A Video-based Vehicle Detection and Classification System for Real-time Traffic Data Collection Using Uncalibrated Video Cameras

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ABSTRACT

Length-based vehicle classification data are important inputs for traffic operation, pavement design, and transportation planning. However, such data are not directly measurable by single-loop detectors, the most widely deployed type of traffic sensor in the existing roadway infrastructure. In this study a Video-based Vehicle Detection and Classification (VVDC) system was developed for truck data collection using wide-ranging available surveillance cameras. Several computer-vision based algorithms were developed or applied to extract background image from a video sequence, detect presence of vehicles, identify and remove shadows, and calculate pixel-based vehicle lengths for classification. Care was taken to robustly handle negative impacts resulting from vehicle occlusions in the horizontal direction and slight camera vibrations. The pixel-represented lengths were exploited to relatively distinguish long vehicles from short vehicles, and hence the need for complicated camera calibration can be eliminated. These algorithms were implemented in the prototype VVDC system using Microsoft Visual C#. As a plug & play system, the VVDC system is capable of processing both digitized image streams and live video signals in real time. The system was tested at three test locations under different traffic and environmental conditions. The accuracy for vehicle detection was above 97 percent and the total truck count error was lower than 9 percent for all three tests. This indicates that the video image processing method developed for vehicle detection and classification in this study is indeed a viable alternative for truck data collection.

Key words: image processing technique, background-based algorithms, vehicle classification, and shadow removals.

1. INTRODUCTION

Due to the considerable differences in performance, size, and weight between long vehicles (LVs) and short vehicles (SVs), length-based vehicle classification data are of fundamental importance for traffic operation, pavement design, and transportation planning. *Highway Capacity Manual (1)* requires adjustments to heavy-vehicle volumes in capacity analysis. The geometric design of a roadway, such as horizontal alignment and curb heights, is affected by the different moving characteristics of LVs due to their heavy weight, inferior braking, and large turning radius. The heavy weight of such vehicles is also important in pavement design and maintenance, as truck volumes influence both the pavement life and design parameters *(2)*. Safety is also affected by LVs: eight percent of fatal vehicle-to-vehicle crashes involved large trucks, although they only accounted for three percent of all registered vehicles and seven percent of total Vehicle Miles Traveled (VMT) *(3)*. Recent studies *(4,5)* also found that particulate matters (PM) are strongly associated with the onset of myocardial infarction and respiratory symptoms. Heavy duty trucks that use diesel engines are major sources of PM, accounting for 72% of traffic emitted PM *(6)*.

All these facts illustrate that truck volume data are extremely important for accurate analysis of traffic safety, traffic pollution, and flow characteristics. Unfortunately, most traffic sensors such as single-loop detectors currently in place cannot directly measure truck volumes. Although dual-loop detectors provide classified vehicle volumes, there are too few of them on our current roadway systems to meet the practical needs. Considering that traffic surveillance cameras have been increasingly deployed for monitoring traffic status on major roadways, effective utilization of these cameras for truck data collection is of practical significance.

In this paper we propose a Video-based Vehicle Detection and Classification (VVDC) system for collecting vehicle count and classification data. The proposed approach can detect and classify vehicles using uncalibrated video images. The ability to use uncalibrated surveillance cameras for real-time traffic data collection enhances the usefulness of this prototype VVDC system. Before presenting the details of the vehicle detection and classification algorithms in the methodology section, related studies are briefly introduced. Experimental results and discussion on the performance of this VVDC system are then described in the section that follows the methodology. The final section concludes this research effort and proposes further research topics.

2. PREVIOUS WORK

Applying image processing technologies to vehicle detection has been a hot focus of research in Intelligent Transpoatation Systems (ITS) over the last decade. The early video detection research *(7)* at the University of Minnesota has resulted in the Autoscope video detection systems that are widely used in today’s traffic detections and surveillance around the world. Several recent investigations into vehicle classification via computer vision have occurred. Lai et al. (8) demonstrated that accurate vehicle dimension estimation could be performed through the use of a set of coordinate mapping functions. Although they were able to estimate vehicle lengths to within 10% in every instance, their method requires camera calibration in order to map image angles and pixels into real-world dimensions. Similarly, commercially available Video Image Processors (VIPs), such as the VideoTrack system developed by Peek Traffic Inc., are capable of truck data collection. However, the cost for such systems is significant and they require calibrated camera images to work correctly. Calibrating these systems normally requires very specific road surface information (such as the distance between recognizable road surface marks) and camera information (such as the elevation and tilt angle) which may not be easy to obtain *(9)*. Furthermore, recent studies *(10, 11, 12)* evaluating some of these commercial systems found that shadows and head-light reflections generated significant problems of false positives and early detections.

Gupte et al. *(13)* performed similar work by instead tracking regions and using the fact that all motion occurs in the ground plane to detect, track, and classify vehicles. Unfortunately, their work does not address problems associated with shadows, so application of the algorithm is limited at the current stage. Hasegawa and Kanade *(14)* developed a system capable of detecting and classifying moving objects by both type and color. Vehicles from a series of training images were identified by an operator to develop the characteristics associated with each object type. In a test of 180 presented objects, 91% were correctly identified. A major disadvantage of this system, however, is the requirement for training images from the location of interest.

