Robust Vehicle Motion Detection and Tracking for Traffic Surveillance

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Abstract

In this paper, we propose a robust vehicle motion detection and tracking algorithm for traffic surveillance. The proposed system is composed of three parts: vehicle motion mask extraction, vehicle object tracking, and motion analysis. The vehicle motion detection algorithm exhibits good properties suitable for traffic surveillance. It also reduces the computation time for vehicle detection and provides robust shadow separation. In this paper, we design a multiple vehicle tracking system based on Kalman filtering, and propose a new technique for removing a temporal clutter, such as a swaying plant by motion analysis. Computer simulation of the proposed scheme shows its robustness to real traffic test sequences.

1 Introduction

In recent days, traffic surveillance is one of the important issues in the Intelligent Traffic System(ITS). A vision-based traffic surveillance system can detect and track individual vehicles moving through the camera scene. This provides a microscopic description of vehicle movements which can reveal new data on events, such as sudden lane changes, vehicles traveling in the wrong direction, and stationary vehicles.

This paper proposes a robust vehicle motion detection and tracking algorithm for traffic surveillance. The algorithm is designed to run with a modest amount of computing resources, and to adapt to slowly changing lighting conditions, such as those related to the time of day. The ability of distinguishing between interesting motion events and temporal clutter enables the system to lower the false detection rate. The proposed system is composed of three parts, as shown in Fig. 1: vehicle motion mask extraction, vehicle object tracking, and motion analysis.

The objective of vehicle motion mask extraction is to segment moving vehicles from their background. In our scheme, we utilize the background approach; however, because the lighting conditions change, especially in case of outdoor environments, we need to update the background.

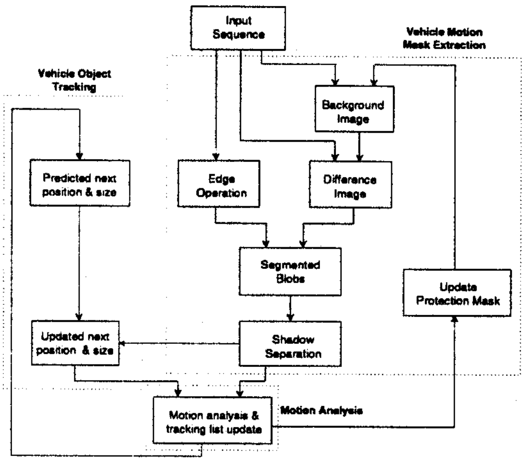


Figure 1: A Proposed System

There are several approaches for the background update. Karmann proposed a motion detection algorithm in the early 1990's for the purpose of traffic flow monitoring[1]. The background image is recursively updated with a dynamic equation within a Kalman filter framework. This approach was extended by Malik, who updated not just a single background image, but also a vector of filtered images to improve the robustness of the detection process[2]. These two approaches have the following problems: when moving objects are present in the background image at the initial time, the convergence time to a steady background is quite long. McFarlane utilizes the temporal median of the image sequence for segmentation and tracking of piglets[4]. The median is computed iteratively and updated for every frame. This operation reduces both the computation time for object detection and the convergence time for the background image to reach a steady state.

In this paper, we have modified the temporal median approach and added some operations for acquiring the stable vehicle motion mask. Due to the shadow cast of a moving vehicle, the motion mask at the first stage may have an incorrect shape. Therefore, we propose a robust shadow separation algorithm.

The aim of vehicle object tracking is to track the detected objects by predicting their respective positions based on a linear predictor model. Among various approaches for tracking a moving object, a Kalman filter approach seems to provide very promising results[2][3]. In order to detect and keep track of a moving object, we can apply a token (point, line, etc.) matching strategy. We have designed a token-based tracking scheme using Kalman filtering[5].

Finally, the motion analysis part manages motion trajectories and decides motion patterns using a rule-based classification. Adaptive background approaches have one general problem: in case of a steady state for a long period of time, stationary objects assimilate the background image. Therefore, we need region masks that can reduce the frequency of updates. In order to solve this problem, conventional methods utilize the moving blob as a protection mask where the background image is not updated. However, this method shows limitations for abrupt background changes or noise blobs. In order to solve the general problem and to overcome this limitation, we propose the following scheme.

2 Vehicle Motion Mask Extraction

For the adaptive background update, we utilize the temporal median operation. Fig. 2 depicts the proposed scheme for vehicle motion mask extraction.

