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Research on detecting moving targets with an improved Kalman filter algorithm

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Abstract

As science and technology evolve, object detection of moving objects has been widely used in the context of machine learning and artificial intelligence. Traditional moving object detection algorithms, however, are characterized by relatively poor real-time performance and low accuracy in detecting moving objects. To tackle this issue, this manuscript proposes a modified Kalman filter algorithm, which aims to expand the equations of the system with the Taylor series first, ignoring the higher order terms of the second order and above, when the nonlinear system is close to the linear form, then it uses standard Kalman filter algorithms to measure the situation of the system. which can not only detect moving objects accurately but also has better real-time performance and can be employed to predict the trajectory of moving objects. Meanwhile, the accuracy and real-time performance of the algorithm were experimentally verified.

Keywords: Moving objects, machine learning, artificial intelligence, detection algorithm, improved Kalman filter algorithm.

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1. Introduction

Thanks to the continuous advancement of science and technology, the detection and tracking of moving objects is a crucial research topic with regard to computer vision, vision and image coding, and video image compression and transmission and other fields have a wide range of applications[1]. It mainly includes two technologies: moving target detection technology and tracking. Moving object detection explores whether there is a moving object in the video sequence, and determines the position, shape, and other features of the moving object, the space-time change, such as the appearance and disappearance of the target, its position, size, and the target's shape, and determine the trajectory of the moving target[2]. Detection and tracking of moving objects are closely related to each other. Detection is the basis of tracking, and target tracking also helps to detect moving objects more accurately in the following image sequences [3]. Moving object detection is to eliminate the irrelevant redundant information in the time domain and space domain in video representation space utilizing computer vision, and the research process of the object with spatial position change is extracted effectively. Most of the previous target detection algorithms come from manual operation and lack of image feature representation, resulting in unclear and inaccurate detection results [4]. In light of this, we must set up a variety of detection algorithms to solve the corresponding problems. In parallel, to address the lack of appropriate resources in the computational process, a more suitable computational algorithm must be sought to further accelerate the extraction of features and make the target detection algorithm clearer and more accurate[5]. This paper presents a modified form of the Kalman filter algorithm, which simply sets up a filter over some time. The Kaman filter follows the basic idea of using a least-squares error as the best criterion. Using the state-space model of signal and noise, the state variables are evaluated by using previous estimates and current visual observations, to reduce errors caused by system noise and noise, to obtain the optimal state variables, the algorithm is established to minimize the signal processed by equations and observation equations, and to predict the error to obtain the corresponding estimates[6]. Instead of storing historical measurements, the Kaman filter uses its state-transition equations to reduce storage and computation by using a set of recursive equations that compute new parameter estimates[7]. So the filter contains relatively little data to handle the noise in the observed data, yielding a good result [8]. The Kalman filter calculates the best predictive value of the instant according to the motion of the moving object in the earlier moment and then derives the best predictive value of the next moment [9]. The key in this process is how to get the Emmerich Kalman gain. Here, the Emmerich Kalman gain is obtained based on the equations of the motion system and the errors produced in the tracking process. Meanwhile, the deviations are corrected by the Kalman filter, resulting in more accurate detection accuracy and better real-time performance [10]. Finally, the experiment shows that the Kalman filter algorithm is excellent in the detection process of moving objects, and its application to the prediction of vehicle trajectory can also achieve better results [11].