Rad and Jamzad *(15)* developed a program to count and classify vehicles as well as identify the occurrence of lane-changes through tracking. Their approach utilized a background subtraction approach combined with morphological operations to identify moving vehicle regions. Although favorable results were reported, only region measurement, splitting, and losses in tracking were analyzed, while the accuracy of vehicle detection and classification were not measured at all. Graettinger et al. *(16)* used video data collected from an Autoscope Solo Pro commercial detection system to provide classifications corresponding to the thirteen FHWA vehicle classes. The method was tested at one location and validated at four other sites. However, use of site-specific models is less feasible since development of new models for each location would have to be produced.

Although several commercial video image processing systems have been developed for traffic data collection, these systems are typically subject to several major problems including complicated calibration processes, poor detection accuracy under certain weather and lighting conditions, etc. Nonetheless, these previous investigations provide valuable insights to the video-based vehicle detection and classification problems to be addressed in this study. The authors are motivated to develop a new video-based vehicle detection and classification system for convenient and reliable traffic data collection using images captured by uncalibrated video cameras.

3. METHODOLOGY

In order to satisfy the requirements for real-time data collection, the complexity of the approach has to be balanced against its effectiveness. Some pattern recognition and model-matching algorithms *(17)* can not be executed for real-time detection due to their over-expensive computational cost. A background-based approach that requires less computational work is therefore employed to meet the practical needs. Without complex calibration processes, several simple yet effective algorithms are integrated to handle problems frequently encountered in video-based traffic data collection, such as slight camera vibrations and shadow removal, to enhance the overall system performance. This section describes the major algorithms of this computer vision-based vehicle detection and classification approach. Before presenting the details of each algorithm, the system is briefly overviewed as follows.

3.1 System Overview

The VVDC system has six modules: live video capture, user input, background extraction, vehicle detection, shadow removal, and length-based classification. Figure 1 shows the flow chart of the VVDC system. The VVDC system can take digitized video images or live video signal as input. Before applying the system for traffic data collection, users must specify virtual loop locations, pixel-represented long vehicle threshold, and a shadow sample to configure the system. Then background image is extracted from video input and updated regularly to adapt to the environmental changes. Once the system starts to collect data, it monitors the virtual loop for vehicle detection. A shadow removal procedure is applied to each detected vehicle before calculating its pixel-based length. Finally, a vehicle is classified into long vehicle (LV) bin or short vehicle (SV) bin based on its pixel-based length and the LV threshold. Figure 2 shows a snapshot of the main user interface for the VVDC system. Algorithms involved in the entire process of the VVDC system are explained in greater details in the following sections.

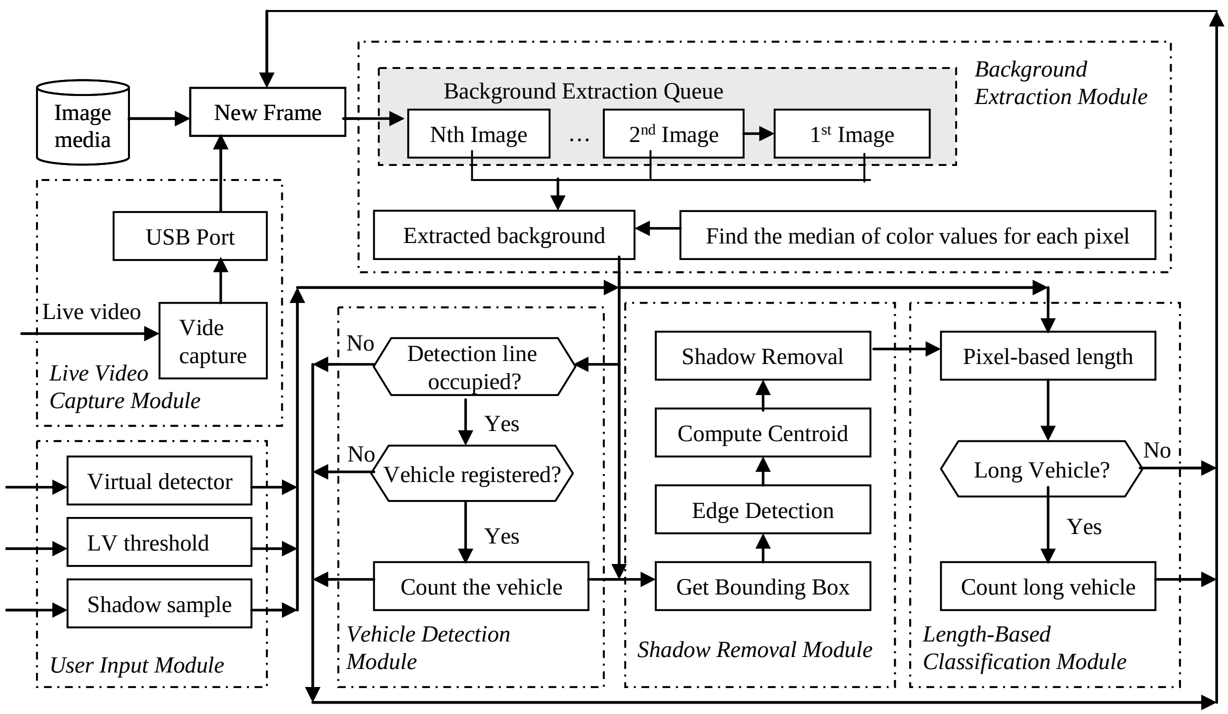

FIGURE 1 Flow chart of the VVDC system.