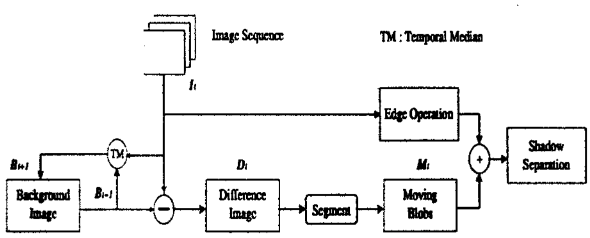


Figure 2: Vehicle Motion Mask Extraction

For a frame I_t in the sequence, the background B_t is updated for the frame as follows:

$$B_{t+1}(x) = \begin{cases} B_t(x) + 1, & if\ B_t(x) < I_t(x) \\ B_t(x) - 1, & otherwise \end{cases} \quad (1)$$

Over a period of time, the background image has the temporal median values of pixels for input image sequences. The moving blob mask M_t is obtained by thresholding the absolute difference of images I_t and B_t at time t.

One of the typical problems in motion segmentation is that a single vehicle object could be splited into multiple regions. This is caused by insufficient contrast between the object and the background. To solve this problem, we apply an edge algorithm over I_t. The resulting binary edge map is logically ORed with the segmentation result.

Another problem is that motion masks may have incorrect shapes due to the shadow cast of the moving vehicle. The proposed shadow separation algorithm works as follows. Given a bounding rectangle of the segmented moving blob, we can refine the rectangle by drawing the profiles of edge points along the horizontal and the vertical directions. We apply a binary morphological opening operation on the segmented blob to eliminate isolated pixels and to thin protrusions. We employ the convex polygon representation for the moving vehicles.

3 Vehicle Object Tracking

After detecting the moving vehicle, we can track the moving object efficiently by predicting the next center coordinate from the observed coordinate of the moving object. We have designed a token-based tracking scheme using Kalman filtering. The center position and size of the moving vehicle are used as a token $t(k)$, as shown in Fig 3.

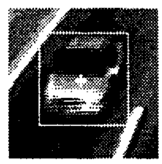


Figure 3: Token for Tracking

We get the next token $t(k+1)$ as the sum of the current token $t(k)$ and a token change $\Delta t(k)$:

$$t(k+1) = t(k) + \Delta t(k) \quad (2)$$

Kalman filtering provides a sequential and recursive algorithm for optimal linear minimum variance(LMV) of error estimation for system states $x(k)$. We define the system state as a four-dimensional vector which represents the positional change of a target object per unit time interval and the size change of a target object.

$$t(k) = \begin{pmatrix} center\_x(k) \\ center\_y(k) \\ xsize(k) \\ ysize(k) \end{pmatrix}, \Delta t(k) = \begin{pmatrix} \Delta center\_x(k) \\ \Delta center\_y(k) \\ \Delta xsize(k) \\ \Delta ysize(k) \end{pmatrix} \quad (3)$$

We assume that a state model is linear and is defined by the following equation:

$$x(k+1) = \Phi(k, k+1)x(k) + w(k) \quad (4)$$

where $x(k)$ denotes the system state at time instant k, $\Phi(k, k+1)$ a state transition matrix during the unit time interval, and $w(k)$ estimation errors. The following equation represents the system state $x(k)$ and the estimation error $w(k)$, respectively:

$$x(k) = \begin{pmatrix} \Delta center\_x(k) \\ \Delta center\_y(k) \\ \Delta xsize(k) \\ \Delta ysize(k) \end{pmatrix}, w(k) = \begin{pmatrix} w_{\Delta center\_x}(k) \\ w_{\Delta center\_y}(k) \\ w_{\Delta xsize}(k) \\ w_{\Delta ysize}(k) \end{pmatrix} \tag{5}$$

Assuming that the trajectory of a target object varies with a constant acceleration and the size of a target object varies linearly, we have the following transition matrix:

$$\Phi(k, k+1) = \begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{pmatrix} \tag{6}$$

The Kalman filtering algorithm tries to estimate the system state based on a set of measurements. We assume a linear relationship between the system state and a set of measurements.

$$z(k) = H(k)x(k) + v(k) \tag{7}$$

where $z(k)$ denotes a set of measurements, $H(k)$ an observation matrix, and $v(k)$ measurement errors. We measure the position and size changes of the target object at each time instant to obtain values of $z(k)$.

$$z(k) = \begin{pmatrix} \Delta center\_x(k) \\ \Delta center\_y(k) \\ \Delta xsize(k) \\ \Delta ysize(k) \end{pmatrix}, v(k) = \begin{pmatrix} v_{\Delta center\_x}(k) \\ v_{\Delta center\_y}(k) \\ v_{\Delta xsize}(k) \\ v_{\Delta ysize}(k) \end{pmatrix}. \tag{8}$$

$$H(k) = \begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{pmatrix} \tag{9}$$

Once we have defined the system and measurement models, we apply a recursive Kalman filtering algorithm to obtain LMV estimates of motion parameters.

4 Motion Analysis

The object tracking part generates motion trajectories of newly detected objects and adds the tracked objects in the motion trajectory according to the image sequence. The motion analysis part classifies the motion trajectories of the tracked objects through a motion classification rule. We represent the tracked objects as $V_n^p(p = 1, ..., K)$: at time n, there are K uniquely moving blobs. Each object has a set of features, such as shape mask, center position and bounding rectangle. An example of the object tracking result is shown in Fig. 4, where there are 2 motion trajectories. The first motion trajectory has 6 tracked objects. The second motion trajectory has 5 tracked objects.

