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A Real-Time Traffic Detection Method Based on Improved Kalman Filter

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***Abstract*—For the lack of current extraction methods of traffic basic data, a traffic information acquisition method based on improved Kalman filtering using traffic video was presented in this paper. The Gaussian mixture model was improved for multi-vehicle moving targets detection. In order to further improve the detection efficiency, a heuristic improvement method was proposed. For the matching problem of multiple targets in the continuous video frame, combining the vehicle movement characteristic, the Kalman filter was used to estimate the vehicle position optimally, a real-time traffic detection method of matching the target chain was proposed. Finally, the experiment was carried out with the actual transportation video, results show that the proposed method can effectively improve the noise interference and foreground blurring in Multi-target vehicle detection, and can extract the vehicle moving target information from different traffic environments with high accuracy, different models and vehicle color The lowest detection rate was 93.08%.**

Keywords-multi-target detection; Gaussian mixture model; Kalman filter; Heuristic calculation

I. INTRODUCTION

Obtaining accurate real-time information of road traffic is a prerequisite of Intelligent Transportation Systems (ITS) for traffic control and prediction. How to improve the real-time detection efficiency of multi-moving targets is a key problem in this research, it is based on two aspects [1]: the first one is the accuracy of vehicle target extraction in the early stage of video detection, second one determines the accuracy of the detected traffic in the process of real-time detection of traffic. Compared with the road static, the traffic scene is basically stationary in the motion sequence images, and the object of detection is the moving vehicle in the video frame, which is used in the road traffic detection video device at present. However, due to the unknown characteristics of vehicle type and color in real-time traffic environment, and the neighboring vehicles have mutual interference, that is, in the image of superposition, body shadow fusion and so on, when based on traffic video images to target the object detection, the above problem is more prominent [2][3] .So accurate target detection will be a prerequisite for the accuracy of vehicle traffic detection in real-time. Therefore, this paper uses improved Gaussian mixture model combined with Blob analysis [4], the Kalman filter algorithm is used to track the moving vehicle target in the video continuously. In the tracking process, the relationship is established to generate the target tracking chain. The tracking chain is matched in real time in order to eliminate misdetection and multiple detection conditions, and to improve the efficiency of multi-target detection. Accurate real-time detection of traffic can be achieved.

II. FOREGROUND DETECTION BASED ON IMPROVED GAUSSIAN MIXTURE MODEL

Gaussian mixture model (GMM) is a classical background modeling algorithm [5]. It is developed from a Single Gaussian model and is used to detect moving targets with relatively stable background. It Has a certain degree of robustness for multi-modal backgrounds [6].

A. Foreground Target Acquisition Based on Stauffer

In order to improve the efficiency of the algorithm, the single Gaussian Model is sorted according to its importance, and the non-background model is deleted. In this paper, according to the vehicle target characteristics of importance ranking, set the importance of discriminant parameters such as the formula (1) shown. The characteristic background model has the following characteristics: The weight ω is big, the background frequency is high, the variance σ^2 is small, the pixel value changes little, in which x, y determines the pixel point, t represents the time.

$$sort\,key = \frac{\omega_i(x, y, t)}{\sigma_i^2(x, y, t)} \tag{1}$$

Choosing the idea of Stauffer to obtain the foreground target, by calculating the weight of N the single Gaussian model of Pixel point and making the background image, the foreground vehicle target image can be obtained by background difference matching as shown in Figure 1, For moving multi-Target detection, the foreground image obtained by this method includes moving target area and noise point, and the foreground vehicle is easy to be falsified, Therefore, for the accurate detection of multiple vehicle targets, the above detection results need to be further processed.

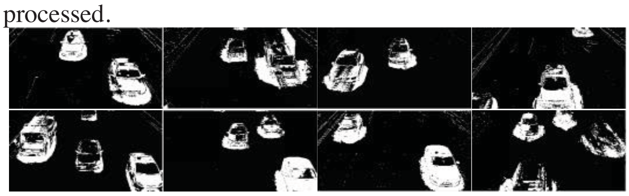


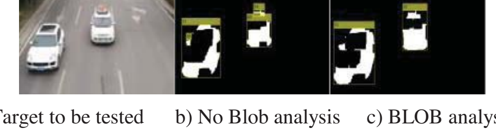
Figure 1. Foreground detection results of GMM

B. Improvement of Foreground Detection Based on Blob Analysis

For the updated foreground, the vehicle target needs to be processed further to the image shape and structure to extract a more complete moving target. In this paper, the image morphological operation [7][8] and Blob analysis are added to improve the accuracy of the foreground detection according to the characteristics of the foreground target.

