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A Traffic State Detection Tool for Freeway Video Surveillance System

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Abstract

Traffic state is one of the most important traffic flow parameters to both the traffic management center and the traveler. It's difficult to extract traffic data using surveillance cameras because of the wider field, panning and zooming of the surveillance cameras. To leverage the existing surveillance camera infrastructure, a surveillance video based traffic state detection system is proposed. The proposed system can estimate traffic flow speed and road space occupancy, and recognize three typical traffic states (congested, slow, and smooth). Experimental results show that the system had good adaptation and high accuracy in daytime.

Keywords: Traffic state detection; Traffic flow speed estimation; Road space occupancy; Freeway; Video Surveillance System

1. Introduction

Traffic states (such as congestion, slow, smooth, accident) are macroscopic description of road's traffic flow. The information of traffic states is critical to transportation agencies and travelers in traffic management and command, traffic information display and guidance, as well as traveler route planning. With the introduction of image processing and computer vision techniques into traffic data collection and the rapid development of computer performance, video-based approaches for traffic state detection are more and more popular due to its low cost and visual nature.

Most traffic state detection methods classify the traffic state based on accurate parameters of each individual vehicle, which can be achieved using kinds of vehicle detection or/and tracking methods (V. Kastrinaki, 2003).

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These methods work very well when the camera is fixed and setup under good conditions. However, for surveillance camera, whose lens is usually set remote focus for a wide view of traffic scene and the view is often panned or zoomed in and out, it's difficult to get each vehicle's information by these traditional methods.

Some researchers dedicate to improving traditional vehicle detection and tracking methods and get traffic flow parameter estimation for surveillance video. Dailey (2000) introduced a traffic speed estimation approach, which used geometric relationships inherently available in the image, frame differencing to isolate moving edges and track vehicles, and vehicle lengths knowledge to calibrate the indexes of camera and estimate speed. Coifman (1998) developed a feature-based tracking system for detecting vehicles under challenging conditions. Instead of tracking entire vehicles, certain vehicle features are tracked to make the system robust to partial occlusion. These methods' effect depends on the individual vehicle detection and still faces challenges in noise, varying illumination and camera panning and zooming as traditional vehicle detection and tracking methods.

Instead of trying to detect each individual vehicle in surveillance video, some methods treat the traffic flow as a whole motion. Hu (2009) presented a vision-based traffic measurement system which extracted and used motion information from MPEG motion vector to get traffic mean speed estimation in traffic surveillance MPEG video. Porikli (2004) detected congestion on the decompressed video based on speed estimation using optical flow field with HMM (Hidden Markov Models) network. In his paper, ROI (Region of interest) setup and Off-line GM-HMM (Gaussian Mixture Hidden Markov Models) training was needed in advance, and ROI was only be used to detect speed of several vehicles instead of all vehicles. Maurin (2002) designed a system which addressed a multi-level approach to monitor traffic scenes using the technologies of optical flow and background removal, and the system was used to locate vehicles, individual pedestrians, and crowds. Li (2011) extracted the feature optic flow vectors to calculate the traffic flow speed on image --- macro optical flow velocity (MOFV), then classified the congestion and smooth state according to the MOFV value. Bi (2011) proposed an average intensity of background subtract image to describe the amount of vehicle running on the road, and proves a linear correlation between the image characteristic and the occupation ratio. Then, all-day traffic states were classified based on the characteristics. Tan (2007) divided traffic flow density to four levels (empty, low, high and full) according to edge texture feature in ROI. Luo (2011) calculated the edge density of road regions and estimated traffic states into three states: smooth, slow and congestion. These motion analysis based methods more match the visual processing of human beings in traffic state detection, and individual vehicle detection is no longer necessary. The precision and adaption to varying scene are the main balks for application.