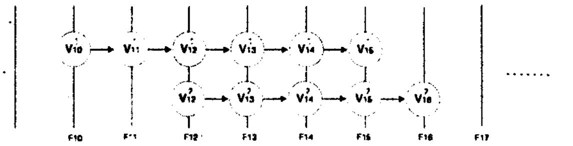


Figure 4: Tracking Results

Three different patterns of motion are defined as follows: (i) rest motion, which represents the motion that a vehicle is entered into the scene and stopped by an accident or a heavy traffic, (ii) moving motion, such as vehicles going on the road, and (iii) stop motion of temporal clutter, which is the motion of no importance to traffic surveillance, such as a swaying plant. Since we are interested in two motion patterns, rest or moving. for traffic surveillance, we should be able to distinguish between the stop motion of temporal clutter and the other motions to enable the system to lower the false alarm rate.

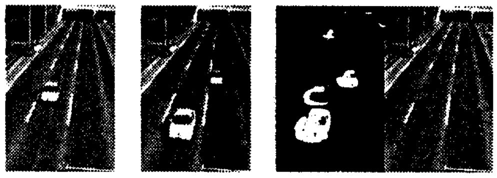
We design a following motion classification rule: if all positions of a tracked object are clustered in a certain area, the motion is classified as a stop motion; otherwise. the motion is a moving or a rest motion. Then, the proposed method updates the protection mask according to the object motion and removes abrupt background changes or noise blobs of the stop motion.

5 Simulation Results

Computer simulations have been performed on video sequences of a highway traffic scene. These video sequences were recorded from a scene with swaying plants. This situation presents an example of an extreme temporal clutter because the fluctuation of intensity between the plant and the background spanned almost the full dynamic range of intensity. In this simulation, we considered left lanes only. We have compared the proposed temporal median update model with the dynamic equation update model of Karmann[1]. At the initial time 0, the first input sequence is assigned to the background, as shown in Fig. 5(a). The adaptive background image includes false objects. Fig. 5(b) is input frame #250. Fig. 5(c) is the result of frame #250 obtained with the dynamic update model. where we can notice some errors. Fig. 5(e) is the result of frame #120 obtained with the temporal median, where most part of false objects is disappeared.

The temporal median approach takes less computation time in detecting objects and has twice faster convergence in reaching the steady background. Then, we apply the shadow separation algorithm to refine the vehicle motion mask. Fig. 6 shows the separated result.

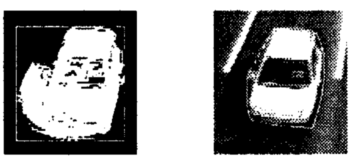
We have also simulated our tracking scheme to a



(a) (b) (c)

(d) (e)

Figure 5: Vehicle Motion Mask Extraction: (a) Initial frame $I_0 = B_0$, (b) Input Frame #250, (c) Results of frame #250 obtained with dynamic eq. model(D_{250}, B_{250}), (d) Input Frame #120, and (e) Results of frame #120 obtained with temporal median model(D_{120}, B_{120})



(a) (b)

Figure 6: Shadow Separation from Vehicle Motion Mask Extraction: (a) Bounding rectangle of the segmented moving blob, and (b) Polygon convex representation

highway traffic scene with the temporal clutter, such as swaying plants. Fig. 7 shows the results of multiple vehicle tracking. After new vehicles are detected in the pre-defined detection area, the algorithm starts to track the vehicles. During the tracking, swaying plants cause some trajectories, but these are classified as stop motions. Therefore, we can remove these stop motion of the trajectories.

From the simulation results, we plot predicted values and measurement values of the y position change along the time axis in Fig. 8. The dimension of the y axis is a y-directional pixel distance. We notice that the predicted values are close to the measurement values, even though they show some differences, especially at the peak points of the plot. At the peak points, motion parameters of a target object change nonlinearly.

Figure 7: Multiple Vehicle Tracking

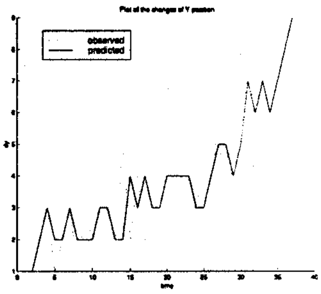


Figure 8: Plot of the changes of y position

6 Conclusions

In this paper, we propose a robust algorithm for vehicle motion detection and tracking for traffic surveillance. To detect and track the objects, we suggest a modified temporal median model including shadow separation, and a new technique for suppression of false detection via motion analysis. In addition, our multiple vehicle tracking scheme, based on Kalman filtering, is designed to run with a modest amount of computing resources. Computer simulation of the proposed scheme shows its robustness to real traffic test sequences.

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