2. Related Work

As time goes on, the recognition algorithms of all kinds of moving objects have been discussed constantly [12]. In recent years, there has been a dramatic change, especially from theory to practice. The corresponding moving object detection algorithm is now a trend of research [13]. For example, Guo Yan proposed a fusion algorithm for a stadium location, which uses a self-optimizing particle filter to combine an improved algorithm for athlete trajectory estimation with a Wifi localization fingerprint algorithm to localize the stadium and then achieve object detection through image recognition [14]. Additionally, Luis Ruiz Suarez et al., “proposed a deep learning-based object detection algorithm in remote sensing images, where the image background needs to be distinguished to achieve accurate recognition results in video surveillance [15]. Yang uses a background subtraction algorithm to detect and recognize moving targets [16]. Besides, the Yolov3 algorithm is put forward in the process of machine vision object detection, and the expected recognition effect is basically achieved [17]. In parallel, Michael et al., “introduced the training of a deep learning detector for better motion recognition [18]. Meanwhile, Zhao Long et al., “studied the recognition algorithm of an intelligent video surveillance system based on multi-camera networks [19]. Li Zhihao et al., “presented an improved resampling particle filter algorithm in a moving target tracking and detection algorithm [20]. Meanwhile, Doksy et al., “combine depth research learning with Yolov to realize visual moving object detection [21]. What’s more, the research of Xu Pengfei et al., “reveals that the moving target monitoring and intelligent tracking algorithm in video surveillance can achieve target tracking recognition [22]. This paper presents a novel algorithm for identifying and tracking moving objects with better accuracy and real-time performance. Mo Yang-hui and others have proposed that a modified Kalman filter algorithm can increase the perceived range of a vehicle by outputting position information, and experimental studies have shown that the algorithm improves the average positioning accuracy[23]. In a paper, Hosek Chua proposed the use of sparse optical flow to detect and track moving objects by determining the location of feature points, the experiments demonstrate that the adopted method can make moving target detection more accurate compared with the optical flow method[24]. To figure the trajectory tracking challenge faced by an automatic straddle carrier (ASC), the state of ASC is estimated by using an improved Kalman filter, and the corresponding experiments were carried out, the results show the modified method overstands among all the with its effectiveness[25]. In order to improve the accuracy of noise covariance matrix measurement, Wang Wei et al proposed an improved Kalman filter algorithm. which was simulated by initial alignment and compared with the conventional Kalman filter, the error accuracy of the misalignment angle is improved by an order of magnitude[26]. In a paper, Xue Renzheng mentioned the improved frame difference method to detect automatically the moving object's automatic detection and tracking algorithm in a quick a precise way [27]. Bissin et al have studied the detection of moving objects. In the course of the research, the improved convolutional neural network can detect moving objects accurately[28]. When Guan Yurong and others study target recognition, they divide the target image into a group of initial regions and then group the adjacent regions according to the region features by using clustering and hierarchical strategies, by using the edge detector to extract the edge from the original image, the target detection system can be refined to improve the accuracy of detection[29]. In his other paper, he proposed that by using multi-level segmentation of super-pixel, we can get a high-quality class-independent scheme, extract feature vectors from it, and then map the features with soft-max classifier, to determine the class of each object and use a deep neural network (DNN)-based high-quality target location[30]. Both of these papers subdivide the target image to accurately identify the corresponding target object. These technologies are aimed at static object recognition. The target position of the moving object can be predicted by using the improved Kalman filter algorithm designed in this paper, and then the target can be accurately identified by the algorithm which continuously corrects the position.

3. Improved Kalman filter algorithm of target detection

3.1 Kalman filter algorithm and its principle

Target detection is the ability of target recognition, and accuracy and real-time are of paramount importance in the system [31]. The accuracy and real-time requirements are particularly high when processing moving targets in real-time in complex scenes. Moving object tracking is a process of adaptive filtering. The basic approach is to identify the information about the current moving target position and then to detect or distinguish it by adjusting the gain and covariance matrix of the filter according to the change in information [32]. The target characteristics are detected in real-time and the optimal prediction value is acquired by the Kalman filter algorithm, thus realizing the tracking and detection of the object. The basic routine is depicted in **Fig. 1**.

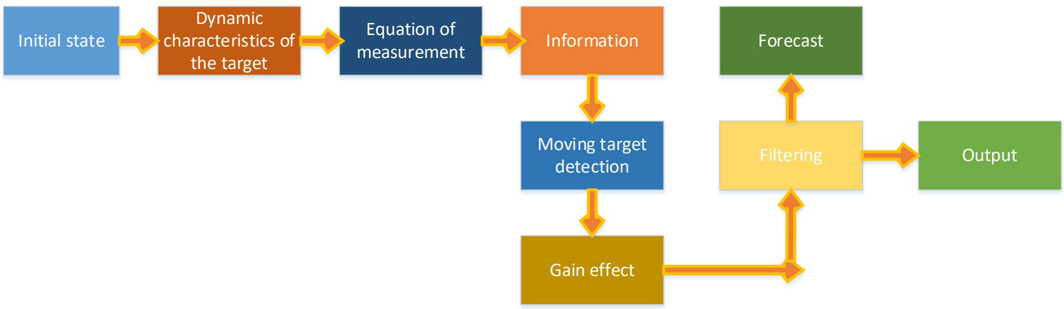

Fig. 1. Schematics of the Kalman filter

As evidenced by the figure, when a detection target appears, its maneuvering characteristics can be determined from the initial state of the target. The corresponding measurement equations are derived from the corresponding properties [33]. As a result, specific information about the target can be acquired. The corresponding gain is determined by target detection and identification, and then the output is obtained by means of a Kalman filter [34]. At the same time, the target is predicted after Kalman filtering and the corresponding novel information will be obtained.

