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An Automated Nighttime Vehicle Counting and Detection System for Traffic Surveillance

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***Abstract*—Robust and reliable traffic surveillance system is an urgent need to improve traffic control and management. Vehicle flow detection appears to be an important part in surveillance system. The traffic flow shows the traffic state in fixed time interval and helps to manage and control especially when there's a traffic jam. In this paper presents an effective traffic surveillance system for detecting and tracking moving vehicles in various nighttime environments. The proposed algorithm is composed of four steps: headlight segmentation and detection, headlight pairing, vehicle tracking, vehicle counting and detection. First, a fast segmentation process based on an adaptive threshold is applied to effectively extract bright objects of interest. The extracted bright objects are then processed by a spatial clustering and tracking procedure that locates and analyzes the spatial and temporal features of vehicle light patterns, and identifies and classifies moving cars and motorbikes in traffic scenes. The experimental results show that the proposed system can provide real-time and useful information for traffic surveillance.**

***Keywords*-Headlight detection, headlight pairing, vehicle tracking, vehicle counting.**

I. Introduction

In recent years, the traffic surveillance system is put forward extensively to be discussed and studied because it can provide meaningful and useful information such as traffic flow density, the length of queue, average traffic speed and the total vehicle in fixed time interval. Generally, the traffic surveillance system requires more sensors. The common traffic sensors include (1) push button (detecting pedestrian demand), (2) loop detectors (detecting vehicle presence at one point), (3) magnetic sensors (magnetometers), (4) radar sensors, (5) microwave detectors, (6) video cameras. Video camera is a promising traffic sensor because of its low cost and its potential ability to collect a large amount of information (such as the number of vehicles, vehicles speed/acceleration, vehicle class, vehicles track) which can also infer higher-level information (incidents, speeding, origin-destination of vehicles, macroscopic traffic statistics, etc). The video cameras (CCD or CMOS) are connected to a computer that performs images/video processing, object recognition and object tracking. Numerous research projects aiming to detect and tract vehicle from stationary rectilinear cameras have been carried out in terms of measuring traffic performance during the past decades [1]-[3]. It is widely recognized that vision-based systems are flexible and versatile in traffic monitoring applications if they can be made sufficiently reliable and robust [4], [5]. As the key goal for a traffic surveillance system, the evaluation of traffic conditions can be represented by the following parameters: traffic flow rate, average traffic speed, the length of queue and traffic density. To more efficiently obtain traffic information from moving vehicles, techniques based on frame differencing [5]-[11] have been applied to differentiate moving vehicles from motionless background scenes based on change detection or other statistical models. Other studies [5], [6] use spatial-temporal difference features to segment moving vehicles, while the methods in [7]-[11] utilize techniques based on background subtraction to extract moving vehicles. These methods can be efficiently applied to daytime traffic scenes with stationary and unchanged lighting conditions. However, spatial-temporal difference features are no longer reliable when vehicles stop or move slowly in congested traffic areas, and vehicles may be falsely detected as background regions and missed. Moreover, in poorly illuminated or nighttime conditions, background scenes are substantially affected by the lighting effect of moving vehicles, making the reliable hypotheses of background models which are effective for vehicle detection during daytime invalid. Thus, most of the aforementioned frame-differencing techniques may be unreliable for handling nighttime and congested traffic environments. However, it is difficult to segment out the entire vehicles at night. For nighttime surveillance videos, foreground objects that can be detected are usually headlights, auxiliary lights, or reflections of lights of the vehicles. Headlights are important features for initializing vehicles for tracking at night. Therefore, locating and pairing headlights are important for nighttime surveillance. To detect vehicles in nighttime traffic conditions, Zhang et al. [12] applied a reflection intensity map and a suppressed reflection map, based on the analysis of the light attenuation model, in order to extract the headlights. Headlights were tracked and paired utilizing a simple yet effective bidirectional reasoning algorithm. Although the accuracy rate of headlight detection

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was 95.2%, the vehicle tracking rate was only 88.2%. This paper presents an effective traffic surveillance system for detecting and tracking moving vehicles in nighttime traffic scenes. The proposed method identifies vehicles by detecting and locating vehicle headlights using image segmentation and pattern analysis techniques. The approach utilized to analyze traffic videos using the following module pipeline:

