conditions such as light, rain, and snow, as well as changes in the appearance and occlusion of target objects. This enables the multi target tracking method based on transient electromagnetic radar to operate stably in various complex environments, providing reliable target tracking results.

In summary, the innovation of using transient electromagnetic radar to collect multi target tracking data at rail transit intersections lies in utilizing non visual perception to obtain information about target objects, and achieving accurate tracking of targets by providing data on key physical characteristics such as distance and speed.

There are also many kinds of frequency modulation modes for transient electromagnetic radar, such as linear frequency modulation continuous wave system, stepped frequency modulation continuous wave system and frequency shift keying system. Taking LFMCW sawtooth FM continuous wave as an example, this paper briefly introduces the principle of distance and speed measurement of traffic radar. Assume that the transmitted signal is sawtooth FM continuous wave, that is, it is composed of each sawtooth continuous linear FM pulse string. At this time, the frequency of the interpolated beat signal in the effective section f_b as shown in (1) below.

$$f_b = \tau K \tag{1}$$

In Formula (1), τ represents the transmitted signal, K represents the signal slope. When different targets are distributed at different distances, the beat signal obtained is the result of the linear addition of the beat signals of each target [10], but the frequency is separate, so the range information of the observed target can be obtained from the beat signal of a single target or multiple targets, and the wave path difference of the radar plane signal at this time φ as shown in (2) below.

$$\varphi = \frac{2\pi}{\lambda} d \sin\theta \tag{2}$$

In Formula (2), d represents the fixed distance difference of antenna, λ represents the length of electromagnetic wave emitted by radar, θ represents the angle between the target and the normal direction of the radar.

When collecting multi-target tracking data, it is necessary to identify and confirm multiple targets detected by radar, and associate, estimate and form tracks of the identified motion state information from the same target. The whole multi-target tracking process is a recursive process. Assuming that each target track has been successfully initiated during the tracking process, the newly received measurement information is first used to update the established target track, and the tracking gate is used to judge whether the newly received measurement data is reasonable. Data association is used to determine which track the measurement matches with the started track, and then the real parameters of the target track can be estimated according to the motion state, filtering and prediction. In the tracking process, the measured values that differ greatly from the established track may be clutter, and their effectiveness can be further judged according to the motion law or starting rules, and a new track can be started according to the appropriate situation; When some tracks do not match many new measurements, the tracks can be destroyed to reduce the amount of calculation; Finally, before the arrival of the new measurement, the center and size of the tracking gate at the next time can be appropriately adjusted according to the target prediction state, and a new round of recurrence cycle can be started again. According to the above reasoning, the data acquisition steps for multi-target tracking of rail transit crossings based on transient electromagnetic radar can be designed, as shown in Fig. 2 below.

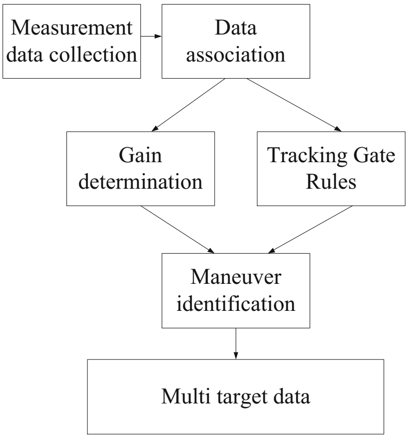

Fig. 2. Multi target tracking data acquisition steps

It can be seen from Fig. 2 that the resolution unit for detecting distance and speed of the above radar is small, so the receiving sensitivity and resolution are high. The size of the target will not cause too much impact when detecting long-distance targets. A target is usually detected to a reflection point. However, as the measured target is getting closer to the traffic radar, the same target will generate multiple reflection points due to different target shapes and large volumes. In the process of traffic radar detection, the transmitted signal returns after encountering multiple reflection points, generating multiple spectral lines in the spectrum, so that spectrum broadening occupies multiple resolution units, and each horizontal and vertical intersection resolution unit corresponds to a reflection point status information. As a result, the same target detected with multiple reflection points will generate multiple plot information, which actually corresponds to the same target. So when tracking multiple targets on the traffic road, it is the key to distinguish which targets belong to different targets from a large number of original plot information and which are from the same target, and to cohere multiple plot information from the same target well to ensure the subsequent high-precision and stable tracking of multiple targets. Therefore, the requirements for the original data preprocessing phase of the traffic radar multi-target tracking are high, especially the plot condensation part is the basis of the whole tracking process.

