Approximate Vehicle Waiting Time Estimation Using Adaptive Video-Based Vehicle Tracking

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Abstract. During the last two decades, significant research efforts had been made in developing vision-based automatic traffic monitoring systems in order to improve driving efficiency and reduce traffic accidents. This paper presents a practical vehicle waiting time estimation method using adaptive video-based vehicle tracking method. Specifically, it is designed to deal with lower image quality, inappropriate camera positions, vague lane/road markings and complex driving scenarios. The spatio-temporal analysis is integrated with shape hints to improve performance. Experiment results show the effectiveness of the proposed approach.

1 Introduction

Traffic monitoring and surveillance is one important research area of Intelligent Transportation Systems (ITS), which aims to collect real-time traffic flow data for road usage analysis and collisions warning. Automatic traffic monitoring is now world-widely accepted as an essential component of advanced traffic management systems [1]-[6].

To obtain accurate real-time data, various sensors/devices have been designed to estimate traffic parameters. Magnetic detectors and the sonar and microwave detectors are the most frequently used ones and proven to yield good performances [7]-[9]. But they are usually costly to install and maintain. In many recent approaches, vision-based monitoring systems appears to be cheap and yet effective solutions, which are able to monitor wide areas and provide flexible estimations of traffic parameters [1]-[6], [10]-[24].

Object (vehicle, pedestrian, bicyclist) tracking is the basic function of a traffic monitoring system. Numerous algorithms had been proposed for accurate and real-time vision based vehicle tracking tasks. Image based object detection using edge/shape hints attracts great interests now [10]-[13]. Usually, the potential traffic participators are first separated from the background scene. Then, to enable precise classification of the moving objects, some characteristics such as length, width, and height are further recovered and examined. Finally, the found objects will be tracked to extract the associated traffic parameters. For instance, adaptive thresholding is a simple but not so effective method, which supposes that vehicles are compact objects having different intensity form their background. Thus, to threshold intensities in regions assumes to be able to separate

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the vehicle from the background. But false detection of shadows or missed detection of vehicles with similar intensities as theirs environment cannot be avoid [15]-[16]. Motion based vehicle detection/tracking is another popular method in traffic monitoring systems. For instance, vehicle detection using optical flow was discussed in [17]-[18]. Since it is time consuming, many research addresses on fast optical flow calculation design. Background-frame differencing and inter-frame differencing are also important methods [19]-[24]. They were proven to be fast and reliable vehicle detection/tracking methods in many literals. However, all the above approaches cannot thoroughly solve all traffic monitoring problems due to variation of lighting condition, vehicle shapes and sizes.

To try to keep up with the steps of U.S., European and Japan, several developing countries begin to apply cutting edge traffic monitoring and management techniques to alleviate their fast growing traffic congestions and accidents. However, the researchers in these countries are now facing the following new challenges:

- because the financial budget for installing city traffic monitoring systems is limited, the obtained image qualities are often therefore limited;
- due to the same reason, these cameras are frequently installed at inappropriate positions, which leads to notable view field and vehicle occlusions problems;
- the lane markings are often vague and diminished, since they are often painted tens of years ago;
- mixed traffic flow, which simultaneously contains pedestrians, bicyclists, motors and vehicles, makes the vehicle waiting time hard to estimate;
- the traffic laws might be violated occasionally or even frequently, which obviously introduce difficulties for traffic parameter extraction.

Under such conditions, most known methods cannot yield acceptable results standalone without modifications. Therefore, a new traffic monitoring system is proposed in this paper as shown in Fig.1. It detects potential vehicles using spatio-temporal analysis at first. Then, it further examines these interested areas based on vehicle/road shape information and driving rules to filter the disturbances caused by pedestrians and vehicle occlusions. Finally, Section 6 concludes the whole paper.

To give a detailed explanation, the rest of this paper is arranged as follows: Section 2-3 analyze driving environment learning; Section 4 examines vehicle detection and identification algorithms; and Section 5 discusses how to track vehicle and estimate average waiting time.

2 Lane Markings Detection

Lane detection is unnecessary in vehicle tracking, if the camera is set at an appropriate position. However, if this condition cannot be met, it is an essential step in order to determine the vehicle's relative position to the lanes/roads.

One difficulty here is to detect the vague and diminished lane markings, especially when parts of the lanes are occluded by vehicles and pedestrians. To solve this problem, the following adaptive algorithm is proposed and employed.

