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Video Processing Techniques for Traffic Flow Monitoring: A Survey

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***Abstract*— Video-based traffic flow monitoring is a fast emerging field based on the continuous development of computer vision. A survey of the state-of-the-art video processing techniques in traffic flow monitoring is presented in this paper. Firstly, vehicle detection is the first step of video processing and detection methods are classified into background modeling based methods and non-background modeling based methods. In particular, nighttime detection is more challenging due to bad illumination and sensitivity to light. Then tracking techniques, including 3D model-based, region-based, active contour-based and feature-based tracking, are presented. A variety of algorithms including MeanShift algorithm, Kalman Filter and Particle Filter are applied in tracking process. In addition, shadow detection and vehicles occlusion bring much trouble into vehicle detection, tracking and so on. Based on the aforementioned video processing techniques, discussion on behavior understanding including traffic incident detection is carried out. Finally, key challenges in traffic flow monitoring are discussed.**

I. INTRODUCTION

WITH rapid development of urbanization, traffic congestion, incidents and violation pose great challenges on traffic management systems in most large and medium-sized cities. Consequently, research on traffic flow monitoring systems, which aim to monitor and manage traffic flow has attracted lots of attention. With the progress in computer vision, the video camera becomes a promising and low-cost sensor for traffic flow monitoring [1].

Generally, traffic flow monitoring systems collect traffic flow information which mainly includes traditional traffic parameters and traffic incident detection.

A. Traditional Traffic Parameters Collection

Systems which collect traffic parameters have been developed for about several decades. Comparing with traditional traffic flow monitoring technologies that apply magnetic loops, ultrasonic sensors or microwave sensors, computer vision using video sensors presents significant advantages.

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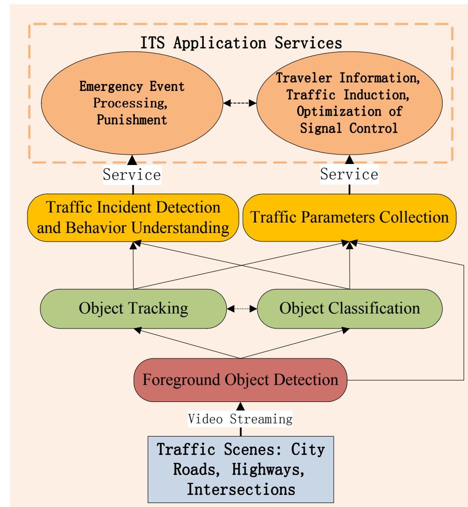


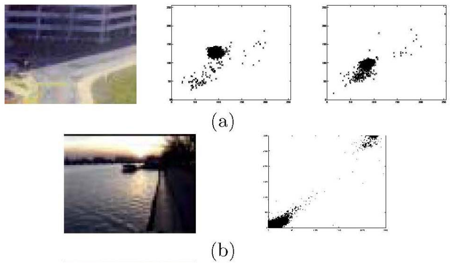
Fig. 1. Framework of video processing techniques in traffic flow monitoring

Video sensors can produce richer information without affecting the integrity of the road and with the possibility to transmit traffic images to Transportation Management Centre (TMC) [2]. Some commercial companies, Autoscope (in America) [4][5], Traficon (in Italy) [6] and Citilog (in France) [7] collect parameters such as vehicle volume, average speed, queue length and so on.

B. Traffic Incident Detection

Comparing with traditional traffic parameters collection, traffic incident detection is more challenging and has much research potentials. Incident detection systems developed by those companies [4][6][7] are used mostly in such scenarios as highways, urban traffic and tunnels. On the highway, stopped vehicle, wrong way drivers and traffic accidents [4][6] are detected. As tunnel applications, pedestrians, smoke/fire and stopped cars detection [4][6][7] are developed. Besides, based on intelligent video analysis, many security and safety applications in transportation scenarios are developed, for example, behavior analysis and people counting [8].

This paper presents a review of processing techniques of vision-based traffic flow monitoring. Reliable and robust foreground vehicle detection is the first step. With the detected results, tracking and classification are usually performed to get the trajectories and categories of foreground objects. Based on aforementioned steps, traffic parameters collection, traffic incident detection and behavior understanding can be done and provide services for the ITS applications [10]. The framework of processing techniques of traffic flow monitoring is presented in Fig. 1.



(a)

(b)

Fig. 2. Background model varies with time and is multi-mode [10]. This figure contains images and scatter plots of the red and green values of a single pixel from the images over time: (a) two scatter plots of the same pixel taken 2 minutes apart have different patterns. (b) a pixel is bi-model.