2.2 Build a Multi-target Tracking Model for Rail Transit Crossings

After collecting the multi-target tracking data of rail transit crossings, in order to effectively track the flow, it is necessary to build a multi-target tracking model of rail transit crossings. In this paper, the Markov decision process is used to model the multi-target tracking problem. The four states of active state, tracking state, lost state and inactive state are used to describe the different states of single target tracking. The whole life cycle of a target is modeled as a Markov decision process. At the same time, the tracking problem is also transformed into the learning problem of the transition strategy between different states of MDP. With the help of the state transition mechanism in MDP, this model structure can deal with the phenomenon of random appearance and disappearance of targets commonly seen in multi-target tracking, and can also take advantage of the performance advantages of existing single target tracking methods. This paper defines an action set composed of seven actions to describe the transition behavior between different states. The reward function is learned by training samples. The learning of the state transition strategy is realized through the reinforcement learning method, so the advantages of online learning and offline learning can be simultaneously used to realize data association. At this time, the multi-target tracking relationship is shown in Fig. 3 below.

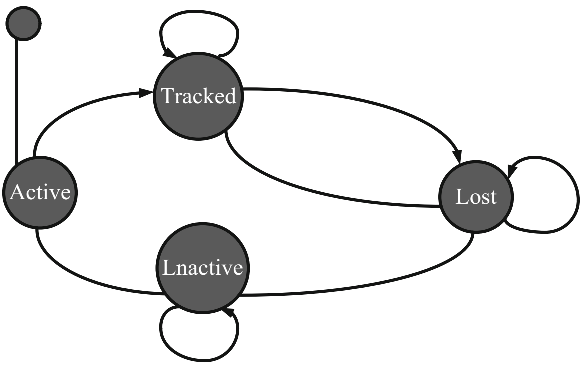

Fig. 3. Multi target tracking relationship

It can be seen from Fig. 3 that the Active state is to preliminarily screen the noisy detection frame obtained from the detector, and directly transfer the unreasonable detection frame to the Inactive state without target tracking. In the Active state, the MDP transfers the target detection frame to the Tracked state and Inactive state. In MDP tracking 131, in the Active state, support vector machine 431 is used to classify the detection frame. SVM uses the 5-dimensional feature vector of the detection frame to extract the 2-dimensional coordinates, width, height, and detection score of the detection frame. Then, the image width and height, maximum area detection frame width and height, and the highest detection score extracted from the training samples are used to calculate the 5-dimensional feature vector as the input of SVM,Take the detection box in the training sample as the parameter of training SVM, and the reward function $R_{Active}(s, a)$ as shown in (3) below.

$$R_{Active}(s, a) = y(a)(w_{Active}^{T}\phi_{Active}(s) + b_{Active}) \tag{3}$$

In Formula (3), $y(a)$ represents tracking 2D coordinates, w_{Active}^{T} represents the highest test score, $\phi_{Active}(s)$ represents a super parameter, b_{Active} represents the state transfer coefficient.

In the Tracked state, you need to decide whether to keep the target in the Tracked state or transfer the target state to the Lost state. As long as the target is not blocked and within the camera's field of view, the target needs to remain Tracked, otherwise the target will turn to Lost. In MDP tracking, an online tracking model based on appearance is established in Tracked to track a single target. The specific method is based on TLD.During initialization, K templates will be set for each target to represent the target's appearance characteristics. During the tracking process, LK tracking used in TLD will be used to calculate the target position through the template and perform single target tracking. The template update adopts the lazy update mechanism, and only one of the K templates is updated each time, so that the K templates retain the historical information of the target, which is the basis for data association in the Lost state. At this time, the rail transit intersection multi-target tracking model is built $R_{Tracked}(s, a)$ as shown in (4) below.

$$R_{Tracked}(s, a) = R_{Active}(s, a) \cdot y(a) \backslash otherwise \tag{4}$$

In Formula (4), *otherwise* represents the continuous detection value of multi-target tracking. The conversion of the Tracked state Lost state is based on two parameters. First, use the value measuring the tracking quality in LK tracking to calculate the median forward and backward optical flow. When the monthly marker encounters occlusion, the tracking quality becomes worse and the emedFB value rises; The second is the average overlap rate of K target templates and detection frames, which is used to determine whether the tracking target is a detector false detection target. If the current tracking target is a detection frame false detection result, the target will not be continuously detected by the detector, and the Omean value will continue to decrease. Finally, the state transition is carried out by setting the threshold value.