The following shows the expression for the target state and the expression for the measurement result (1)(2)

$$P(k+1) = \phi(k+1,k)P(k) + U(k)X(k) \tag{1}$$

$$M(k) = F(k)P(k) + Q(k) \tag{2}$$

$P(k)$ is a vector representing the state of a target, and $M(k)$means the measuring vector. $W(k)$ represents state noise and $Q(k)$stands for measurement noise. In parallel, the state transition matrix is marked by$\phi(k+1,k)$,$U(k)$stands for noise-driven matrix, and $F(k)$is the measurement matrix. $W(k)$and $Q(k)$satisfies the following expression.

$$E[X(k)] = 0, \quad cov[X(k), X(j)] = E[X(k)X(j)^T] = J(k)\chi_{kj} \tag{3}$$

$$E[Q(k)] = 0, \quad cov[Q(k), Q(j)] = E[Q(k)Q(j)^T] = R(k)\chi_{kj} \tag{4}$$

$$cov[X(k)Q(j)] = E[X(k)Q(j)^T] = 0 \tag{5}$$

The above formula: $J(k)$is considered a non-negative definite matrix for the variance matrix of the noise sequence of the system.$J(k)$measures the variance matrix of the noise sequence of the system, which is presumed a positive definite matrix.

The status further predicts:

$$\hat{P}(k|k-1) = \phi(k,k-1)\hat{P}(k-1|k-1) \tag{6}$$

State estimation:

$$\hat{P}(k|k) = \hat{P}(k|k-1) + S(k)\big[M(k) - F(k)\hat{P}(k|k-1)\big] \tag{7}$$

Filtering gain:

$$S(k) = N(k|k-1)F^T(k)[F(k)N(k|k-1)F^T(k) + R_k]^{-1} \tag{8}$$

Predicted mean square error:

$$N(k|k-1) = \phi(k,k-1)P_{k-1}\phi^T(k,k-1) + U(k-1)L(k-1)U^T(k-1) \tag{9}$$

Estimated average square deviation:

$$N(k|k) = [I - S(k)F(k)]N(k|k-1) \tag{10}$$

Expressions 1-10 are the basic logical representation of the Kalman filter. Given the original values$P(0)$ $N(0)$, the state evaluation of the k-moment is calculated recursively, taking the measurements from the k-moment$\hat{\boldsymbol{P}}(\boldsymbol{k})$into consideration.

When using Kalman filtering, two update methods are implemented to guarantee the accuracy of the detected target information. One approach concerns the time update, which is well described by the expressions (6) and (7) above during Kalman filtering. The other approach is the measurement update, where there may be some errors in the identification and detection process. [35]. The update process mainly uses a comparison of the error and the measurement value to obtain the new measured value [36].

3.2 Methodology of the Improved Kalman filter algorithm

As a matter of fact, system models are often non-linear, and an improved Kalman filter is often adopted to solve such problems. This improved Kalman filter algorithm can convert some hard-to-express non-linear functions into approximate probability densities [37]. A third-order Taylor expansion was applied for better accuracy, avoiding degradation of the sampled data due to defined algorithms.

The principal processes of the algorithm are listed below:

One: Predictions calculated according to the previous filtering value $\hat{P}(K-1/K-1)$,

$$\hat{P}(k/k-1) = \psi(k,k-1)\hat{P}(k-1/k-1) \tag{11}$$

Two: The filtering error variance matrix was obtained according to the previous $N_{\tilde{P}}(k-1/k-1)$. The predictive error variance matrix was calculated.

$$N_{\tilde{P}}(k/k-1) = \psi(k,k-1)N_{\tilde{P}}(k-1/k-1)\psi^T(k,k-1)\Gamma(k-1)L(k-1)\Gamma^T(k-1) \tag{12}$$