3.2 Image Digitization and Background Extraction

For online applications, a live video capture module is developed to digitize live video signals into image frames from common video sources, such as a surveillance cameras or a video cassette player. In this research, a WinTV USB card produced by Hauppauge Digital, Inc., was used to connect a video source to a personal computer. The built-in features of this device in choosing digitization rate, image format, and color representation provide great flexibilities for image input to the VVDC system. The Microsoft DirectX technology is used in this video capture module. This technology provides a standard development platform for Windows-based computers by enabling software developers to access specialized hardware features without having to write hardware-specific codes *(18)*. In this system, the image format of the Joint Photographic Experts Group (JPEG) and the video frame rate of 20 frames per second (fps) are adopted. When the VVDC system is executed offline, it reads digitized video images from a storage media directly. Based on digitized images, background extraction is conducted to generate a good quality background for future use.

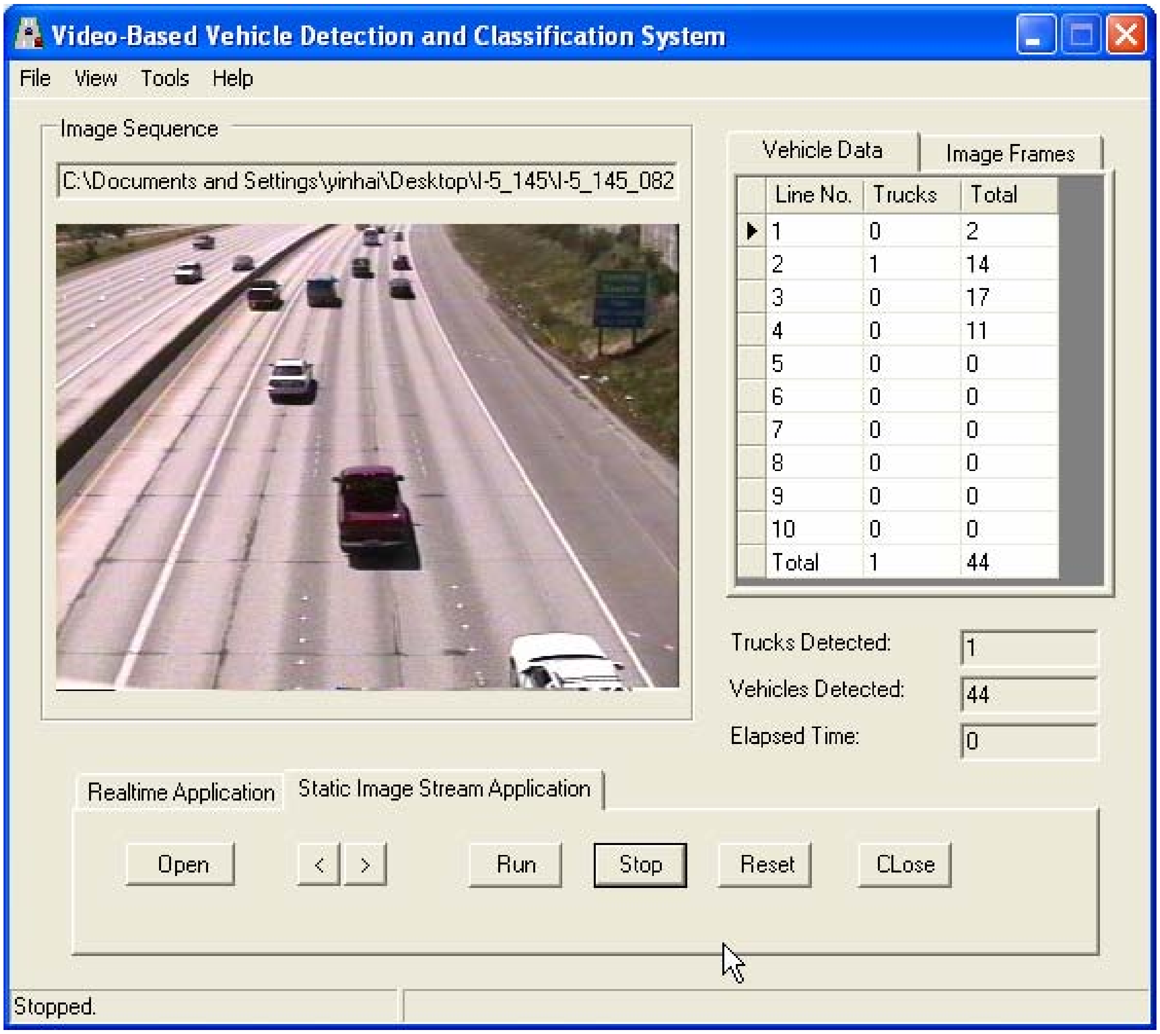

FIGURE 2 The main user interface of the VVDC system.