Recently, Buch et al. [3] reviewed the computer vision techniques for traffic video in urban traffic. Comparing with [3], we discuss more about top-layer incidents detection and behavior understanding and with less focus on object classification. The remainder of this paper are organized as follows: In section II, we provide a detailed review of techniques of foreground vehicles detection and discuss the problem of shadow detection and removal. Based on foreground vehicle detection, vehicle tracking methods are summarized and occluding problem is discussed in section III. Section IV discusses behavior understanding including traffic incident detection. Section V discusses the key challenges in video-based traffic flow monitoring applications.

II. FOREGROUND VEHICLE DETECTION

Generally, reliable and robust foreground vehicle detection is the first step of video processing. In this section, we suppose that vehicles are moving and discuss detection methods from two perspectives, namely, detection in general and detection in special scenarios. And we pay special attention on the problem of shadow detection and removal.

A. Vehicle Detection in General Scenarios

In this subsection, general scenarios are defined as good and relatively stable lighting condition, usually at sunny daytime. The light condition of scenarios is proper and camera's contrast is good. Here we classify vehicle detection methods as background modeling based methods and non-background modeling based methods.

1) Background Modeling: Object detection based on background modeling is to model the background, subtract background from current frame and get the difference frame, of which pixels are foreground pixels if their values are greater than a threshold. Different modeling methods employ different background models and different model updating methods. As specified in [10], Background model is multi-mode and changes slowly over time as shown in Fig. 2.

Various background modeling methods are developed since 1990s. In the simplest case, a period of image sequences are averaged to obtain a background model [12]. To filter out the noisy and foreground moving pixel values, the alpha-trimmed strategy can be employed [13]. Ridder et al. [11] introduced a Kalman Filter into an adaptive background estimation, which can handle illumination change of daylight and moving clouds.

Methods based on statistical models and probability calculation are mostly used. Lin et al. [14] extracted color background by exploiting the appearance probability (AP) of each pixel's color for sufficient long time. If current instance is recognized as background pixel, a color class with maximum AP belongs to the background.

Stauffer et al. [10] proposed a method based on adaptive background mixture model. The authors considered the values of a particular pixel as a "pixel process" and used Gaussian Mixture Model (GMM) to model each pixel. The probability of current pixel value is

$$P(X_t) = \sum_{i=1}^{K} \omega_{i,t} * \eta(X_t, \mu_{i,t}, \Sigma_{i,t}) \tag{1}$$

where K is the number of distributions and uses 3 to 5, $\omega_{i,t}$ is the weight of the i^{th} Gaussian at time t, η is a Gaussian probability density function.

After the distributions being created, the second step is to update the parameters including weights $\omega_{i,t}$, variances σ and means μ. The last step is background model estimation. They order the Gaussians distribution in ascending order of ω/σ. Then the first B distributions are selected as background distributions, and B satisfies

$$B = argmin_b(\sum_{k=1}^{b} \omega_k > T) \tag{2}$$

The most significant advantages of this model is that it applies to multi-mode and slowly changing background.

2) Non-Background Modeling: In this subsection, we mainly talk about frame differencing and optical flow methods, which we call methods based on non-background modeling.

a) Frame Differencing: Frame differencing is to compute difference of a pixel in two or three adjacent frames and detect an object pixel using a threshold of the difference. The basis of frame differencing is that values of background pixels do not change between two or three frames while values of moving object pixels have much difference.

Comparing with background modeling, this method is more robust and not sensitive to illumination change. Lipton et al. [54] extracted moving objects using two frame differencing method. While Cucchiara et al. [55] improved this methods with three frame differencing and it still performed well even with slight shake of the camera. There are also some drawbacks. Firstly, the detected region is union of object regions in adjacent frames. Secondly, this method will fail in the situations with slowly moving objects. Thirdly, if objects have little texture, there will be many holes in the detected region.

b) Optical Flow: Optical flow is the pattern of apparent motion of objects, surfaces, and edges in a visual scene, caused by the relative motion between an observer and the scene [16]. When objects move relatively with background, their velocity vectors are different and then moving objects

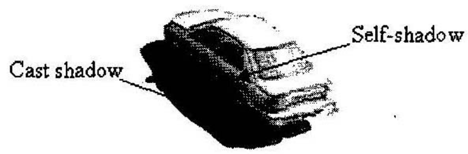


Fig. 3. Types of shadow [17]

can be detected and located. By computing optical flow, Nagai et al. [56] developed a smart video-based surveillance system which was robust to light variation and moving background.