Three: The Kalman gain calculation:

$$S(k) = N_{\tilde{P}}(k/k-1)D^T(k)[D(k)N_{\tilde{P}}(k/k-1)D^T(k) + R(k)]^{-1} \tag{13}$$

Four: Computational filtering estimation:

$$\tilde{P}(k/k) = P(k/k-1) + S(k)[Z(k) - D(k)\tilde{P}(k/k-1)] \tag{14}$$

Five: The calculation of the Filter Error Variance Matrix:

$$N_{\tilde{P}}(k/k) = [1 - S(k)D(k)]N_{\tilde{P}}(k/k-1) \tag{15}$$

To achieve a deeper insight into the improved Kalman filtering process, **Fig. 2** displays a flow chart of the Kalman filtering procedure, and **Fig. 3** presents a flow chart of the computation of the improved Kalman filtering gain.

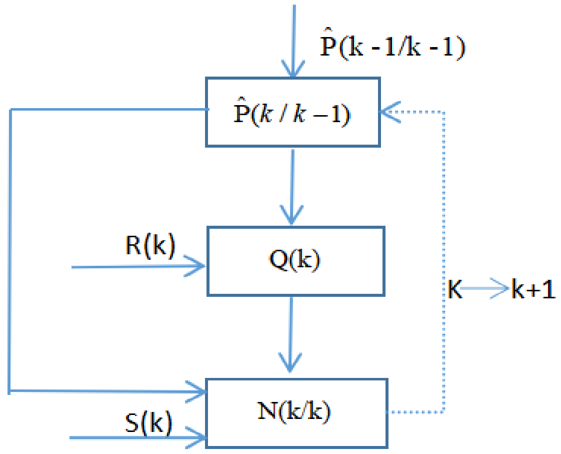

Fig. 2. Chart of the Kalman filter process

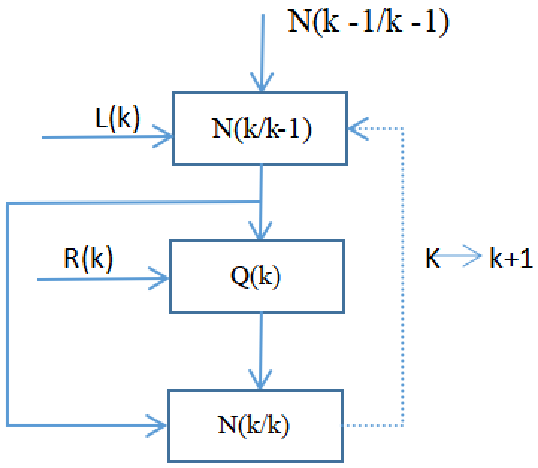

Fig. 3. Chart of the computation of the improved Kalman filtering gain

The flow of the modified Kalman filtering algorithm in the actual detection procedure is depicted below:

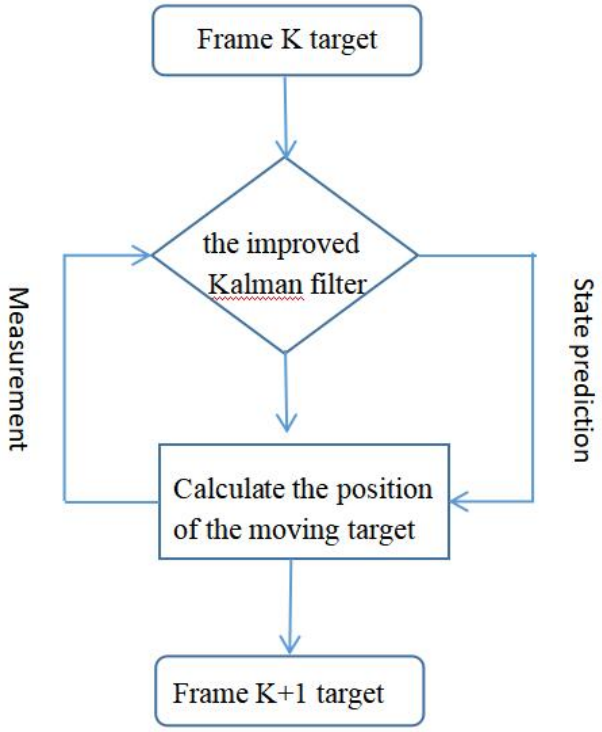

Fig. 4. A flow chart of the improved Kalman filter algorithm

Fig. 4 displays a flowchart of real-time target tracking using an upgraded Kalman filter algorithm. First, the initial target position is obtained from the measured value, then the target position of frame K is calculated with the algorithm functional formula, and the corresponding state prediction value is obtained, the expected position of the moving target in K + 1 frame is predicted, and the specific position of the moving target is obtained by iterating the expected value of K + 1 frame, the improved Kalman filter algorithm is adopted to modify and update the moving target's position. Under this circumstance, the real-time monitoring and tracking of the moving target is achieved.