A background image is required to represent the base state of the area under observation for further detection purposes. It is rarely possible to obtain an image of the observation area that does not contain any vehicles or other foreground objects. Thus, it is necessary to extract the background image from the video stream itself. In this program, the background image is obtained by constructing an image using the median value of each pixel from a collection of images. Three channels in the RGB color space, the Red channel *(R)*, the Green channel *(G)*, and the Blue channel *(B)*, are used. The color values of a pixel at location *(i, j)* at the time series t can be expressed as $I_{i,j} = \{R_t, G_t, B_t\}$. In our study the median value of each color channel needs to be calculated for each color pixel. The color values of the pixel at *(i, j)* in the extracted background image $BG_{i,j} = \{R_{bg}, G_{bg}, B_{bg}\}$ can be obtained as follows,

$$BG_{i,j} = \begin{cases} R_{bg} = Median\{R_1, R_2, R_3 \cdots R_t\} \\ G_{bg} = Median\{G_1, G_2, G_3 \cdots G_t\} \\ B_{bg} = Median\{B_1, B_2, B_3 \cdots B_t\} \end{cases} \tag{1}$$

where, $R_1, R_2, R_3 \cdots R_t$ is the red channel value of the pixel *(i, j)* in the sequence with *t* images, similarly to *G* and *B*. By using the median value, it is assumed that the background is predominant in the image sequence. This assumption works reasonably well for freeway applications under free flow to moderately congested situations. Figure 3 shows a snapshot of a video scene and the background image extracted. For data collections in locations with consistent higher volumes, a background extraction based on the mode of each pixel would be preferable *(19)*.

To dynamically adapt to the luminance change, the background will be updated periodically. The update cycle can be specified arbitrarily in accordance with weather and lighting conditions.

(a) (b)

FIGURE 3 An example video scene and its background: (a) a snapshot of a video scene; and (b) extracted background.

3.3 Vehicle Detection

Before executing vehicle detection and classification algorithms the basic system configuration needs to be set up. Virtual loop detectors were applied to establish the detection zone. The concept of virtual loop is analogous to an inductive loop in that it is placed where vehicles are to be detected. Different forms of virtual loops were proposed by researchers depending on the specific tasks. In our study, a virtual loop is comprised of three parts, a registration line, a detection line and a longitudinal line. This form not only caters to detection requirements, but also maintains flexibility and simplification in the sensor configuration. Although the virtual detector can be configured in any direction to adapt to detection demands, it should be placed at locations where vehicles are clearly visible with minimal occlusion problems. Each virtual detector will handle the traffic measures on one lane to ensure accurate traffic count and classification data collected. Additionally, the configuration process involves selecting the Automatic Gain Control (AGC) area (light filter box) and sample shadows. Figure 4 demonstrates the system configuration and illustrates a virtual loop discussed above.