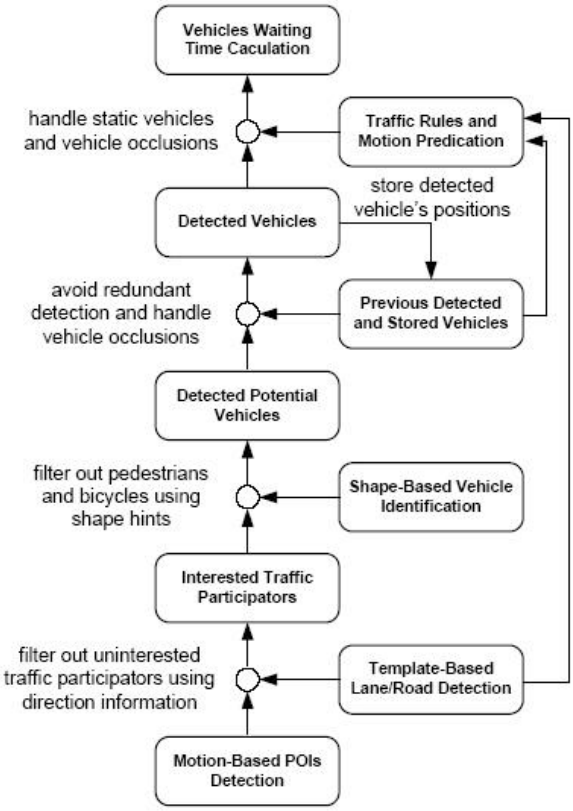
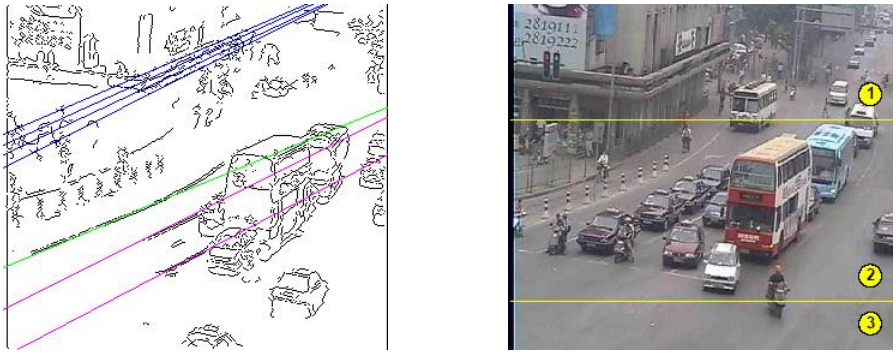


Fig. 1. The proposed traffic monitoring system workflow

Adaptive Lane Markings Detection Algorithm:

1) Set an initial edge detection threshold σ_e;
2) Use Canny edge detection algorithm to detect those apparent edges regarding to σ_e and filter out the unexpected margin lines generated by camera problems;
3) Set an initial line detection threshold σ_l;
4) Use Hough Transformation and *a priori* road shape templates to find the potential lane markings in the obtained edge image;
5) Gradually increase σ_l until only one line is selected as the dominant lane line. If the dominant lane line cannot be determined by choosing different σ_l, adjust σ_e and go back to step 1);
6) Store the found lane marking line and its direction θ_l;
7) Use Canny edge detection algorithm to detect as much edges as possible with a lower threshold σ_e.
8) Set an relatively lower line detection threshold σ_l;
9) Use Hough Transformation to find other lane by only searching potential lines with angles similar to θ_e;

10) Adjust σ_l and go back to step 8), if too many or too few lanes are found based on *a priori* knowledge of lane sum. If problem still cannot be solved, Adjust σ_e and go back to step 7).
11) Eliminate false lines by calculating their distances to the dominant lane marking line.



(a) (b)

Fig. 2. (a) lane markings detection results; (b) division of monitoring area

Lane detection does not need to be carried out frequently. Namely, once or twice a day would be enough. In most situations, to model the lane markings as lines will yield acceptable results. If really needed, those template-based lane detection algorithms, i.e. the one described in [25]-[26], will be applied. However, this will introduce significant calculation cost.

Fig.2(a) shows lane detection example, where the 5th line (top to bottom, same as follows) indicates the dominant lane marking line, and the 6th and 7th lines are the other detected lane marking lines. And the first four lines indicate disturbance lines which has similar angles of the lane markings. They are eliminated by check their distances to the dominant lane marking line. If the distance is relatively large comparing to other found lane lines, the corresponding line will be considered as out of Area of Interest (AOI) and eliminated. The two vertical margin (left and right) lines caused by camera problems are intensionally discarded. The Hough transformation referring point is the top left corner.