4. Experiments on moving detection based on improved Kalman filter

The technology of moving target detection has a far-reaching impact on people's lives [38]. Traditional target detection algorithms focus on pre-processing of images [39]. To boost the accuracy of the recognition process, an enhanced Kalman filter target detection algorithm is utilized here. For demonstrating the advantages of the algorithm better, simulation experiments were conducted on the improved algorithm, and the experimental outcomes are depicted below.

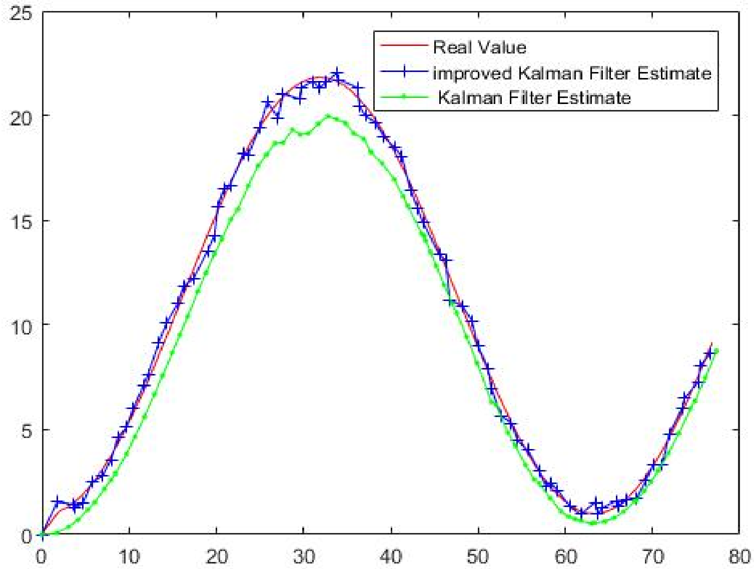

Fig. 5. Improved Kalman filter simulation

This diagram displays the trajectory of a moving subject, with time as the horizontal coordinate and the Kalman filter as the vertical coordinate. As can be seen from the diagram, the improved model can track the moving object more accurately and thus achieve experimental effects.

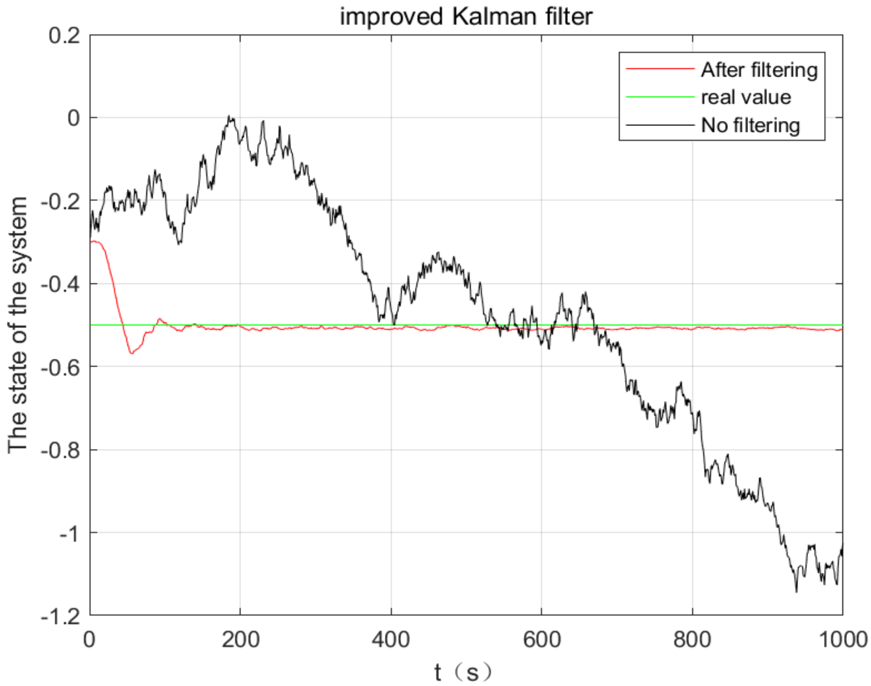

Fig. 6. The status of the improved Kalman filter system

As disclosed in Fig. 6, the motion of the modified Kalman filter tracking system is superior to the unfiltered tracking system, with higher accuracy.