This method also applies to moving cameras detection and is robust to background noise. One drawback of this method is time-consuming and real-time problem should be treated specially. So it is usually combined with other detection methods.

3) Shadow Detection and Removal: In strong lighting condition, shadow brings great challenges and difficulties to accurate detection. It is erroneously extracted with vehicle and brings negative effects mainly in two aspects: (1) Shadow makes separate objects be connected, increasing the difficulties of object separation and recognition. (2) Vehicle's shape and trajectory are inaccurate and tracking and recognition systems are confused [20][21]. Generally, shadows can be divided into cast and self shadow, as shown in Fig. 3 [17]. Self shadow which is a part of the object is similar with cast shadow in intensity. It is difficult to remove cast shadow only.

Wang et al. [17] detected shadow based on shadow characters such as lower lightness and the lack of textures and edges. Object edges were obtained by subtracting background edges from foreground edges, using a Canny edge detector. Object shapes were recovered based on object edges and attributes of shadow. Kilger et al. [21] extracted only the edges of detected object region to detect and remove shadow. They aggregated some knowledge about date, time and shadow's direction into shadow detection to increase the plausibility of shadows occurring.

Zhu et al. [18] utilized the grayscale difference between vehicle and its shadow. A matrix of optical gain D was computed, as shown in (3).

$$D(i,j) = \frac{Gray_{curr}(i,j)}{Gray_{back}(i,j)} \tag{3}$$

where $Gray_{curr}$ is the current grayscale image and $Gray_{back}$ is background grayscale image. The optical gain factor k is distributed uniformly in shadow region and shadow has little gradient. Values of optical gain in a rough domain [T1,T2] were considered to be in shadow region. Finally, they removed shadow edges by employing some shape discipline.

Vargas et al. [22] detected vehicle's shadow using the rule that a shadow does not affect the texture of the surface on which it cast. A modified quotient image was computed firstly, as shown in (4). The image quotient remains almost constant in shadow.

$$C_3(i,j) = \frac{I(i,j) - M(i,j)}{I(i,j) + M(i,j)} \in [-1, +1] \tag{4}$$

where I is the current grayscale image and M is background image. To remove the edges of shadow contours, morphological erosion was done on the detection mask.

B. Vehicle Detection in Special Scenarios

In this subsection, special scenarios are defined as abnormal lighting conditions such as cloudy, rainy and nighttime scenarios. All of these scenarios have a common character-bad illumination. Particularly, we talk about the nighttime detection.

Gritsch et al. [31] constructed a night-time classification system-smart eye TDS. The frequency of y-values in the Region Of Interest (ROI) were evaluated and the x coordinates parallel with the car's motion were projected. The y-histogram contained two peaks which represented the vehicle headlights and their distance was used to distinct trucks and cars.

Robert et al. [1][27] proposed a nighttime detection framework. Firstly, they sought candidate vehicle lights by detecting bright blobs in the image. Secondly, assuming the two headlights of a vehicle were aligned horizontally, they filtered out some wrongly detected lights. At last, they used a decision tree to get more precise detection results. Inspired by [27], [29] proposed a two-layer nighttime detection method. In the first layer, headlights were detected using the same methods as [27]. In the second layer, Haar-feature based on AdaBoost cascade method [30] was employed to classify vehicle frontal and false positives were decreased significantly.

III. VEHICLE TRACKING

Vehicle tracking is to get trajectories of moving vehicles, enabling higher level tasks including traffic incident detection and behavior understanding [3][32]. Substantively, tracking is to match the detected objects in consecutive frames. Various filtering algorithms are used, such as Bayesian Filter, Kalman Filter and Particle Filter [25][32].

A. Tracking Classification

Early in the 1980s, lots of vision-based tracking methods emerged. They can be classified into four categories: 3D model-based tracking, region-based tracking, deformable template-based tracking and feature-based tracking [26].

1) Model-based Tracking: Model-based tracking firstly creates geometric model using prior knowledge. And the models are used to match with vehicles in image sequence and then description of vehicle motions is obtained [35]. This method can accurately analyze trajectories of vehicles and is robust to posture variation. But it costs much computational power and accurate geometric model is difficult to obtain.