When the target is in the Lost state for more than a certain time threshold, the target will be directly transferred to the Inactive state to end tracking. Whether the target will remain in the Lost state or be transferred to the Tracked state is essentially a data association problem. If the target can match a detection frame in the current frame, it will be transferred to the Tracked state, otherwise it will remain in the Lost state.When tracking fails, the tracking target has saved K templates representing appearance information, and 12 dimensional feature similarity coding can be designed based on templates and detection frames *MDP*, , as shown in (5) below.

$$MDP = \frac{y(a)}{R_{Tracked}(s, a)}(W_{\max}(t) + b) \tag{5}$$

In Formula (5), $W_{\max}(t)$ represents the number of corresponding detection frames when the target realizes data association, b represents training initialization SVM parameters. According to the above feature similarity coding and multi-target tracking model, linear regression solution can be carried out $F(Z)$ as shown in (6) below.

$$F(Z) = \min \sum_{i} (f(x) - y_i)^2 + \lambda \|w\|^2 \tag{6}$$

In Formula (6), $f(x)$ represents the target input function, y_i represents the weight matrix, w represents the ridge regression learning parameter matrix. According to the above model solution values, the sample cyclic shift parameters can be obtained, and the tracking transformation eigenvalue can be obtained to maximize the accuracy of multi-target tracking.

2.3 Design Multi-target Tracking Algorithm for Rail Transit Crossings

The most original data received by the 24 GHz transient electromagnetic radar used in this paper is in hexadecimal form, and each frame counts as a packet of data. The refresh rate of the radar is 50 ms, so the radar receives 20 frames of data per second, and each frame of data can detect up to 160 targets, that is, each frame packet data can contain up to 160 target motion status information in addition to the relevant information such as the unified header data format of each frame of data. Therefore, it is the first and key step to accurately analyze the original frame packet data in hexadecimal form. When parsing the original packet data of a frame, because the frame header identifier of each frame of data is the same, first judge and identify the frame header information of each frame of data, until the complete frame header data is detected and identified, then proceed to the next step, and convert the hexadecimal data after the frame header information into decimal data according to the corresponding bytes occupied by each part.

The received original frame packet data may contain some errors or receive incomplete frame header data due to various reasons of the radar itself or data transmission, which is called outlier in practical engineering applications. They generally differ greatly from the real measured values, or do not contain the effective motion state information of the detected target. Therefore, in the process of original data analysis, outlier removal is also included to reduce the calculation amount for the next step of plot condensation preprocessing.

In the process of radar data acquisition or transmission, some received frame packet data may have errors or incomplete data. The most obvious is that the frame header information is incomplete, which leads to great errors in the target motion parameters after the frame header information. Therefore, such frame packet data with incomplete header data will also be eliminated in the original plot pre-processing stage. The specific method is to first detect whether the header format of each received frame of data is consistent, directly eliminate the frame packet data with incorrect or incomplete header data format, do not convert from hexadecimal to decimal data, and then detect the next frame of data.

According to the performance indicators of the radar, this radar has a certain detection range. The measurement data outside the detection range itself is not meaningful for subsequent algorithm processing, and has a large difference from the measured value of the actual observation target. Therefore, these outliers can be eliminated in the pre-processing phase of the original plot. The radar detection range of this paper is shown in Fig. 4 below.

Longitudinal distance (m)	0~400
Angle (°)	-60~60
Speed (m/s)	-70~70

Fig. 4. Detection range of this radar

It can be seen from Fig. 4 that in the original data analysis, not only useful target motion parameters such as frame number, radial distance, speed and angle of the target detected by the radar are obtained, but also invalid values are eliminated, which reduces the amount of calculation for the following target tracking algorithm and improves the operation speed. In addition, the original data analysis also includes the calculation of the coordinates under the traffic radar coordinate system where the target is located. Through the radial distance and angle of each target plot, the coordinate value of the target plot is calculated, as shown in (7) below.

$$\begin{cases} x = d \cdot \sin\theta_a \\ y = d \cdot \cos\theta_a \end{cases} \tag{7}$$

In Formula (7), d represents the radial distance of the target, θ_a represents the target angle. After analyzing the original data, the multi-target tracking equation can be generated, as shown in (8) below.

$$\begin{cases} y_l = -a \\ y_r = W - a \end{cases} \tag{8}$$

In Formula (8), y_l, y_r represents the radar detection range, W represents the width of the traffic road, a represents the distance between the radar and the edge. Generally speaking, the traffic radar is installed on the road perpendicular to the driving direction of the road target. It is easy to know the width of the road where the traffic radar is installed and the specific position of the radar in the direction of the road width. The traffic radar uses the radar coordinate system in the target tracking process, so according to the above road information. The edges of traffic roads can be identified in the radar coordinate system. Since the installation position of the radar is perpendicular to the driving direction of the traffic road vehicles, the edge marking line of the traffic road is parallel to the radar normal. The method designed in this paper comprehensively compares and analyzes the distance, angle and speed, sets a comprehensive threshold value. The original plots from the same frame with similar angles and within the comprehensive threshold value are marked as points from the same target, and then the information of these marked plots is condensed D as shown in (9) below.

$$D = \sum_{i=1}^{m} \frac{p_i d_j}{\sum_{i=1}^{m} (p_i)} \tag{9}$$

In Formula (9), p_i represents the tracking amplitude, d_j represents the radial distance. Using the above multi-target tracking algorithm for rail transit crossings, multi-target tracking can be carried out quickly to solve the tracking problem caused by the dynamic change of tracking state.