1. Headlight segmentation and detection.
2. Headlight pairing.
3. Vehicle tracking.
4. Vehicle counting and detection.

The system works by detecting the entering objects to the scene, and tracking them throughout the video. The input to the algorithm is the raw video data of a site. The algorithm then performs the following steps: First, a segmentation process based on adaptive thresholding is performed to extract pixels of bright objects from the captured image sequences of nighttime traffic scenes. Then, to locate the connected components of these bright objects, a connected-component analysis procedure is applied to the bright pixels obtained by the previous stage. A spatial clustering process then groups these bright components to obtain groups of vehicle lights for potential moving cars and motorbikes. Next, a feature-based vehicle tracking and identification process is applied to analyze the spatial and temporal information of these potential vehicle light groups from consecutive frames. This step also refines the detection results and corrects for errors caused by noise and errors during the segmentation and spatial clustering processes. Thus, actual vehicles and their types can be efficiently detected and verified from these tracked potential vehicles to obtain accurate traffic flow information. The remainder of this paper is organized as follows. Section II describes the software structure of the vehicle counting and detection system; Experimental results are discussed in Section III, followed by a conclusion in Section IV.

II. System Review

The proposed system employs a loop-based approach to detect and count moving vehicles in the scene. In virtue of the PC software, the user is able to view the real-time image sequence and define a set of regions of interest (ROIs) in a video image. Each ROI is denoted as a virtual detector on every lane (see Fig 1).

The ROIs are laid out to facilitate vehicle detection and may be linked to make the counting more accurate. Loop-based vehicle detection methods mainly have two advantages:

1. only ROIs in the image are processed, as to reduce the computation load;
2. object tracking, occlusion handling, and some other complex processing steps are not required to count vehicles.

Figure 1: Representative ROIs in the image.

On the other hand, it is clear that the major disadvantage of such methods is their limited monitoring ability due to reduced processing areas. The flowchart of the proposed system is shown in Fig 2.

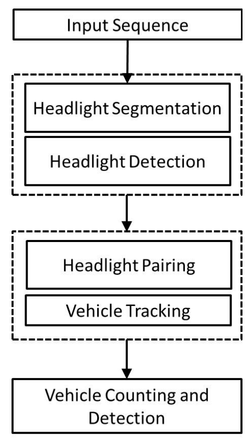


Figure 2: System Overview.

A. Headlight segmentation and detection

The headlight is a strong and consistent feature in revealing the presence of a vehicle at night. Therefore, locating and pairing headlights are important for nighttime surveillance. The first step in the headlight detection process is to extract bright objects from the road image to facilitate subsequent rule-based classification and tracking processes. To reduce the computational complexity of extracting bright objects, we first extracted the gray-scale image, i.e., the L-channel, of the grabbed image by performing an RGB-to-Lab transformation. To extract bright objects from a given transformed gray-intensity image, the pixels of bright objects must be separated from other object pixels of different illuminations. For this purpose a fixed static threshold is not suitable for headlight detection because in some sections of the roads, the lighting conditions are better than others. Therefore, we use an adaptive threshold, where the threshold value is a weighted sum (cross-correlation with a Gaussian window) of the *(blockSize $\times$ blockSize)* neighborhood of (x, y). The default σ (standard deviation) is used for the specified *blockSize*. After thresholding, an opening followed by a closing morphological operation [13] is then applied to concatenate the close headlights, to remove the noise, and to smooth the boundaries of bright objects. The Fig 3 shows the output of the headlight segmentation.

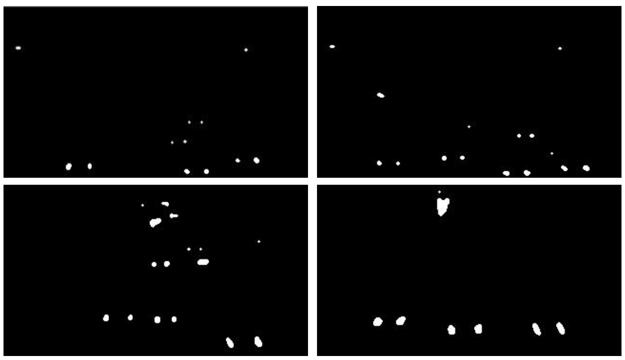


Figure 3: Results of headlight segmentation in different situations.