In this paper, a traffic state detection system for surveillance video based on a new motion analysis method is presented. The system can automatically detect three typical traffic states (congestion, slow, and smooth), which are issued in most management traffic information display system and traveler information system by different colors (e.g. Google Live traffic). The most difference between the new method and above motion analysis based methods is that two traffic parameters are estimated and used to distinguish the traffic states. These two traffic parameters are traffic flow speed and road space occupancy, which are the basis of LOS in transportation engineering. The system can be embedded in existing video surveillance system and relieve the hard work of human beings' traffic monitoring.

2. Traffic state detection method

The process of traffic state detection system is shown in Fig. 1. Two traffic parameters, traffic flow speed and road space occupancy, are estimated using image features extraction and analysis at first. Then traffic state detection algorithm is introduced. The application system design and implement are presented finally.

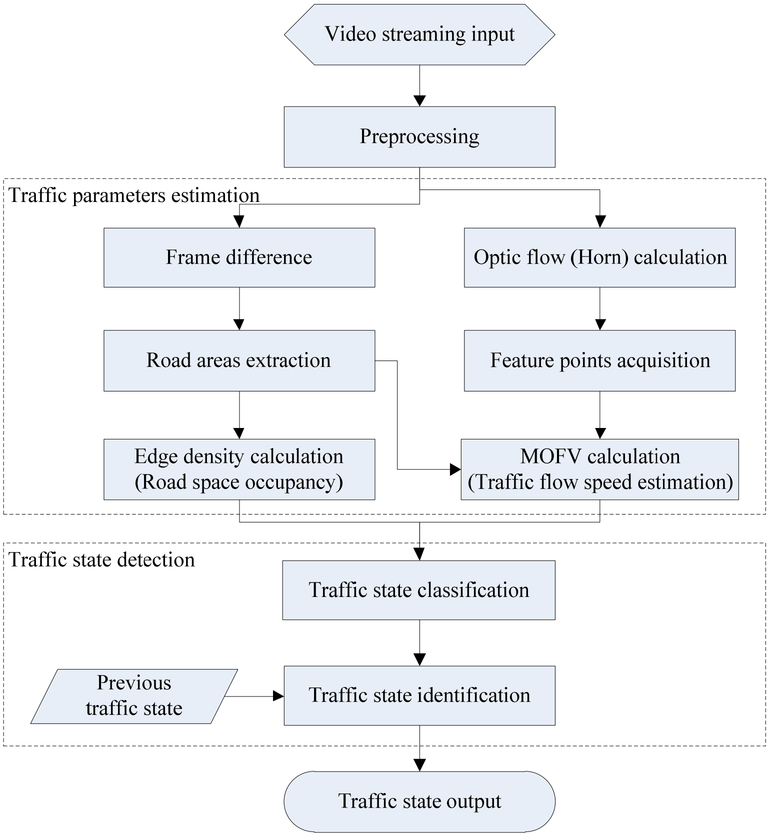

Fig. 1. Flow chart of traffic state detection system

2.1. Motion Detection and Road Areas Extraction

Road areas extraction is the basis of road occupancy calculation, and also helpful to get calibration parameters and diminish the calculation work. In traffic surveillance video, it can be supposed that the road areas are regions where vehicles move on and background are regions which has little change. So the road areas can be extracted by motion accumulation. Frame difference is usually used to detect vehicle movement in a consecutive sequence of frames. The movement in image can be extracted through the equation (1):

$$\Delta F_t(x, y) = F_t(x, y) - F_{t-1}(x, y) \tag{1}$$

Where $F_t(x, y)$ is the current frame at the moment *t*, $F_{t-1}(x, y)$ is the previous frame, and $\Delta F_t(x, y)$ is the difference image.

To discard noise and simply the calculation, the binary image $\Delta B_t(x, y)$ is obtained by $\Delta F_t(x, y)$, and the white pixels with gray value 255 describe motion information. After a consecutive sequence of binary frame difference image accumulation, the whole motion regions --- road areas can be extracted by the following equation:

$$B_R(x,y) = \bigcup_{t\in[0,T_A]} \Delta B_t(x,y) \tag{2}$$

Where $B_R(x,y)$ is the road image accumulated after time period T_A.