The precision of detection and identification is the most fundamental index to judge the moving object. Tests were conducted to better compare the accuracy of moving object monitoring and recognition using the improved Kalman filter versus conventional detection and recognition. The outcomes revealed that the modified Kalman filter algorithm has higher accuracy and better effect versus the traditional algorithm. The experimental data are exhibited in the table below [40].

Table 1. Table of average data compared in three dimensions.

Categories of moving target detection	Identification accuracy	Identification speed (vehicles/ sec)	Manual time (s)
Moving target detection based on improved Kalman filter	98.4%	10.2	2.8
Traditional moving target detection	84.6%	3.6	10.4
Difference	12.8%	6.6	7.6

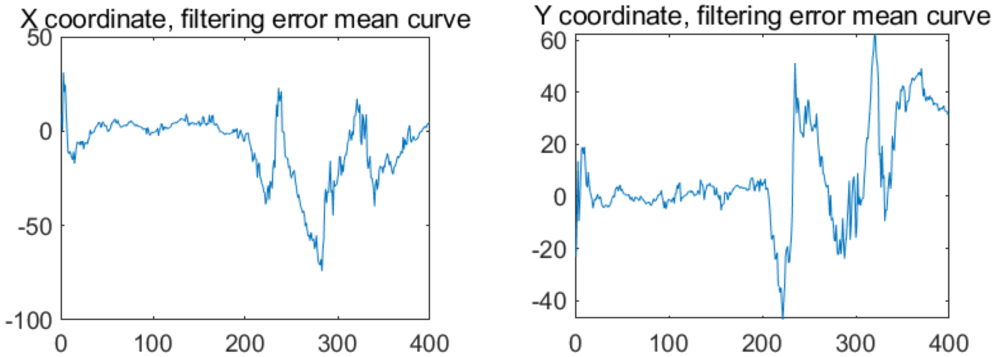

Fig. 7. Average filtering error curve on the X and Y axes

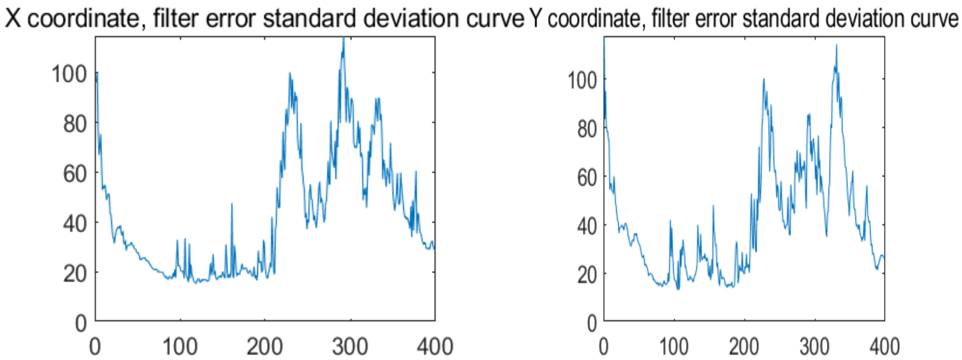

Fig. 8. Standard deviation cures of filter errors on X and Y coordinates

The horizontal coordinates of **Fig. 7** and **Fig. 8** represent the number of iterations, where the horizontal coordinates of **Fig. 7** are the mean of the filtering errors in the x and y directions, respectively, Hence, judging from the figure, the average value of filtering error is stable around 0, the longitudinal coordinate in **Fig. 8** is the standard deviation of filtering error. From **Fig. 8**, the standard deviation of the filtering error of a moving object is stable around 30, by using a modified Kalman filter and iterating accordingly, it is possible to make X and y motions with an error of 0 and a standard deviation of about 30, a target that can accurately detect a moving object.