To extract potential vehicle headlight, the pixels detected are grouped, in current frame, together by utilizing a contour detection algorithm [14]. The contour detection algorithm groups the individual pixels into disconnected classes, and then finds the contours surrounding each class. Each class is marked as a candidate headlight (CH). The location and dimension of a CH can be represented by the bounding box surrounding it.

To preliminarily screen out non-vehicle illuminating objects, such as street lamps and traffic lights located at the top side of traffic scenes, and to effectively and rapidly locate the sufficiently reliable and clear features of moving vehicles, and efficiently save the redundant computational costs, we apply a set of ROIs for each frame. The CH extraction are only performed on the bright objects located in the ROI

A classification procedure can be applied to the ith CH_i to identify a vehicle headlight (VH) and filter out most non-vehicle-illuminant light components, such as large ground reflectors and beams. For this purpose, a CH is identified as VH if it satisfies the following conditions:

1. since most vehicle lights have a nearly circular shape, the enclosing bounding box of VH should form a square shape, i.e., the size-ratio feature of CH must satisfy the following condition:

$$\tau_{RL} \leq W(CH_i)/H(CH_i) \leq \tau_{RH} \tag{1}$$

   where $W(CH_i)$ and $H(CH_i)$ denotes respectively width and height of a CH, while the thresholds τ_{RL} and τ_{RH} for the size-ratio condition are set as 0.7 and 1.3, respectively, to determine the circular-shaped appearance of a VH;
2. a potential vehicle headlight should also have a reasonable area compared to the area of the ROI. Thus, the area feature of CH must satisfy the following condition:

$$\tau_{AL} \leq A(CH_i) \leq \tau_{AH} \tag{2}$$

   where the thresholds τ_{AL} and τ_{AH} for the area condition are determined as $\tau_{AL} = (W(ROI)/20)^2$ and $\tau_{AH} = (W(ROI)/5)^2$, respectively, to adaptively reflect the reasonable area characteristics of a CH. $W(ROI)$ denotes lane width associated with a CH.

The detected VH serve as the input of the headlight pairing module. The Fig 4 shows the output of the headlight detection module.

Figure 4: Results of extracted potential vehicle headlight (VH) in different situations.

B. Headlight pairing

The proposed headlight pairing module includes two steps. First are paired all VH that are in the same ROI, then the same process is applied to all those VH that does not were paired in the previous step, because belong to a vehicle which is located between two adjacent ROIs. Two vehicle headlight VH_i and VH_j are paired as belonging to the same vehicle based on their size and aligned horizontally on the image plane, if the following pairing conditions are satisfied: simultaneously:

$$|VH_i(y) - VH_j(y)| < \tau_Y \tag{3}$$

$$|VH_i(x) - VH_j(x)| < W(ROI) * 0.6 \tag{4}$$

$$|A(VH_i) - A(VH_j)| < \tau_A \tag{5}$$

where x and y are the vertical and horizontal coordinate of the centroid of a VH, while threshold τ_Y and τ_A are selected respectively as 5 and 25. Utilizing the location and size of each VH, the relevant parameters of a PV are defined as follows:

$$PV(x) = \frac{VH_i(x) + VH_j(x)}{2} \tag{6}$$

$$PV(y) = \frac{VH_i(y) + VH_j(y)}{2} \tag{7}$$

$$W(PV) = |VH_i(x) - VH_j(x)| + Max(W(VH_i), W(VH_j)) \tag{8}$$

$$H(PV) = Max(H(VH_i), H(VH_j)) \tag{9}$$

The detected PV is used as the input of the vehicle tracking module. The Fig 5 shows the output of the headlight pairing module.

Figure 5: Results of headlight pairing in different situations.

C. Vehicle tracking

The aforementioned processes identify PV entering the ROI, which are represented by lighting object sets in each image frame. However, since complete information for determining the types of vehicles may not be immediately obtained from single image frames, a tracking and grouping procedure is applied to analyze the motion information of these PV based on consecutive image frames. This procedure accurately classifies moving vehicles. This tracking information is used to refine the detection results of PV and correct the errors caused by noise and errors in the headlight segmentation and detection. The tracked PV that move rigidly together are grouped as whole moving vehicles by evaluating their common motion information. After the whole moving vehicles are obtained, it is possible to identify the types of tracked. The proposed method will track each PV within successive image frames. When a PV is initially identified in a ROI, a tracker will be created to associate this PV with those in subsequent frames. In the tracking process of the PV, trackers may be in one of the following two states: Appear or Update. The tracking states and relevant tracking are defined as follows:

1. **Appear**: if a new PV^t does not match any PV^i $(t-1 \leq i \leq t-3)$, a new tracker T_k is created for this PV^t.
2. **Update**: intuitively, two PV that are spatially closest in the adjacent frames are connected. Euclidean distance is used to measure the distance between their centroids. Besides, the area of a PV is also considered for enhancing the vehicle tracking. For each PV^t in the current frame, an PV^i with the minimum distance and similar size needs to be searched in the previous frames. The match function are described in equations (10) and (11).

$$dist^n = \min_{t-1 \leq i \leq t-3} (ED(PV^t, PV^i)) < \delta \tag{10}$$

$$\rho^n = |(A(PV^t) - A(PV^n)| < \gamma \tag{11}$$

where n is the number of the previous frame, $ED(PV^t, PV^i)$ is their euclidean distance and δ and γ are the thresholds. If $dist^n$ is minimal and the conditions $dist^n < \delta$ and $\rho^n < \gamma$ are met, the vehicle in the current frame is considered to be an vehicle in the previous frame n and the PV that identifies it is assigned the same tracker T_k.

The tracking terminates, when for at least two consecutive frames in each ROI is not detected PV. The detected T_k are used as the input of the vehicle detection and counting module.

D. Vehicle detection and counting

The main object of this part is to count and register the vehicle flow for each lane. To achieve automatic bi-directional counting for the vehicle passing, the proposed method sets two base lines, as shown in Fig 6, for each ROI. The moving vehicle is counted when it passes the base line. When the vehicle passes through the area-R, the frame will be recorded. In each ROI the T_k (computed by the vehicle tracking) are analyzed and the vehicle count is incremented by one if the following constraints are satisfied:

$$PV_{T_k} > 3 \tag{12}$$

$$|PV_{T_k}[start].y - PV_{T_k}[stop].y| > \delta \tag{13}$$

$$|PV_{T_k}[stop].y > H(ROI)/2 \tag{14}$$

where PV_{T_k} denotes a set of PV in the same T_k, δ is an appropriate threshold, while $PV[start].y$ and $PV[stop].y$ denote the minimum and maximum y coordinate of the PV in the set PV_{T_k}. Specifically, the method is able to count for each ROI fore and aft vehicles. The system will also calculate the velocity of the vehicle in the counting process. By measuring the distance in the real road and frame rate of capturing, the velocity can be deduced when the vehicle is passing through area-R.

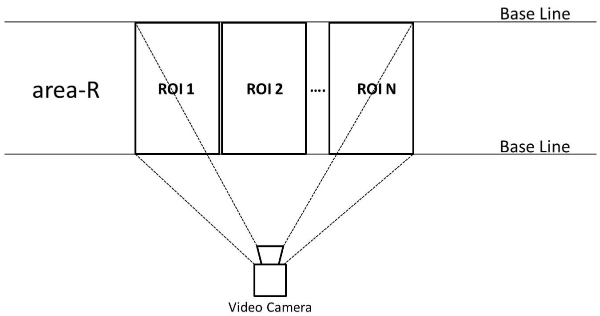


Figure 6: The setting of the proposed vehicle-counting and detection system.

To identify motorbikes, we can adopt the fact that a motorbike usually appears as a single and nearly square-shaped or vertical rectangular shaped lighting component in nighttime traffic scenes. Therefore, a set PV_{T_k}, is a motorbike if the size-ratio feature of its enclosing bounding box reflect a square or vertical rectangular shape and satisfy the following discriminating rule:

$$\tau_{m1} \leq W(PV_{T_k})/H(PV_{T_k}) \leq \tau_{m2}$$

where the threshold values τ_{m1} and τ_{m2} on the size-ratio condition are selected as 0.6 and 1.5, respectively, to suitably identify the shape appearance characteristic of the motorbikes, which are obviously different from those of the cars. The aforementioned discriminating rules can be obtained by analyzing many experimental videos of real nighttime traffic environments, in which vehicle lights appear in different shapes and sizes, and move in different directions at different distances. The threshold values utilized for these discriminating rules were determined to yield good performance in most general cases of nighttime traffic scenes.