The white pixels in Fig. 2 (b) denote the points within road regions when accumulation time is 15 seconds. White points on the top of images caused by camera shaking because there are some words on the video. A tunnel cross under the road, and there are some white regions on the left bottom. So, more image processing are doing to release the road areas we are interested in, and the road structure of straight or approximately straight roads are modeled by a group of lines (Luo, 2011), which are shown in Fig. 2 (c). A couple of blue lines are borderlines of left road lanes, where vehicles move down; and a couple of red lines are borderlines of right road lanes, where vehicles move up.

(a) (b) (c)

Fig. 2. Road areas extraction. (a)Traffic surveillance video; (b) Motion regions accumulated 15 seconds; (c) Road structure.

2.2. Road Space Occupancy Estimation --- Edge Density of Road Areas

Road occupancy includes time occupancy and space occupancy. Road time occupancy is the amount of standard vehicles passed a section in a period of time, which can be detected using a loop or virtual loop in video. Road space occupancy means the percentage of used road area, which is the area ratio that vehicles' projective area is divided by road area at a moment, and can be called vehicle density on road at the moment. Road time occupancy is usually positive proportional to road space occupancy.

As vehicle region is a set of image features of vehicle (such as intensity, edge, and so on), it is obvious that if the vehicle density on road is high, the density of vehicle's feature on road also reaches a high level. While it is difficult to distinguish the individual vehicle in surveillance video, we can use the density of image features to substitute the density of vehicle. Edge is a kind of robust image feature with few changes while illumination is changing, so edge pixels' density on road areas is used to represent the road space occupancy.

Sobel algorithm is used to extract the vehicle edge map in the road areas. Then binary image of edge map is used to count the amount of edge pixels N_E and the amount of pixels in each direction' road area N_{RA}. Edge density O_E is calculated by following equation:

$$O_E = N_E / N_{RA} \tag{3}$$

The value region of O_E is in the range of [0, 1], and bigger value means higher road space occupancy. Figure 3 shows the edge pixels in road areas which are shown as blue points, whose scene is shown as figure 2(a). It is obvious that the edge density of right lanes is much higher than left, while there are more vehicles and high road space occupancy on the right lanes.

Fig. 3. Edge pixels in road areas of Figure 2(a).

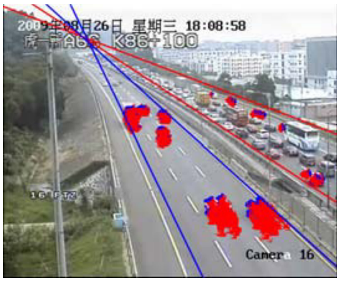

Fig. 4. Feature optical flow vectors in road areas of Figure 2(a).

2.3. Traffic Flow Speed Estimation --- MOFV

Optical flow field analysis is a common method that obtains the motion vector distribution image. Optical flow is the distribution of apparent velocities of movement of brightness patterns in sequential images. Most vehicles on freeway have similar direction and speed, thus the optical flow vector essentially meets traffic flow vector. A macroscopic velocity, MOFV, is presented to estimate whole traffic flow speed in our previous research (Li, 2011).

Horn algorithm and LK (Lucas-Kanade) algorithm are two classic and faster gradient-based algorithms with simple principles and low computational complexity. Horn algorithm can calculate motion vectors in any scale, and make the background's optical flow very small under suitable index. LK algorithm is limited in local motion, such as the image speed less than one pixel, but has good precision. So optical flow vectors (u,v) are firstly calculated by Horn algorithm and some features of optical flow vectors are extracted. Then MOFV is calculated using Pyramid LK algorithm every frame.