3 Environment Learning and Vehicle Detection

Similar to [27], in order to improve tracking performance, an image got from the video is divided into three areas as shown in Fig.2(b): distant view, near view and disappear areas. In Area 1 (distant view), all the moving objects will be labeled and memorized. While in the Area 2 (near view), only the objects approximately moving alone the lane direction will be further examined. Any vehicle moves from

Area 1 into Area 2 will be tracked, even it stops. The lane direction information will help a lot to remove the disturbances caused by vehicles and bicyclist moving in the opposite directions. If vehicles move from Area 2 into Area 3 (disappear areas), it will soon be discarded after a short time, or several frame equivalently.

The area sizes are determined by the focus and range of view of the camera. Due to the image quality limits of the applied camera, the motion detection threshold for the objects moving in Area 1 is set smaller than that used for Area 2. Notice that vehicles usually have larger size than pedestrians and bicyclists, the proposed motion-based vehicle detection algorithm is designed as:

Adaptive Vehicle Detection Algorithm:

1) Set an initial motion detection threshold σ_{m1} for Area 1;
2) Use frame differencing algorithm to detect moving object. If less than 5 objects are detected on average, choose a smaller σ_{m1} and go to step 1); otherwise, if more than 10 objects are detected, chose a larger σ_{m1} and go to step 1). The sum of the vehicles here is estimated by lane sum and previous traffic records;
3) Choose an motion detection threshold σ_{m2} so that $\sigma_{m1} \approx \sigma_{m2}$. Here 1.5 is an scale factor chosen by considering the applied camera quality;
4) Filter out the objects using lane direction information generated by optical flow estimation.

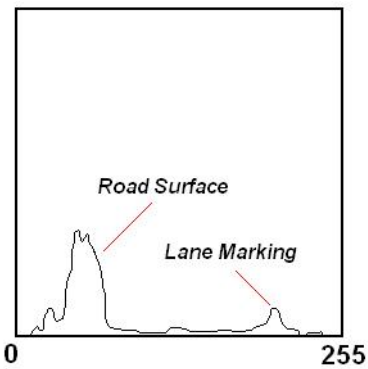


Fig. 3. Diagram of two peaks in the histogram of the road areas

To detect all potential road participators in the complex driving scenarios, frame differencing is employed to deal with multiple moving objects first. Then, background differencing is used to get the more precise contours of the moving objects. The road areas is determined by color hints like what proposed in [12]-[14] and the lane information obtained above. Particularly, the road surface color is retrieved from the images that satisfy the following two heuristic rules:

– no (moving) objects are detected on the road areas;
– the shape of the gray histogram of road areas roughly fits the passed record. This could partly reduce the effect of varied lighting conditions. Normally, there will only exist two apparent peaks in the histogram as shown in Fig.3, which indicate dark road surface and light lane markings respectively.

4 Vehicle Identification

To distinguish vehicles, motors and bicyclists in the real time is a difficult problem, since the size information cannot be easily retrieved in the images obtained here. Thus, shape information is employed here similar to what discussed in [28]-[29].

Knowledge-based methods employ *a priori* knowledge to find potential vehicles in an image. Comparing to the following frequently considered cues: vehicle geometry structures, shadow beneath the vehicle, texture, symmetry, color, rear-lights, horizontal overlap assumption yields better results here. Due to low image quality, vehicle texture and color information cannot be properly used here. Moreover, since the traffic monitoring systems is required to work in cloudy day time, shadow and rear-lights cues do not work well, either.

It is frequently assumed that road vehicles, especially cars and lesser extent lorries, consists of a large number of horizontal structures, particularly windows and bumpers. For example, the horizontal overlap assumption was used in [28] to each image column may result in several Areas of Interest. The horizontal edge response in each image column is summed and smoothed with a triangular filter. And each locally maximal peak which is extracted from the smoothed column responses will indicate a potential vehicle. A similar method is used to here to roughly identify bicyclists, motors and vehicles. More specifically, is could be described as follows:

Adaptive Vehicle Identification Algorithm:

1) Determine the Areas of Interests (AOI) using motion detection. If the width of an AOI is larger than a pre-selected threshold σ_w, than split this AOI into two AOIs from the middle. Repeat this action until all the widths of AOIs are shorter than σ_w;
2) Set a relatively large edge detection threshold than what is used for lane detection, i.e, set $\hat{\sigma_e} \approx \sigma_e$;
3) Use Canny edge detection algorithm to detect the edges for each AOI found with $\hat{\sigma_e}$, then obtain the edge response column sums for each AOI;
4) Distinguish the detected objects based on the heuristic rules listed as below:
   i. if the width of an AOI is larger than a pre-selected threshold $\bar{\sigma_w}$, it may not be a motor;
   ii. if the height of an AOI is larger than a pre-selected threshold $\bar{\sigma_h}$, it indicates a vehicle;
   iii. if there exit two or more than two dominant peaks in the edge response column sums, or equivalently there exits apparent valley(s), it must indicate bicyclists;

iv. if there exits only one dominant peak in the edge response column sums plot, it usually indicates a motor;
v. if there is a flat top in the edge response column sums plot, it often indicates a vehicle.