III. Experimental Results

The above system have been implemented in C++. The system can process around 30 frames per second on a dual core processor at 2.4 GHz and effectively satisfy the demands of real-time processing. We have performed an evaluation of the system on vehicles video with 320×180 pixels on different test sequences. For instance, on a urban road scene and on a highway traffic scene with different traffic flows and different environmental illumination conditions. The evaluation consists of comparing the automatic count of vehicles in videos against the manual count (ground truth). From the tables, it manifests that the average of the F-Measure [15], [16], which combines precision (PR) and recall (RE) in the form of their harmonic mean providing an index that is more representative than the pure PR and RE measures themselves, is above 97%. To objectively evaluate the performance of the proposed algorithm, the time span of each video in the experiment was more than 50 min. The results are tabulated in Table I-III. First, Fig. 7(a) shows a nighttime highway traffic scene with a dim illumination. Although non-vehicle illuminating objects and reflected beams on the ground coexist with the vehicle in this scene, the proposed system correctly detected and tracked nearly all moving cars and motorbikes by locating, grouping, and classifying their vehicle lights. However, a few detection errors occurred when some cars with broken (single) headlights were misclassified as motorbikes. Table I depicts the quantitative results of Fig. 7(a).

	Precision	Recall	F-Measure
Cars	99.83%	98.19%	99.00%
Motorbikes	91.30%	90.5%	90.90%
Time span of the video	50 minutes		

Table I: Rate of accuracy of the proposed approach for test sequence 1 (Fig. 7(a))

Fig. 7(b) shows another test sequence of a congested nighttime highway at rush hour under a light environmental illumination condition. The proposed method still successfully detects and tracks almost all vehicles. Table II shows the quantitative results of the proposed approach for vehicle detection on a nighttime highway.

	Precision	Recall	F-Measure
Cars	99.61%	98.12%	98.86%
Motorbikes	100%	100%	100%
Time span of the video	50 minutes		

Table II: Rate of accuracy of the proposed approach for test sequence 2 (Fig. 7(b))

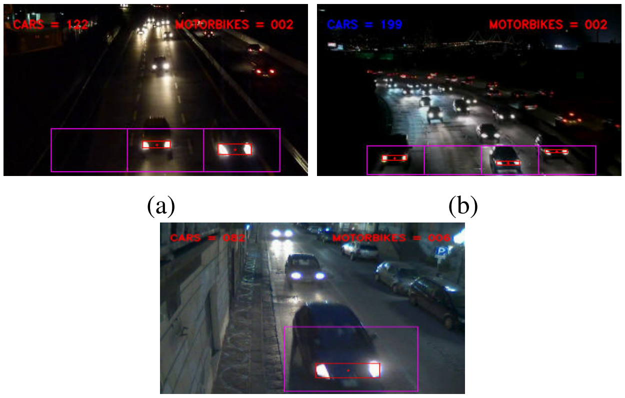
Fig. 7(c) shows a nighttime urban traffic scene with illumination and low traffic flow. The proposed method still successfully detects and tracks almost all vehicles. Table III shows the quantitative results of the proposed approach for vehicle detection on an urban road.

	Precision	Recall	F-Measure
Cars	98.71%	98.51%	98.60%
Motorbikes	95.45%	100%	97.67%
Time span of the video	50 minutes		

Table III: Rate of accuracy of the proposed approach for test sequence 3 (Fig. 7(c))

IV. Conclusions

In this paper has proposed an effective nighttime vehicle detection and tracking system for identifying and classifying moving vehicles for traffic surveillance. The virtual loop-based method is used to detect and count moving vehicles. Experimental results shown that the proposed system is effective and offers advantages for vehicle detection and



(a) (b)

(c)

Figure 7: Results of vehicle counting in different situations: (a) highway traffic scene with dim illumination, (b) highway traffic scene with illumination, (c) urban road scene with illumination.

classification for traffic surveillance in various nighttime environments. Long term tests on actual traffic scenes show that the proposed system is reliable to estimate real-time traffic flow rate. For further studies, the vehicle type classification function can be further improved and extended by integrating some sophisticated machine learning techniques such as support vector machine classifiers on multiple features, including vehicle lights and vehicle bodies, to further enhance the classification capability on more detailed vehicle types, such as buses, trucks, and light and heavy motorbikes.

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