Because of Aperture limit and motion blurring effect, there are some noise and irregular optical flow vectors, which will cause the obvious error in speed estimation. To screen the regular optical flow vectors, the optical flow vector speed threshold vector and main direction are introduced (Li, 2011). There are one or two main directions, which matched the real traffic flow direction.

Comparing to the strict calculation and limit amount of corner feature, edge is easier to obtain and have more amounts. It is good for stability of MOFV's calculation. So the edge pixels achieved by Sobel algorithm is substitute for corners in feature points filtering in our previous work. The pixels in the binary edge map in Fig. 3 are seeds to get feature points.

The last feature points to calculate MOFV are those that meet three constraint conditions: vector speed is larger than threshold; vector anger meets main direction; and they are edge pixels in road areas. To improve the accuracy of optical flow velocity calculated, 4-level pyramid LK algorithm is used to calculate optical flow of the feature points. The lowest lay's optical flow vectors of feature points are shown in Fig. 4 with red arrows, whose direction matchs traffic flow direction.

The MOFV are calculated using the feature optical flow vectors. MOFV's value V of each main direction can be calculated as follow:

$$V = \sqrt{\bar{u}_0^2 + \bar{v}_0^2} \tag{4}$$

Where the average optical flow vector value $(\bar{u}_0, \bar{v}_0)$ of feature points (the amount is *m*) is calculated as following:

$$\bar{u}_0 = \frac{1}{m}\sum_{k,l} u_0(k,l) \quad , \quad \bar{v}_0 = \frac{1}{m}\sum_{k,l} v_0(k,l) \tag{5}$$

The values of each main direction's MOFV are the estimation of traffic flow speed of corresponding direction.

2.4. Traffic State Detection

Usually, in smooth state, traffic flow speed is large, and road space occupancy is also low; in the congestion state, traffic flow speed is small even zero, and road space occupancy is high; and in slow state, two parameters are between smooth state and congestion state. So the three states can be classified based on MOFV value and edge density threshold segment.

The thresholds of MOFV and road space occupancy, T_V and T_E, are set according to the video scene and experience value. The classification method of traffic state detection is designed as Figure 5.

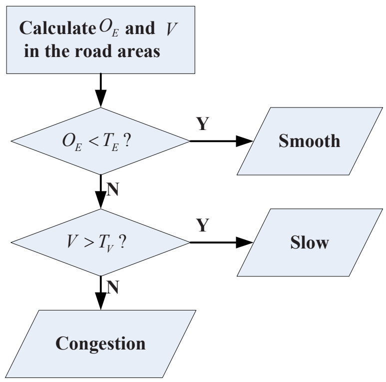

Fig. 5. Classification method of traffic state according two traffic flow parameters

Fig. 6. Three typical traffic state scenes. (a) Smooth state; (b) Slow state (right lanes); (c) Congestion state (left lanes)

There are three typical traffic state scenes in Figure 6, which extracted from G4-Guangdong freeway surveillance videos. The resolution of these videos are 704×576 pixels. Table 1 lists values of O_E and MOFV, and the traffic state judging results. Here, edge density threshold T_E is 0.4, and MOFV threshold T_V is 0.8 pixels/frame. The traffic states classification results meet the real state.

Table 1. Test Results of Video Shown in Fig. 6 Unit of MOFV: pixels/frame

Lanes	O_E	MOFV	$O_E < T_E$?	$V > T_V$?	Classification	True traffic state
Left lanes in Fig. 6(a)	0.15	2.51	Y	/	Smooth	Smooth
Right lanes in Fig.6(b)	0.58	0.96	N	Y	Slow	Slow
Left lanes in Fig. 6(c)	0.91	0.28	N	N	Congestion	Congestion

There is some failure caused by failed road area extraction when there is no motion in image, such in extreme statues: “no-car” (without any vehicle on road) and “full-congestion” (all vehicles are not moving). In order to improve the stability of traffic state identification, the traffic state relationship among each state should be thought over. If the sampling time and calculation time are short enough, three typical traffic states (smooth, slow and congestion) can be assumed as follow:

(1) If one traffic state is stable, its state will last in a period of time.
(2) Only the transfer relations of the following relations exist between three kinds of traffic state model elements: smooth to smooth, smooth to slow, slow to congestion, congestion to congestion, congestion to slow, and slow to smooth.