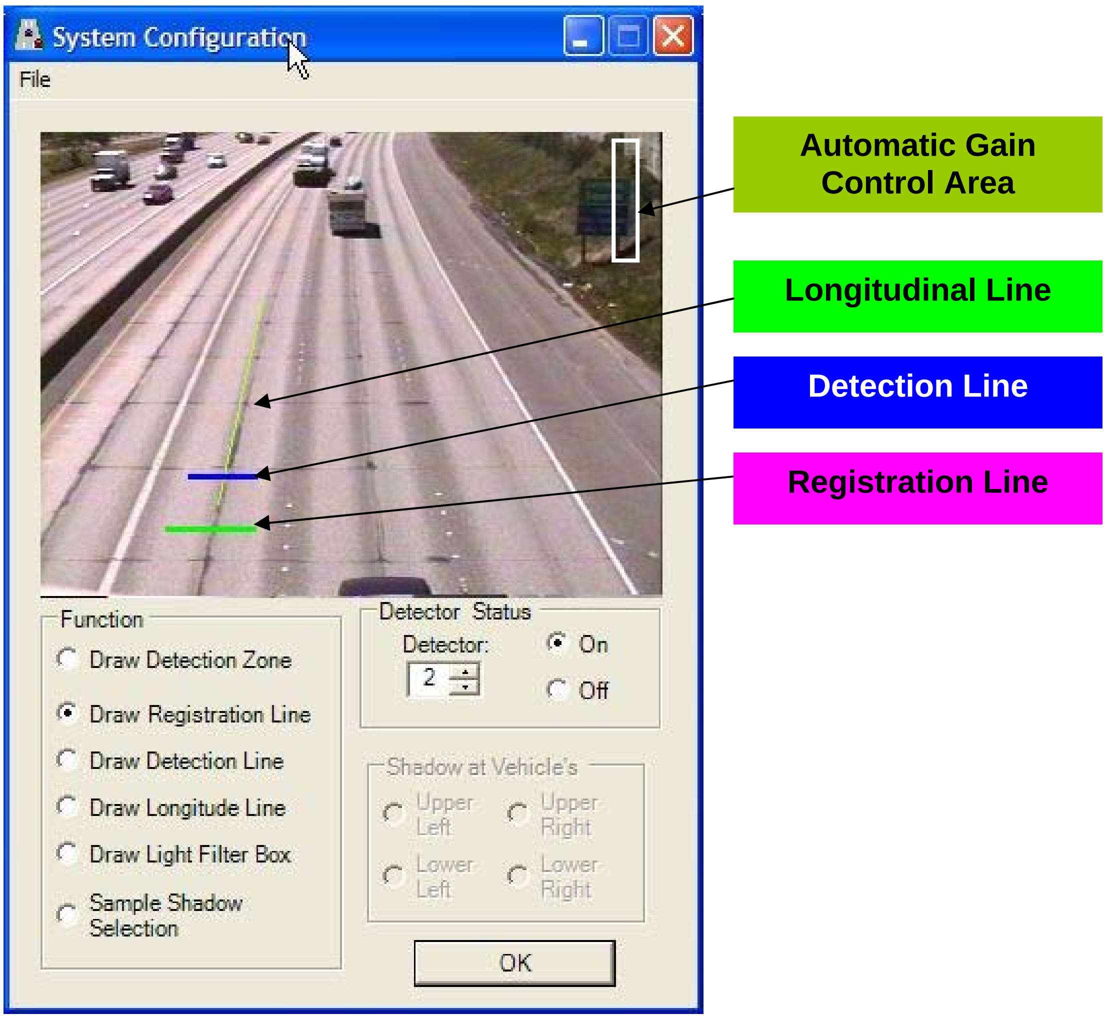

FIGURE 4 The system configuration and components of the virtual detector.

One potential disadvantage of background-based algorithms is that they do not account for transient lighting changes in the scene *(20)*. Such effects are often caused by the entrance of a highly reflective vehicle into the scene, such as a large white truck. These environmental illumination effects must be accounted for. Correction is performed via the use of AGC in this study. The AGC is a rectangular area that is placed in a part of the scene where the background is always visible. The average intensity change over this area from the background image can be determined and applied to the entire image to avoid false vehicle detections. The intensity changes of AGC can be obtained as follows:

$$\overline{\Delta int} = \frac{\sum_{A_{agc}} (bgint_{i,j} - imint_{i,j})}{A_{agc}} \tag{2}$$

where, $\overline{\Delta int}$ is the average intensity difference over the AGC area; A_{agc} is the area of the AGC in number of pixels; $bgint_{i,j}$ represents a pixel intensity in the background image normalized to the interval [0, 1]; $imint_{i,j}$ represents a pixel intensity in the foreground image on the interval [0, 1].

Vehicle detection is then performed using virtual detectors configured on each lane. Our vehicle detection algorithm first inspects for vehicles on the registration line,

$$\{p_{i,j} : p_{i,j} \in line\} : d_{i,j} = bgint_{i,j} - imint_{i,j} - \overline{\Delta int} \tag{3}$$

Where, $p_{i,j}$ represents a pixel location; *line* represents the set of all pixels on the registration line; and $d_{i,j}$ is the differenced pixel intensity. We can then define a set C that contains all differenced absolute pixel intensities greater than some threshold τ (in this study, a difference of 0.05 was used):

$$C = \{p_{i,j} : |d_{i,j}| > \tau\} \tag{4}$$

If more than 30% of the members of set *line* are also contained in set C, we consider the line to be occupied by a vehicle. To present this fact graphically to the user, the color of the registration line is changed from green to magenta as a visual cue after each detected vehicle.

There are two stages for vehicle detection: entrance detection and exit detection. A vehicle must experience both stages to be counted. Entrance detection detects the moment when a vehicle occupies the registration line for the first time, i.e. no vehicle was present over the line in the previous frame. Exit detection captures the instance when the vehicle just leaves the registration line (i.e. it occupied the registration line in the previous frame) and occupies the detection line. A vehicle is registered as soon as its entrance is detected. However, the vehicle will not be counted until its exit is detected. Such an entrance-exit detection mechanism double validates a detection process and effectively counteracts false positives resulted from stochastic disturbances and slight camera vibrations. For example, when a camera vibrates, its image scene appears cyclical fluctuation that may trigger false positives on both the registration and detection lines due to pixel position changes, although there is no vehicle occupying them. However, because of the two-stage detection mechanism employed in the VVDC system, such slight camera vibrations will not result in over count of vehicles.

3.4 Shadow Identification and Removal

Shadows may cause serious problems in video-based vehicle detection and classification. Since shadows keep the same movement pattern in accordance with that of vehicles, shadows extended to adjacent lanes can easily generate false positives. Furthermore, shadows cast over several vehicles can result in misclassification of vehicles due to the merging moving blobs of these vehicles. Hence, shadow identification and removal is among the few most important issues for vehicle detection and classification. Although many shadow detection appraoches *(21~26)* were proposed, they were mostly constrained by service conditions in practicality. Therefore, the authors developed a new shadow identification and removal approach for vehicle detection and classification.