To better account for the advantages of this algorithm and the accuracy of recognition, this paper applies the algorithm to a real-life situation where a section of the road is identified by the number of cars [41]. As can be observed from the diagram, moving vehicles are recognized as long as they pass through the junction within the time limit. The number of vehicles identified is visible at the top of the right-hand part of the display.

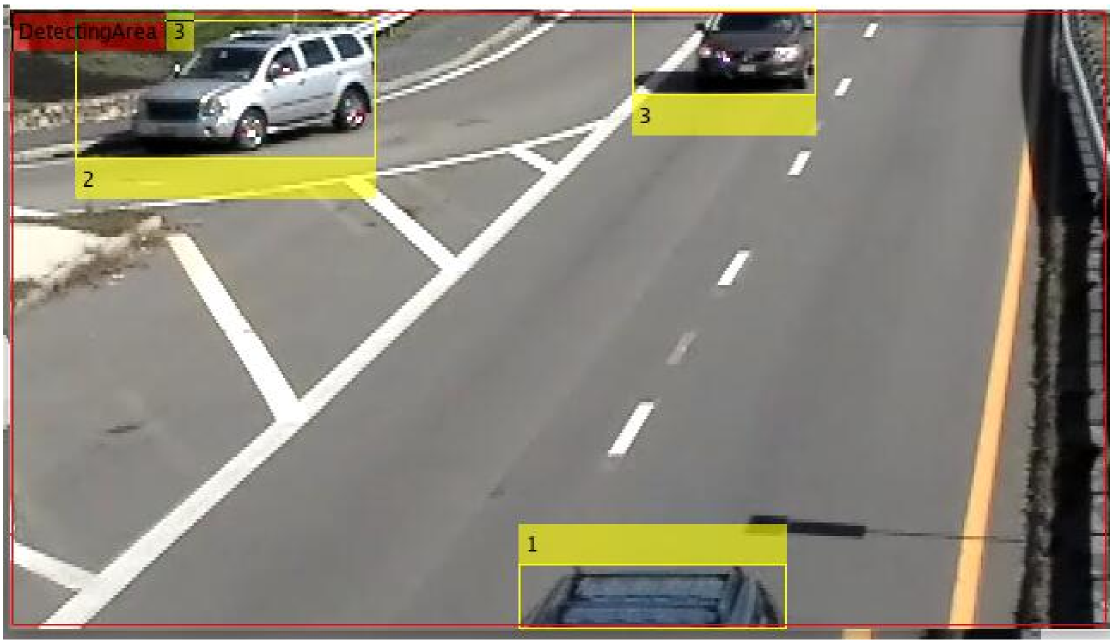

Fig. 9. The practical application of the improved algorithm

5. Discussion

This paper presents an improved Kalman filter algorithm that combines previous state estimates with current state observations to estimate the current state values, to improve the tracking precision of the moving target, the target is processed quickly by iterative method and the position of the target is modified continuously. This research firstly compared the improved Kalman filter algorithm with the traditional one, and the simulation showed that the improved Kalman filter algorithm can locate the movement of objects in real-time and quickly. Secondly, the improved Kalman filter algorithm can track the situation of the target better than the algorithm without filtering. Finally, the algorithm is applied to the recognition of moving vehicles, able to accurately identify passing vehicles at intersections. Thus, the improved

Kalman filter algorithm can accurately recognize moving objects in real time. Aiming at elevating tracking accuracy and state dimension of the robust target tracking system in dynamic scenes, and how to improve the tracking capability in complex environments, further research on the Kalman filter is needed.

6. Conclusion

Based on the experiments, the paper studies object recognition during the movement of objects and draws the following conclusions:

(1) The modified Kalman filter algorithm has a better tracking effect in comparison to the traditional algorithm, together with faster recognition speed and higher recognition accuracy of objects.

(2) The algorithm in the filtering process has clear advantages over the algorithm in the non-filtering process.

(3) The mean values of errors in the x and y coordinates were simulated and tested during the use of the algorithm, which is also an aspect of future research to optimize the algorithm. To demonstrate the effect of the recognition process better, this paper applies the improved Kalman filter algorithm to reality and finds high recognition efficiency and fast recognition speed.

In future research, the improved Kalman filter algorithm needs to be further modified to improve the searchability of the algorithm. At the same time, we will combine other frontier research methods to optimize the prediction model and study how to use the historical information more effectively to make the algorithm perform better, to make a breakthrough in the research of the algorithm.

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