In mathematical morphology. Because the object in the image processing is shape rule and approximate rectangular vehicle target, the square structure element is used in mathematical morphology processing. At the same time, combining the correct opening and closing operations. You can remove specific image details that are smaller than structural elements, while ensuring that no global geometric distortion is generated.

Because the pixel connection of target area is dense, and the noise points are relatively dispersed, In the process of vehicle target detection, the foreground mask obtained from the foreground detection of the mixed Gaussian model is mainly based on BLOB analysis: 1) The enhancement of the foreground image by BLOB analysis; 2) Blob region segmentation, the BLOB analysis utilizes the pixel global scanning to segment the foreground target region to divide the disjoint closed region, and the foreground target and the noise band coexist in the closed region; 3) BLOB connectivity analysis; 4) The extraction of target feature by BLOB analysis: the characteristic of each vehicle target area is calculated, including vehicle area, minimum external rectangle, Position of center of mass.



a) Target to be tested b) No Blob analysis c) BLOB analysis

Figure 2. Blob analysis of experimental results

After being processed by BLOB analysis above, compared with b) in Fig.2 and c), Blob analysis can effectively eliminate the false target detection frame caused by the larger noise points in the interior of the left vehicle and the rear of the right vehicle as shown in Fig2.b). and the accuracy of target detection can be improved significantly, it can also provide the centroid position, area and direction of the object in the image, and also provide the topological structure between the related targets.

III. TARGET TRACKING AND TRAFFIC REAL-TIME DETECTION

In the traffic detection process, mainly in the unit time through the vehicle as the test object, therefore, in the use of traffic video as the basic data, how to two frames or adjacent video frames in the one by one corresponding to the vehicle, that is, no missing, no re-inspection, error detection and other issues, is the main content of this paper.

Firstly, this paper uses the detection method in the above section to obtain the initial position of each video frame, and then uses the Kalman filter to predict the moving state information of the target. Finally, the results of the moving target detection are used to evaluate and correct, the target feature is matched and the vehicle target is calibrated in the image sequence.

A. Moving Target State Prediction Based on Kalman Filter

The basic idea of moving target tracking based on Kalman filter is: The state equation of linear system is used to estimate the state of the system through the input and output data of the system, and the dynamic information of the target can be obtained effectively, obtain an estimate of the target location to achieve the purpose of tracking. So it can be introduced Linear stochastic difference equation, this paper for specific traffic detection objects of the system regression operation process:

STEP1: Sets the current system state to K and predicts the current state based on the previous state of the system as shown in the formula (2):

$$X(k \mid k-1) = A * X(k-1 \mid k-1) + B * U(k) \quad (2)$$

In the formula (2), $X(k \mid k-1)$ is the result of the previous state forecast, $X(k-1 \mid k-1)$ is the optimal result of the last state, $U(k)$ is the amount of control in the current state, which can be 0 if there is no control.

STEP2: Covariance update of estimation error. In formula (2), The covariance of $X(k \mid k-1)$ is represented by P, and its update is as shown in the formula (3):

$$P(k \mid k-1) = A * P(k-1 \mid k-1) * A^T + Q \quad (3)$$

In formula (3), $P(k|k-1)$ is the covariance predictive equation corresponding to $X(k \mid k-1)$, $P(k-1|k-1)$ is the covariance prediction equation corresponding to $X(k-1|k-1)$, A^T represents the transpose matrix of A, Q is the state noise covariance matrix of the system process. Formulas (2) and (3) are predictions of the system.

STEP3: Optimal value estimation. Based on the current state of the predicted results and the current state of the measured values, the optimal estimate $X(k \mid k)$ can be obtained according to the formula (4):

$$X(k \mid k) = X(k \mid k-1) + Kg(k) * (Z(k) - HX(k \mid k-1)) \quad (4)$$

In the formula (4), Kg is the Kalman Gain:

$$Kg(k) = P(k \mid k-1) * H^T / (H * P(k \mid k-1) * H^T + R) \quad (5)$$

STEP4: In order to ensure the autoregressive operation of the Kalman filtering algorithm, we need to update the covariance matrix equation of the current K-state $X(k|k)$, as shown in the formula (6):

$$P(k \mid k) = (I - Kg(k) * H) * P(k \mid k-1)) \quad (6)$$

where I is the unit matrix.