2) Region-based Tracking: Tracking based on region first detect foreground region which may be rectangular or some irregular shape. Then matching process is performed based on the correlation of objects in consecutive frames. Region-based tracking processes were implemented in [13][33]. But there are some drawbacks that it is computation-costive, the object shape would not change much and it will fail in relatively crowded circumstances with vehicle occlusion [34][35].

3) Deformable Template-based Tracking: Deformable template is a panel or curve of which the texture or edge can be deformed with some restrictions [35]. As a deformable template, active contour model, also known as Snake model, proposed by Kass in 1987 is more common [36]. Active contour model which defines an object is tracked in a transformed space instead of the pixel space. Comparing with region-based tracking, this technology reduces much computational cost. In [53], deformable object model which was composed of a root filter and six part filters was used to detect vehicles. They employed a latent support vector machine(LSVM) and histograms of oriented gradients (HOG) to learn features like the texture and shape information as a deformable object model.

Active contour-based tracker can consecutively track objects by initializing contours of objects before tracking. But initialization is usually difficult.

4) Feature-based Tracking: Similar with region-based tracking, feature-based tracking detects features of an object and performs matching process in consecutive frames as well. The difference is that an object defined by its features is tracked in a transformed space instead of the pixel space.

Corners and edges are usually used to represent objects in an image [37][38]. After being tracked, the sub-features usually need to be grouped together into objects using motion constraint [38]. Tu et al. [39] combined region-based tracking with Scale Invariant Feature Transform (SIFT) features based tracking. It can gain good results even when some frames are lost and cope with partial occlusion.

Feature-based tracking can work well in relatively crowded circumstances. But the key of this method is to choose appropriate set of features which can effectively present the object.

B. Tracking Algorithms

In previous subsection, tracking methods are classified into four categories based on vehicles' attributes [34]. With these attributes, tracking process can be performed using tracking algorithms including Meanshift [41] algorithms, Kalman Filter, projective Kalman Filter [41], Particle Filter.

In the simplest case, centroid and size of objects are computed. The Euclidean distance between the centroid in the previous frame and that in the current frame should not exceed a threshold. Size difference between them should also be restricted [14][42]. Except distance constraints, angle constraints between detected objects and existed trajectories can also be considered [14].

As improved, Kalman Filter can be used to get an estimated position in the current frame and the object nearest with the estimated position is matched [27]. In general, we must assume that objects move with uniform velocity and acceleration. Bouttefroy et al. [32] realized an improved Particle Filter in tracking process.

Object tracking based on MeanShift algorithm is an appearance-based tracking method and performs well in tracking moving objects even in dense traffic [35][57]. But this method needs manual initialization of a target model and does not apply to automatic traffic flow monitoring.

There are also some hybrid methods. In [41], MeanShift algorithm was used to determine the position of a blob center and kinematic variables including position, speed and size of the vehicle were estimated with a projective Kalman filter to initialize the MeanShift tracker.

C. Occluding Problem

In the situation of dense traffic or traffic congestion, vehicle occlusion is usually encountered which places great interference and challenges on vehicle tracking.

Lin et al. [14] resolved occluding problem with occlusion detection and queue detection. Most vehicles were supposed to be occluded side by side across adjacent lanes and occlusion was resolved using lane mask. If the distance of two subsequent trajectories' nodes was below a threshold, vehicle queue occurred. Method with horizontal edges detection was used to split queue-occluded vehicles.

Given the assumption that two overlapped objects have similar sizes, Chen et al. [60] handled the case of two objects overlapping. As improved, [42] considered the cases where a large object overlaps with a small one. A difference binary map reasoning method was proposed to identify which objects the "overlapping" segment may include.

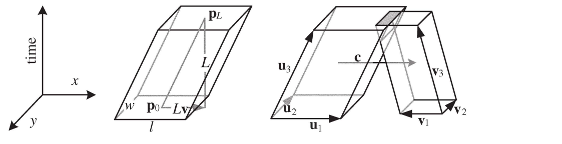
IV. TRAFFIC INCIDENT DETECTION AND BEHAVIOR UNDERSTANDING

Based on object detection and tracking, behavior understanding is to analyze and recognize moving patterns of vehicles and describe them using natural language [34]. A behavior can be as simple as a single event, for example, a car is speeding, or can be as complex as a sequence of multiple events such as a car is violating the checkpost norms [9]. In the 1990s, some research on traffic flow monitoring systems gave high-level description of both cars and their behaviors such as lane changing and braking [43].