The major contribution of the new algorithm is to utilize the semitransparent characteristics of shadows in continuous image sequences to extract shadow-robust features and then, effectively discriminate them from vehicles. Instead of trying to identify the shadow region based on grayscales of pixels, this method identifies areas with few edges or edges with high similarity to the background edges in a moving blob as shadow regions. The Canny edge detection method (*27*) is utilized to produce an edge image of each moving blob. Figure 5 shows a shadow removal example that demonstrates the effectiveness of the algorithm.

(a) (b) (c) (d) (e)

FIGURE 5 A step by step illustration of the shadow removal process: (a) original Image; (b) bounding box area (shown in blue); (c) detected edges; (d) shadow identification; and (e) shadow removed.

This algorithm outperformed several other algorithms tested in this research. More details of this algorithm are described in (*28*).

3.5 Vehicle Classification

Previous work performed by Wang and Nihan *(29)* indicated that the difference in length is significant between SVs and LVs. This makes the robust pixel-based length classification possible. A feasible solution is proposed in our system by using the apparent pixel-based length of vehicles rather than the physical length. Because the only desire is to classify vehicles by length; it is not necessary to know the actual length of each vehicle so long as it is properly classified. As soon as a vehicle exits the registration line, shadow removal algorithm is triggered to eliminate the shadow area from the moving blob. Then the length calculation algorithm steps along the longitudinal line counting the number of pixels as the pixel-based length of the vehicle. This makes the lengths of all the vehicles in a lane be measured at almost the same starting point so that the measured lengths are comparable. In this manner, vehicles can be separated by pixel-represented length without requiring camera calibration, which increases the flexibility and attractiveness of this mobile traffic detection system.

In implementation, vehicle length is simply the length along the longitudinal line that is occupied by the vehicle region V :

$$len = \sqrt{(e_x - s_x)^2 + (e_y - s_y)^2} \qquad (5)$$

Where, s_x, s_y are the start coordinates of the line; e_x, e_y are the end coordinates of the line; and len is the pixel-based length of the vehicle.

The pixel-based length of each vehicle is then compared with a threshold value to determine if it belongs to the SV category or the LV category. Since a vehicle looks different in cameras with different lens and posture settings, the threshold value cannot be a universal predetermined value. The threshold value for each lane is specified by users using the interactive interface with the VVDC system. The length of the longitudinal line of each virtual loop serves as the threshold. Vehicles longer than the longitudinal line are assigned to the LV category. Specifying the length threshold this way provides users the flexibility for collecting classified vehicle volumes of desired lengths. Note that this detection and classification algorithm is robust to most vehicle occlusions in the horizontal direction. Because each virtual loop handles traffic measures on one lane, only the pixel-represented lengths of vehicles along the longitudinal direction will be measured. If vehicles are occluded horizontally, it won't trigger any false positives. Figure 6 shows a snapshot of the system when a vehicle is detected and classified. A red line indicating the detected vehicle length is drawn together with the bounding box describing the rough region of the detected vehicle.