Based on the characteristic information of the previous detection results, the Kalman filter is initialized, and then according to the prediction and correction process of the formula (2) to (6), the moving vehicle target position can be predicted in real-time sequence image.

B. Real-Time Detection of Traffic Based on Target Chain

In order to effectively track traffic real-time detection of single target and multi-target, in the matching stage, the moving information in the vehicle target tracking process is used to establish a continuous 3 kinds of target tracking state chain *new(k)*、*run(k)*、*out(k)*to store the new target in the video frame, Target that is being tracked, leaving the field of sight.

In the experiment, because of the dispersion of noise signal, the target chain of the noise target is short, and the noise false target can be eliminated by the size of the target chain in *new*(k) and the limitation of the number of frames. According to the continuity of the track of the vehicle in the field of sight and the speed of the vehicle in the fixed time, it is possible to determine whether there is a false target by two frames before and after the traffic video, and further improve the veracity of the real-time detection of the vehicle traffic.

The list of trace chains is shown in table 1: The first row represents the target that has been tracked (the target position state of the Kalman filter prediction), and the first column represents the target position status detected in section 1.2. A_1B_1, A_2B_2…A_iB_j are the Euclidean distance between the predicted centroid and the centroid of the detected target. Setting the spatial threshold, when the distance is less than the threshold value, can be determined to be measured and tracked target as the same goal. when the distance is greater than the threshold, it is considered a false target, in the list to be eliminated.

Space threshold setting: in the direction of vehicle movement, the longitudinal pixel of the screen is 320, the actual distance of the screen is about 30m, The actual length of approximately 11 pixels/m in the video; Taking the maximum speed 70km/h as the maximum speed threshold, the upper limit is considered, per1s vehicle moves 213 pixels, the camera acquisition speed is 30 frames/s, the maximum speed of the vehicle through the 70km/h, the target in the adjacent two frames between the maximum difference of 7.1 pixels, When the vehicle speed is less than 70km/h, the difference between the same target and each adjacent frame must be less than 7.1 pixel. Therefore, for the experimental object in this paper, the threshold pixel of the integer 8, when the vehicle approximate speed, the Kalman filter prediction results are close to the real value, so this threshold can be applied to the Kalman filter results.

TABLE I. TRACKING CHAIN TARGET DETECTION LIST

	A_1	A_2	…	A_i
B_1	A_1B_1	A_2B_1	…	A_iB_1
B_2	A_1B_2	A_2B_2	…	A_iB_2
…	…	…	…	…
B_j	A_1B_j	A_2B_j	…	A_iB_j

a. Target fusion generation target tracking chain: to the target in the tracking list, first the initial tracking chain of the label ID set to 0, start matching, find all *AB* value, add it to the tracking list, identify each observation value corresponding to the smallest *AmBn*, if the *AmBn* is less than the threshold of 8, then identified as the same target, and the target fusion. Generate a new label ID in trace chain *run (k)*, keep this ID continuously tracked.

b. The emergence of new targets in the field of vision: In space, the new target may only appear in the boundary area of the video image frame, if observed value is detected in the image boundary area, for the target detected in the first column, if there is no matching element in the first row, it is considered as a new target in the field of sight. A new target tracking chain *new(k)* is generated by assigning a new Kalman filter and a new ID label (that is, ID +1) for the target based on the previous tracking chain.

c. The departure of the target in the field of sight: the disappearance of the target from the field of sight can only occur in the boundary region of the image, for a target that is tracked in the first row, if there is no element in the first column that matches it, consider it a target that may have been lost, and if the consecutive N frames (N take 5 in this paper) do not match successfully, The target is considered to have officially left the field of view and the tracking chain *out (k)* is removed.

Through the above steps, the status information of the target in the current frame is analyzed, the label ID is assigned to the target, and each ID is provided as a reference for the target tracking in the next frame. The ID status of the detected target is the traffic information that is required to be counted.

IV.EXPERIMENT AND RESULT ANALYSIS

A. Experimental Environment and Experimental Construction

1) Environment of experimental section

In order to verify the validity of the algorithm, the video material in the actual traffic environment is taken as the experimental sample, the camera position, the shooting angle is fixed, the road speed limit is 70km/h, the number of lanes is 3. only three lanes in the main lane for vehicle detection.