3 Experiment

In order to verify the tracking performance of the designed transient electromagnetic radar based multi target tracking method for rail transit intersections, this paper selected experimental datasets that meet the experimental requirements and compared the proposed method with conventional deep learning based multi target tracking methods and multi-sensor fusion based multi target tracking methods.

3.1 Experimental Software and Hardware Environment Settings

The experimental software and hardware environment is shown in Table 1.

Table 1. Experimental hardware and software environment

experimental environment	ambient condition
CPUmodel	Inter(R) Xeon E5-2697 v3
GPU	NVIDIA Tesla k40c Video storage 11 GB
	NVIDIA Quadro k420 Video storage 2 GB
Running memory (RAM)	192 GB
Programming Language	Python 3.5
Deep learning framework	Keras 2.1.5

From Table 1, it can be seen that the above software and hardware environments meet the training requirements of the experiment, improve the efficiency of the experiment, and ensure the effectiveness of the experimental results. At this point, subsequent multi target tracking experiments at rail transit intersections can be conducted.

3.2 Experimental Sample and Indicator Settings

Based on the experimental requirements, this article selects the MOT16 dataset as the experimental dataset. The MOT16 dataset includes 11 annotated training video sequences and 11 unlabeled test video sequences with only detection results. Figure 5 shows some experimental sample images.

Fig. 5. Experimental Scenario

After the dataset is selected, experimental indicators are set. In this paper, multi-objective tracking accuracy is selected as the experimental indicator, and the calculation formula is as follows (10):

$$MOTA = 1 - \frac{\sum_t m_t + fp_1 + mme_t}{\sum_t g_t} \tag{10}$$

In Formula (10), m_t represents the number of missed detections in t frame, fp_1 represents the number of false detections in t frame, mme_t represents the number of mismatches in t frame, g_t represents all the matching quantity in t frame. The higher the MOTA multi-target tracking accuracy is, the better the multi-target tracking effect is. On the contrary, the tracking effect is relatively poor.

3.3 Experimental Results and Discussion

Based on the above experimental preparation, a multi target tracking experiment for rail transit intersections was conducted. The designed multi target tracking method for rail transit intersections based on transient electromagnetic radar, conventional deep learning based multi target tracking method, and multi-sensor fusion based multi target tracking method were used for multi target tracking. Formula (10) was used to calculate the tracking accuracy of the three methods for different tracking targets, The experimental results are shown in Table 2 below.

Table 2. Experimental Results

Tracking target	Multi target tracking method for rail transit crossing based on transient electromagnetic radar (%)	Multi object tracking method based on deep learning (%)	Multi target tracking method based on multi-sensor fusion (%)
C1#a	95.44	75.36	65.65
C2#a	93.89	61.45	73.34
C3#a	96.32	62.28	62.53
C4#a	95.48	63.54	63.96
C5#a	94.14	76.12	66.45
C6#a	92.52	69.69	75.28
C7#a	96.95	65.85	74.66
C8#a	99.47	56.74	72.85
C9#a	98.58	64.26	66.42
C10#a	95.23	65.84	79.39

From Table 2, it can be seen that the multi target tracking method for rail transit intersections based on transient electromagnetic radar designed in this article has high accuracy in tracking different targets, while conventional deep learning based multi target tracking methods and multi-sensor fusion based multi target tracking methods have relatively low accuracy in tracking different targets. The above experimental results prove that the multi target tracking method designed in this paper has good tracking performance, high tracking accuracy, and effectiveness, with certain application value.

4 Conclusion

With the rapid development of road traffic, the total mileage of roads in China is getting higher and higher, resulting in many problems such as traffic congestion, mixed traffic, frequent accidents, low level of traffic management, among which the problem of frequent traffic accidents is the most serious. According to statistics, about 200000 road traffic accidents occur every year in China, resulting in more than 60000 deaths and about 210000 injuries. According to the investigation, most accidents are caused by drivers' illegal driving and abnormal parking without supervision; If the road management party can strengthen the monitoring and timely find out the violations of vehicle drivers or give early warning guidance to other vehicles after the accident, the occurrence of traffic accidents can be reduced. In this context, in order to deal with the severe traffic safety situation, it is necessary to carry out multi-target tracking for vehicles. In this paper, based on the characteristics of the current traffic, a multi-target tracking method for rail transit intersections is designed based on the transient electromagnetic radar. The experimental results show that the designed track crossing multi-target tracking method has good tracking effect, accuracy and certain application value, and has made certain contributions to improving traffic safety.

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