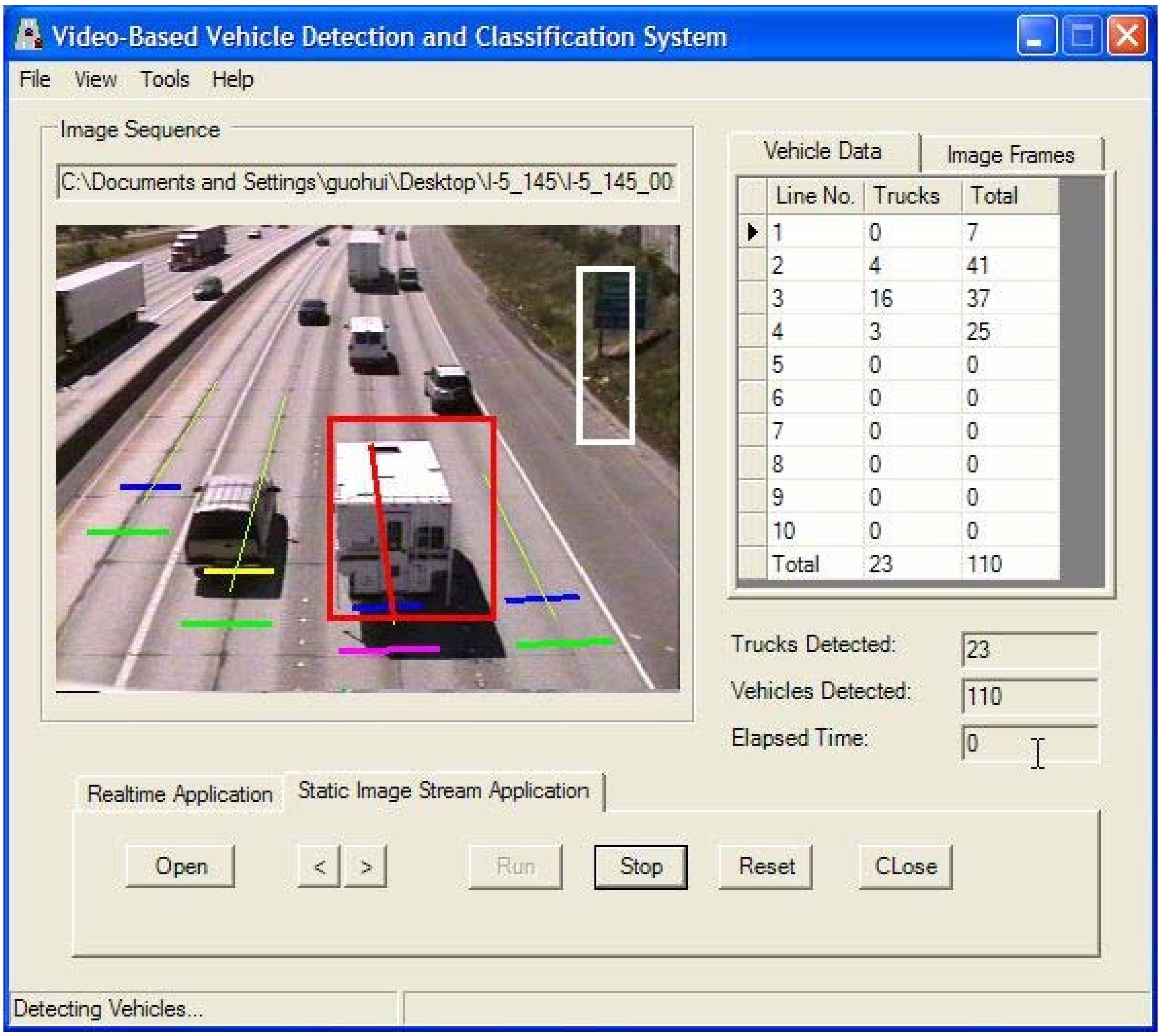

FIGURE 6 A snapshot of the VVDC system when a vehicle is detected and classified.

4. EXPERIMENTAL TESTS

To demonstrate the effectiveness of the VVDC system, two offline tests with archived video images and one online test with live video data were conducted. For the offline tests two locations were chosen: test site one from Southbound I-5 near the NE 145th Street over bridge, and test site two from Northbound SR-99 near the NE 41st Street over bridge. The I-5 test video tape was recorded between 11:30 AM and 12:30 PM on June 11th, 1999. The SR-99 test video tape was taken from 4:00 pm to 5:00 pm on April 22, 1999. Twelve minute video clips were extracted from the video tapes and digitized. Online test data were from the live video feed link from the WSDOT surveillance video system to the Smart Transportation Applications and Research Laboratory (STAR Lab) at the University of Washington. The camera selected for online testing was the camera shooting Southbound I-5 near the NE 92nd Street over bridge (test site three). The test period is chosen from 2:00-5:00pm on Jan. 3, 2006. Selection of these three test locations is determined by the facts that they represent wide-ranging application environments: ideal weather and flow conditions with test site one, challenging shadow conditions with test site two, and a more challenging weather and lighting conditions with test site three. Furthermore, test conditions for site three were further complicated with light rain, slight camera vibration, and significant light reflection from the wet pavement. All these factors made this test very challenging. A snapshot of each of the three test locations is shown in Figure 7.

(a) (b) (c)

FIGURE 7 Test site situations (a) test site one (southbound I-5 & NE 145th St.); (b) test site two (northbound SR-99 & NE 41st St.); and (c) test site three (southbound I-5 & NE 92nd St.)

Table 1 shows the results of system evaluation for both offline and online tests at these three sites, including manually observed results (ground-truth data), system operation results, and comparisons between the two.

For the offline test at test site one, given the camera location and traffic volume at this site, vehicle occlusion was rare. There were not any shadows that tended to stray into other lanes. Thus, this image set provides an ideal test condition. Test results indicate that there is an overall detection error of only 1.06 percent, and trucks were properly identified approximately 94 percent of the time. One should note that although the VVDC counted trucks were equal to the observed results for lane 1 in Table 1, this fact does not necessarily reflect perfect performance of the system. Comparisons to ground-truth data indicated that there were two mistakes produced by the system: one truck was missed (a false dismissal) while another was double-counted (a false positive). Further investigations of the errors found that the major reason for missing trucks was because the colors of trucks were too similar to the background to have their length properly measured. On the other hand, a truck occupied two lanes was counted by both lanes and resulted one over count. Figure 8 shows two cases that illustrate these problems. Additionally, several vehicles are over-counted. These false positives are likely caused by the reflection of vehicle head lights from Northbound I-5 traffic.