Since the image quality is limited and AOI are much smaller than the whole image, the obtained response column sums plot usually need to be averagely smoothed to easily find the peaks/valleys/top.

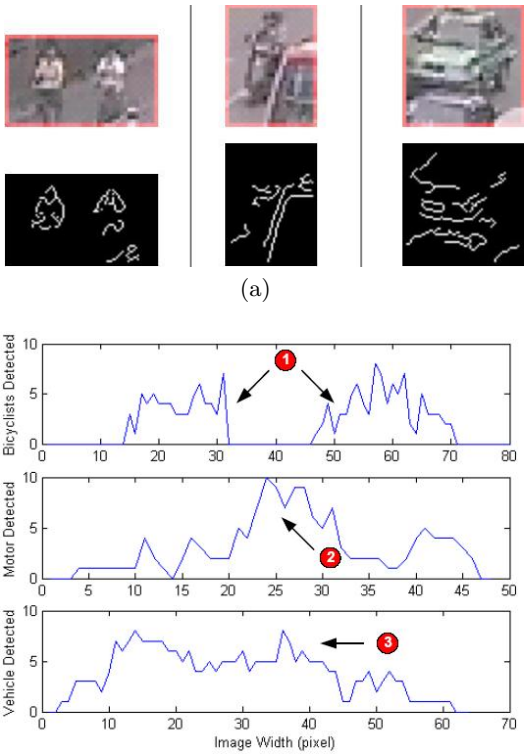


Fig. 4. (a) detected traffic participators: (left) bicyclists, (middle) motor, (c) commercial vehicles; (b) the associated edge response column sums plot

Fig.4(a) shows several typical examples of detected objects. Usually, bicyclists are detected only because two or more than two bicyclists moving to the same direction side by side. Thus, there usually exit valleys between peaks as shown in Fig.4(b).1. The windows, plates and bumpers add significant edge information to vehicles comparing to bicyclists and motors (a single hill), which results in a relatively flat top in the edge response column sums plot, see Fig.4(b).3. Besides, vehicles usually generate larger AOI than bicyclists and motors. These

hints cannot perfectly distinguish a vehicle from bicyclists or a motor, however, experiments shows it works well in many cases and fast enough to guarantee real-time processing.

5 Vehicle Waiting Time Calculation

In order to apply optimal traffic light control and relieve traffic congestion, the average vehicle waiting time needs to be approximately estimated. Due to varied passenger capacity and occupancy, different vehicles/motors waiting times will be scaled by proper factor first and then added up together.

The most difficult problem is to calculate the waiting time for the stopped vehicles. Here, a simple yet effective method is applied. It assumes that all the identified vehicles enter from Area 1 to Area 2 will be registered with their approximate positions and labeled with an auto-increase ID, respectively. The waiting time of such a vehicle will be accumulated until it leaves Area 2 to Area 3, or after a pre-determined die-away time span, i.e. ten minutes. Any start to move vehicles in Area 2 will be compared to the registered vehicles (mainly position information and traffic rules) to check whether it is a new vehicle or not. However, the traffic rules used here consider all the possible driving scenarios including the illegal driving behaviors.

However, the proposed approach makes wrong tracking when the following cases occur in the practical experiments:

- a vehicle drives backward for a notable distance will be recognized as a new vehicle or simply discarded;
- some vehicles cannot be detected if the vehicle queue is too long and extents out of view;
- track-trailers might be recognized as two vehicles;
- the system cannot work well under foggy or heavy rain conditions. New types of traffic monitoring systems are still in bad need for those cities where such bad weathers are easily encountered.

Further discussions and experiments will be carried out to improve the tracking performance of the proposed system and make it more practicable for the fast growing transportation markets in the near future.

6 Conclusion

To fast track vehicles in complex driving scenarios, a video-based traffic monitoring system is discussed in this paper. Both motion vehicle motion and shape information is considered to accurately recognize commercial vehicles and motors from varied road objects including pedestrians and bicyclists. Experiment results show the effectiveness of this method.

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