2) The construction of the experiment

Camera distinguishability is 320*560, to ensure that the video sequence includes vehicle type and vehicle color diversity, and according to the difference of light and traffic density, this paper collects free flow, synchronous flow, blocking flow and so on[9], and three sets of video such as morning, noon and evening. Video 1 (free flow, 6:30-7:30, number of vehicles < 300 vehicles/hour), Video 2 (synchronous flow, 12:30-13:30 vehicle number < 900 vehicles/hour), video 3 (blocking flow, 17:30-18:30, vehicle number < 1200 vehicles/hour), As shown in tables 2, 3.

B. Experimental Results analysis

1) validity analysis of the algorithm

The experiment of the method is used to detect the traffic real-time detection results as shown in Fig 3.

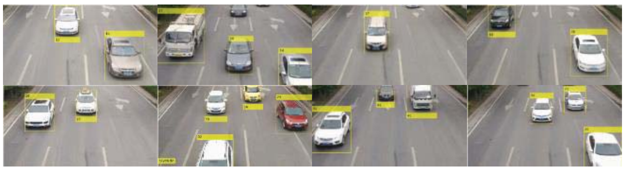


Figure 3. Detection of traffic volume in real time

As can be seen from fig.3, the real time detection algorithm used in this paper has a good detection effect on multiple lanes, three kinds of traffic flow under different video material, different vehicle models, different car body colors, and has a stable and continuous generation of target tracking chain to maintain accurate label cohesion ability, it can achieve more accurate traffic real-time detection results.

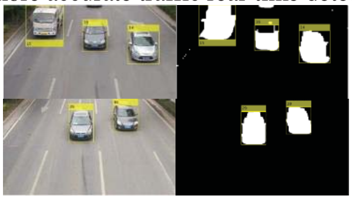


Figure 4. Detection results of the color of the target vehicle and the color of the background Lane

The traditional background difference method, which is represented by Gaussian mixture model, it is difficult to extract the vehicle body color and the background color close to the background accurately. In this paper , As shown in the result of Fig. 4 above, a heuristic algorithm is used to further deal with the foreground of Gaussian mixture model, which has good effect on background updating, can restrain the noise, enhance the target vehicle and improve the accuracy of real-time detection of vehicle traffic. From the following fig.5 detection results and their corresponding two value graph can be seen, the different body color to achieve a considerable detection effect, so the paper used detection traffic algorithm for the body color is universal.

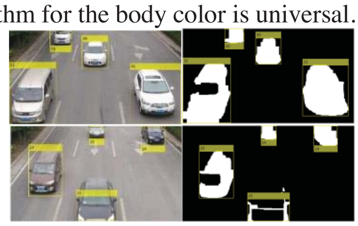
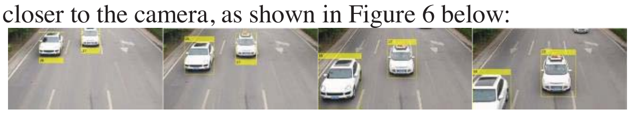


Figure 5. Real time detection of traffic volume of different vehicle body color in the same model

How to make use of the target sequential information in video is the key to improve real-time detection accuracy of video target traffic, for real-time detection of video target traffic, not only to ensure accurate detection on every frame image, but also to ensure consistency and continuity of detection results. During the process of tracking, if the rectangular frame can't increase its length and width as the vehicle is moving closer to the camera's vehicle scale, it will result in a large error in the vehicle's spatial positioning during the tracking process of the moving vehicle. The algorithm used in this paper can solve the problem that the vehicle scale becomes larger when the vehicle is moving closer to the camera, as shown in Figure 6 below:



a. Frame No. 850 b. Frame No. 862 c. Frame No. 876 d. Frame No. 889

Figure 6. Tracking of vehicle scale changes

The results of the above analysis, On the basis of the prediction of the foreground target State based on Kalman filter, we make a blob analysis of the obtained foreground, obtain the centroid position and the frame of the connected region in the foreground. Then set up a tracking list, generate the target tracking chain, update the acquired foreground area. Updates the size of the rectangle frame in a timely fashion based on the border features of the foreground area. In the process of tracking, the length and width of the rectangular box will increase with the moving target vehicle scale, the vehicle centroid position and the center of the rectangular frame always remain coincident, which ensures the accuracy of the moving vehicle positioning in space position and the stability of the target tracking chain, and it has a good tracking effect. It is the necessary precondition for accurate traffic real-time detection.

2) analysis of accuracy of test results

In order to verify the effectiveness of the method under different traffic flow. video 1, video 2, video 3 are at the same location at different times The results of the test are as shown in table 2, table 3, respectively, according to the different models, different colors of the actual number of vehicles and the corresponding detection of traffic real-time detection statistics and analysis.