TABLE 1 Summary of Results for Both Offline and Online Tests

Time Period 12 minutes		Ground-truth		System Detected		Comparison Error	
		Trucks	Total vehicles	Trucks	Total vehicles	Trucks	Total vehicles
Location: Southbound I-5 near the 145th Street over bridge	Lane 1	12	244	12	245	2[a,c] 16.67%[b]	3[d] 0.82%
	Lane 2	37	335	35	335	2 5.41%	0 0
	Lane 3	4	409	4	412	0 0	3 0.73%
	Lane 4	5	149	5	154	0 0	5 3.36%
	Subtotal	58	1136	56	1146	4 6.89%	11 1.06%
Location: Northbound SR-99 near the NE 41st Street	Lane 1	15	192	15	194	0 0	2 1.04%
	Lane 2	7	244	6	245	1 14.28%	1 0.41%
	Lane 3	8	270	7	270	1 12.5%	2[e] 0.74%
	Subtotal	30	706	28	709	2 6.67%	5 0.41%
Location: Southbound I-5 near the 92nd Street over bridge	Lane 1	5	170	5	173	0 0	3 1.76%
	Lane 2	5	380	6	389	1 20%	9 2.36%
	Lane 3	36	378	37	387	3[f] 8.33%	9 2.38%
	Lane 4	13	388	14	397	1 7.69%	9 2.31%
	Subtotal	59	1316	62	1346	5 8.47%	30 2.27%

[a] absolute error; [b] relative percentage error; [c] one was missed and one was over-counted; [d] two cars missed and one truck over-counted; [e] one vehicle missed and one over-counted; [f] one truck missed and two trucks double counted.

(a)

(b)

FIGURE 8 Error investigation: (a) a truck occupied two lanes is measured twice; and (b) a misclassified truck with a color of the bed similar to the background color

For the offline test at test site two, the major purpose was to verify the system operation under challenging shadow conditions as shown in Figure 7 (b). At this location vehicle shadows projected into adjacent lanes, which could produce spurious vehicle counts if shadows cannot be properly removed. Additionally, at this location the traffic flow was interrupted periodically due to signal control at the upstream intersection. The periodical heavy traffic flow could also generate unexpected longitudinal occlusions. The overall results were satisfactory considering that the test conditions were challenging. During the testing period the overall count error was less then 0.41 percent and more than 93 percent of the trucks presented were correctly recognized. Detailed investigations of the errors indicated that the system successfully handled the negative impacts of shadows. Major problems at this site were caused by sun light reflection from vehicle bodies and other reasons similar to those that appeared at test site one.

The online test at test site three provides us a good chance to examine the robustness and reliability of the VVDC system when applied to live video images generated from a typical surveillance camera under challenging situations. Compared to the ideal test condition at site one, the image quality of this data set was seriously affected by the low-intensity rain and slight camera vibrations. The moving objects were very small relative to the field of view. Additionally, reflections of vehicle lights on wet pavement became another notable source of disturbance. Therefore, this test is the most challenging among all the three tests. The test results shown in Table 1 concluded that the overall accuracy for vehicle count was 97.73 percent and the truck count accuracy was 91.53 percent. The performance of the VVDC system was slightly lower in this online test than the two offline tests. However, considering that the test conditions were more complicated and challenging, the accuracy levels achieved in this online test are satisfactory. In-depth investigations of the errors revealed that in addition to the typical reasons summarized above, false positives in vehicle detection were mainly caused by wet pavement reflection. False dismissals were largely due to lane-changing vehicles or vehicles driving on the shoulder without triggering the virtual sensors. Two major causes for vehicle classification errors were longitudinal occlusion and inaccurate estimates of pixel-based length. For some combination trucks with two containers connected by a hitch bar, the vehicle length calculation algorithm failed to find the front edge of the vehicle and therefore misclassified it as a short vehicle. Trucks with a trailer or bed in a color similar to the image background experienced similar problems.

In general, results from the three tests to the prototype VVDC system are encouraging. If further improvements are made to the VVDC system, reliable traffic volume and truck data can be collected from surveillance video cameras in real time.

5. CONCLUSION

Acquisition of reliable vehicle count and classification data is necessary to establish an enriched information platform and improve the quality of transportation management. However, classified vehicle volumes are not directly measured by the ubiquitously deployed single-loop detectors. To better utilize the existing video equipment, we propose to use un-calibrated surveillance video cameras as a cost effective means to collect real-time SV and LV volumes for each lane on roadways.

The research approach undertaken integrates several robust algorithms to alleviate the negative impacts from shadows, slight camera vibrations, and vehicle occlusion in the horizontal direction. Evaluation results from the three test locations are encouraging. The accuracy for vehicle counting was above 97 percent for all three test sites. The total truck count error was lower than 9 percent for all tests. The accuracy for vehicle classification was lower than that for vehicle detection, but is still in the acceptable range. The test results indicate that the proposed VVDC system worked stably and effectively in the tested traffic conditions. However, this prototype VVDC system developed in this study cannot handle longitudinal vehicle occlusions, severe camera vibrations, and head light reflection problems at the current stage. Depending on the presence frequency of these problems, the actual application results may vary from site to site.

Further improvements to the VVDC system are necessary to make it robust to congested conditions. Algorithms should be developed to handle longitudinal occlusions. Also, more robust algorithms addressing light reflection should be investigated and explored to enhance the reliability of the system.

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