So, the output of traffic state detection is identified according the classification results in current detection period and detection output of last detection period.

The traffic state detection algorithm is show in Figure 7.

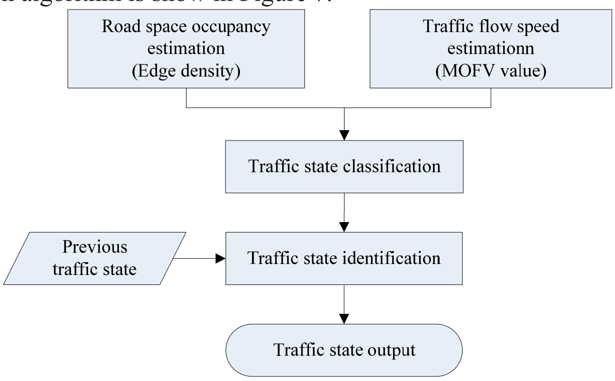

Fig. 7. Flow chart of traffic state detection

3. Application system design and implementation

3.1. Traffic state detection system design

The traffic state detection system is designed to be embedded in the existing video surveillance system. According the requirements of traffic management, the system can detect 8 video data flow inputs at the same time using a personal computer. The system software is developed by Visual C++ 6.0 and DirectShow on

Windows 2000 Professional or Windows XP system. The basic hardware configuration is Pentium4 2.4GHz CPU with 512M memory at least.

The interface of the software is shown in Fig. 8. The output window shows the traffic state detection result of each video in red words.

Fig. 8. Software interface of traffic state detection system

3.2. System Experiments

The system was tested in freeway G4-Guangdong. There are 165 traffic surveillance cameras in G4 Guangzhou-Shenzhen section (G4-GZ) and 96 traffic surveillance cameras in G4 Shaoguan-Guangzhou section (G4-SG). The G4-GZ is one of the busiest freeways in China. The designed traffic capacity is 80,000 vehicles per day and practically actually reaches 180,000 vehicles per day in last few years, so congestion is very frequently. On the other foot, there are many mountains and sometimes there is no vehicle on freeway in G4-SG. The scenes in Fig. 9 and Fig. 6 are some typical roads in G4-SG and G4-GZ.

Fig. 9. Some typical traffic scenes of G4-SG

We choice 90 suitable surveillance cameras to test traffic state detection system. The video frame rate is 25fps and image resolution is 704×576 pixels. Roads in these videos are all straight or approximately straight, few videos has ramp or intersection. The traffic state detection accuracy ratio during daytime is more than 85%, where the state detection result can get in 30 seconds.

After setup in G4-Guangdong freeway video surveillance system, the traffic state detection system monitors 74 cameras, which include 62 cameras in G4-GS and 12 cameras in G4-SG. Reports of congestion alarm in daytime of weekdays in three weeks showed that system alarmed the congestion and heavy slow 305 times, and 280 times is true. The accuracy of congestion reaches 91.8%, which meets the requirement of traffic management agents.

4. Conclusions

The presented method can be detect traffic states (include congestion) automatically using traffic surveillance videos with high accuracy and high speed in daytime. Individual vehicle detection is not necessary, and two important traffic flow parameters, the traffic flow speed and road space occupancy, are estimated easily. The presented system is implemented in existing freeway traffic surveillance system, and about 30% existing surveillance cameras can be used. It provides a tool to collect traffic state information based on existing freeway surveillance video system. To improve the precision of traffic flow speed and road space occupancy estimation and adaptive traffic parameter thresholds by self-calibration are next goals.

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