As can be seen from the experimental results shown in table 2, when the density of vehicle traffic increases, the accuracy rate of real time detection of car and SUV is decreasing, the accuracy of traffic of bus and truck is increasing, and the medium business vehicle also reflects the trend of increasing accuracy of traffic real-time detection; In this paper, the results of real time detection of vehicle traffic under different flow density can be found: When the density of traffic is rising, smaller vehicles and easy to follow large vehicles are blocked, resulting in traffic density increase in the case of small vehicle traffic volume real-time detection accuracy of the decline; The shape of MPV vehicles and buses are more regular, so with the increase of traffic density, the accurate rate of traffic of such vehicles are increasing. But at the same time from the data statistics can be seen, buses and trucks often have multiple inspection situation, this kind of vehicle is larger than the car, when its running track and a close to a small vehicle similar, Kalman filter prediction results will be affected.

TABLE II. STATISTICS OF TEST RESULTS FOR DIFFERENT MODELS

vehicle type	Video1(<300 vehicles/ hour)		
	Actual number	Number of detections	accuracy rate
Lorry	30	28	93.33%
Sedan	109	105	96.33%
SUV	92	90	97.83%
BUS	32	34	94.12%
MPV	29	27	93.10%
Video2(>700 vehicles/ hour)			
Lorry	87	92	94.57%
Sedan	271	259	95.57%
SUV	197	189	95.94%
BUS	72	76	94.74%
MPV	98	105	93.33%
Video3(>1200 vehicles/ hour)			
Lorry	137	130	94.89%
Sedan	513	478	93.18%
SUV	393	369	93.89%
BUS	97	101	96.04%
MPV	178	186	95.70%

TABLE III. STATISTICS ON THE DETECTION EFFECT OF DIFFERENT COLORS

Vehicle body color	Video1(<300vehicles/hour)		
	Actual number	Number of detections	accuracy rate
Silver / white	101	103	98.06%
Gray	41	39	95.12%
Yellow	23	22	95.65%
Black	73	68	93.15%
Blue	17	16	94.12%
Red	22	23	95.65%
Brown	15	14	93.33%
Video2(>700 vehicles/ hour)			
Silver / white	255	266	95.86%
Gray	97	93	95.88%
Yellow	57	55	96.49%
Black	123	117	95.12%
Blue	55	58	94.83%
Red	103	99	96.12%
Brown	35	33	94.29%
Video3(>1200vehicles/ hour)			
Silver / white	527	497	94.31%
Gray	159	148	93.08%
Yellow	96	93	96.88%
Black	195	188	96.41%
Blue	113	120	94.17%
Red	153	147	96.08%
Brown	75	71	94.67%

The traditional background difference method, which is represented by Gaussian mixture model, is difficult to extract the vehicle with the background color close to the background. However, we can see from the test results in table 3 that using this method, the color of the body in the video does not change with the traffic density and illumination. it can be found that the difference of vehicle color and background color still has a certain effect on the test result under the method of this paper: In the video 1 time period, the Black Vehicle detection traffic detection accuracy rate is obviously less than the video 3 period, the opposite Video 1 silver/white vehicle detection rate slightly above the video 3, explained that the illumination caused the target and the road bright change, has affected the final detection traffic real-time detection result. it was found that the yellow, red, blue-colored vehicles, in the experimental results are less affected by the external light, traffic real-time detection accuracy small change.

The experimental results show that the real-time detection method of traffic designed in this paper has the lowest accuracy rate of 93.08% for different vehicles with different car body colors.

V. CONCLUSION

For the real time detection of the traffic of multi vehicle moving target, in this paper, an improved Gaussian mixture model combined with extended Kalman filter is proposed to obtain the real-time traffic of vehicle moving target. Through the prediction results and detection results target position status information real time matching analysis.

The experimental results show that the proposed method can effectively improve the effect of the traditional Gaussian mixture model in the detection of multiple vehicle targets, and the heuristic algorithm can reduce the noise disturbance and the foreground blur. The extended Kalman filter can be used to track the target in real time from complex background, and to realize the mark count of the target chain and obtain the real-time traffic. The accuracy of real-time detection of traffic volume under different vehicle and flow rate is 93.08%. But at the same time, the traffic video acquisition environment is simpler and the light effect is better, so how to solve the complex traffic scene and the multiple target counting of complex light condition is the main research content in the future.

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