A. Traffic Incident Detection

Traffic incident detection is a typical situation of behavior understanding. Usually, it can be treated as a class of recognition problems to classify time series observations [44]. Incidents such as illegal stop vehicles, converse driving, illegal lane changing, and crashes are common. They are usually detected given that the vehicles behave abnormally at speed and travel lane changes [34][45].

Huang et al. [46] utilized speed, moving direction and position of the vehicle and recognized vehicle activities including breaking, changing-lane driving and opposite-direction driving. Kamijo et al. [44] employed a Hidden Markov Model (HMM) to detect events including bumping accident, stop and start in tandem and passing. Pucher et al. [47] used both video and audio sensors to detect incidents such as wrong-way drivers, still standing vehicles and traffic jams on highways.



(a) (b)

Fig. 4. Rectangles extruded in time. a) A $w \times l$ rectangle at position P_0, moving for L time units with velocity v(reaching point P_L); b) Two overlapping parallelepiped with labeled edges [51].

Instead of detecting traffic incidents, research on predicting traffic incidents and analyzing severities of incidents are also developed.

Akoz et al. [48] detected severity of traffic accidents at intersections. Training trajectories were clustered into normal vehicle trajectories by continuous HMM. They matched new partial observation with normal vehicle behaviors to detect accidents, described in detail in [49]. Severity of vehicle collision was categorized using Multiphase Linear Regression method. Hu et al. [50] proposed a method of predicting traffic accidents. In the setup phase, trajectories and features of moving vehicles were input into a neural network to obtain K activity patterns. After that, by matching observed partial trajectory with each activity pattern, vehicle motion was predicted. With the motion of two vehicles, a probabilistic model was employed to predict the collision. Atev et al. [51][58] descript collision detection problem as follow: "Given the position, orientation, and size, at each time step, of n oriented rectangles in 2-D, find all possible pairs of rectangles that intersect in the current and future time steps." The two-dimensional vehicular bases along a time axis were extruded to obtain three-dimensional vehicular polytopes, as shown in Fig. 4. If two polytopes were joint, the two vehicles might collide.

B. Behavior Understanding

Behavior understanding is to understand a behavior of object which may consist of single event or a series of events [9][52]. Context of the scene is usually utilized as prior information.

Kumar et al. [9] implemented real-time behavior interpretation at checkpost. Shape, position, motion and trajectory of an object were extracted and the contextual information of the scene was utilized. The events such as "moving toward the checkpost" and "stopped in front of the checkpost" were considered. A confidence factor k was used in the process of behavior understanding. They analyze behaviors such as "normal crossing of checkpost" and "breakdown of the checkpost". Similarly, Medioni et al. [52] interpreted behaviors of mobile objects at checkpoint using object trajectories and contextual information. They recognized scenarios such as "the car passes through the checkpoint" and "the car avoids the checkpoint".

V. DISCUSSION AND CONCLUSION

This section will discuss the challenges in video-based traffic flow monitoring applications and conclude the whole architecture.

Shadow detection and removal is a main challenge on vehicle detection. Fortunately, comparing with the vehicle, cast shadow has some unique features. Shadow does not affect the texture of background while the vehicle will affect it [19][20]. A shadow is edge-less while the vehicle have lots of edges [21][22]. The brightness of the shadow is less than that of the vehicle [17]. Color space of shadow are within a certain range [18][23][24]. Another challenge in vehicle detection and tracking is vehicle occlusion in dense traffic. Occlusion makes separate objects merge into single object which will confuse vehicle detection and lead to tracking loss. It is usually detected using the relation of consecutive frames. Feature-based tracking can restrain the influences brought by occlusion. Besides, night-time vehicle detection is a great challenge in practical applications. Vehicles headlights, taillights and dark windshields are chosen to be the most significant features to present vehicles [1][27][28][29].

Traffic incident detection has developed for more than 20 years, but little of them are used in practical application. From the point of our view, there are some difficulties in it. On the one hand, samples of traffic incidents are difficult to obtain. On the other hand, traffic scenarios are diverse. They can be dense or sparse. Angle of camera views varies in different applications.

This paper attempts to provide a comprehensive survey of video processing techniques used in traffic flow monitoring. Techniques of vehicle detection at daytime and nighttime are reviewed. In particular, shadow detection and removal is talked about specially. Tracking process of objects is presented with recent progress in it. We focus on the problem of vehicle occlusion. Behavior understanding including traffic incident detection is surveyed. At last, we discuss on key challenges in video-based traffic flow monitoring systems. We believe that more and more techniques can be integrated into traffic flow monitoring applications.

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