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Full Length Research Paper

A robust traffic quantity measurement with video surveillance

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Video and image processing have been used for traffic supervision, analysis and monitoring of traffic condition in many cities and urban areas. The system described in this paper aims to approach the precise method to obtain the traffic flow, time headway and traffic volume through a sequence of images captured with a stationary video camera. The method consists of three algorithms. First, background modeling and update, second, a boosting method to enhance the foreground image and reduce the noise and at last determining best match of region of interest (ROI) to extract information to conclude if there is a vehicle in the detection zone or not. Based on this structure, the traffic quantity measurement (TQM) algorithm is represented to compute the important parameters in traffic sense that will be useful for traffic condition observation and management as well. In this research, the traffic quantities such as time headway and traffic flow have been measured. The experimental result shows this method obtains traffic flow and time headway with around 91% of accuracy in shadow free area and can be used in real time condition.

Key words*:* Vehicle time headway, traffic flow, computer vision.

INTRODUCTION

Extract reliable and precise traffic parameters have been one of research objectives in last three decades. For the traffic planning and management, obtaining the traffic parameter is the critical step. Traffic parameter must be carried out at different environments where the traffic condition changes as well as the light illumination. Vehicle detection for parameter extraction could be performed by using the magnetic loop detector which is the electromagnetic communication and detection device and it is still widely used. The disadvantages of loop detectors are their high cost for installing, maintenance, closure the roadway for maintenance, and uncertain data detection. Because of these disadvantages here, we want to present the novel method for a sufficient way to collect traffic data.

The vision based method is more convenient than the magnetic loop sensors because, first, it does not cause the closure of the roadways while installation and maintenance, second it can be use in comprehensive activities such as traffic surveillance, vehicle classification, counting, tracking and emergency conditions. The advantage of traffic vision based on camera is that only one camera can monitor and obtain the information of a large part of road or freeway.

Although the vision based method has several benefits, there are still many difficulties and stimulating tasks. Some challenges are light illumination and image intensity changes, changing of weather condition, shadows and noise, differents between vehicles such as their colors, sizes and classes.

In last few years, a lot of research has been done about the application of image processing techniques and computer vision to solve and improve the issue of extraction of traffic parameters. Hsu et al., (2002) introduced and used entropy measurement approach to extract traffic parameters. They used the entropy measurement as an important feature to describe the degree of confusion in thermodynamics, and underlying feature in their work. Based on an entropy measurement, several

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important traffic data such as mean speed and traffic flow are obtained. Viarani (1999) introduced an approach to obtain traffic data in real time with named 'virtual inductive loop'. In this approach, the grey pixel information have been utilized to detect vehicles and eventually to collect traffic parameters. Experimental results show that this method has some problem like light illumination and vehicle shadow.

Zhu et al. (2000) introduced a system using two different spatio-temporal images. They used two types of 20 spatio-temporal (ST) images in their system, the panoramic view image (PVI) and the epipolar plane image (EPI) but, their proposed system suffers from illumination of light and vehicle shadow.

Lee and Park (2006) purposed detecting vehicles based on shadow classification for reducing the affect of shadows.

If the traffic flow is not excessively loaded, the traffic parameter can be recognized properly, and collect number of vehicles passing the scene, the length of vehicle, the vehicle velocity, the time headway and the rate of road occupancy correctly within a reasonable amount of error. Rad et.al (2010) proposed a new method for velocity estimation based on centroid of the vehicles.

Coifman et al. (1998) introduced a vehicle feature based on a tracking algorithm for extraction of traffic parameters. This algorithm has the ability to measure many micro-scaled parameters such as instant vehicle velocity. The weakness of algorithm is that it is sensitive to the vehicles pass directions and when vehicles have the multiple pass directions through the detection zone, the experiment was not fair.

This paper consists of three steps, first, it presents a method that generates background and is self updating to get reliable background and eliminate light illumination. Then it subtracts the background from the current frame to extract foreground which is useful and contains the traffic information. In the second step, we introduce another algorithm which boosts the foreground by removing noises and identifying the boundary for the vehicle to distinguish them. In the third and final step, we introduce an algorithm to determine the best place for detection region called virtual-loop sensor which acts like the inductive loop sensors and therefore measure the time headway and vehicle flow. This algorithm is simple and also powerful and needs small calculation and less memory to store the images, and has high performance speed, and ability for real-time processing.

In this research, we use three types of successive images which is captured by digital cameras installed over the three different roads to evaluate our algorithm. The algorithm needs only a single video camera and a Cor2Duo computer possessor with Matlab software which is installed on computer to operate the detection of the vehicle. The procedure only requires installing the camera directly above the roadway. In addition, we only need the specification of the camera, like frame rate and frame size, which are obtainable through the software, and are essential.

MATERIALS AND METHODS

Here, we introduce the whole system algorithm which consists of particular parts and in addition, we describe each part in detail. First, the vehicle detection system architecture is described followed by a description of each component in the framework respectively. In this paper, the first step is background extraction which needs to update constantly because of the affect of environment conditions like the light illumination and weather change. The camera location must be set up over the surface of the road with its optical axis inclined downward to the roadway to cover the road plane.

Traffic parameter estimation algorithm

The software system consists of three subsystems as shown in Figure 1, called background modeling and update unit, foreground extraction and enhancement unit, and traffic quantity measurement (TQM) which are shown in Figure 1. The result accuracy will be compared with manual references and will be shown in the final step.

BACKGROUND MODELING AND UPDATE

One of the important parts of the vehicle detection is background extraction and removal which is necessary for the acquisition of foreground infor-mation. Moreover, if background image difference was used with no update of background image, this would lead to incorrect and unsuitable results. Hence, the dynamic background update method which can estimate the background while there are environmental changes in a traffic scene is necessary.

Background extraction algorithms are divided into several types. Bailo et al. (2005) used background estimation with Gaussian distribution for image segmentation. Ridder et al. (1995) used adaptive background estimation and foreground detection using kalman filter. Asaad and Syed (2009) utilized morphological background estimation and Shi et al. (2002) introduced adaptive median filter for background generation.

For our approach, we need background generation and update algorithm which handle light illumination and background motions such as natural motions caused by the wind. That is the reason we adapt background Gaussian models (Stauffer and Grimson, 1999).

One of the advantages of this algorithm is that different thresholds are chosen for each pixel. These thresholds are adopted by time and are very useful because of light illuminations.

Objects such as parking vehicles besides the road are allowed to become parts of the background without tearing down the living background. Finally, this algorithm supports fast recovery and less employment memory which affect the calculation speed. In Figure 2, we show the result of background generation.

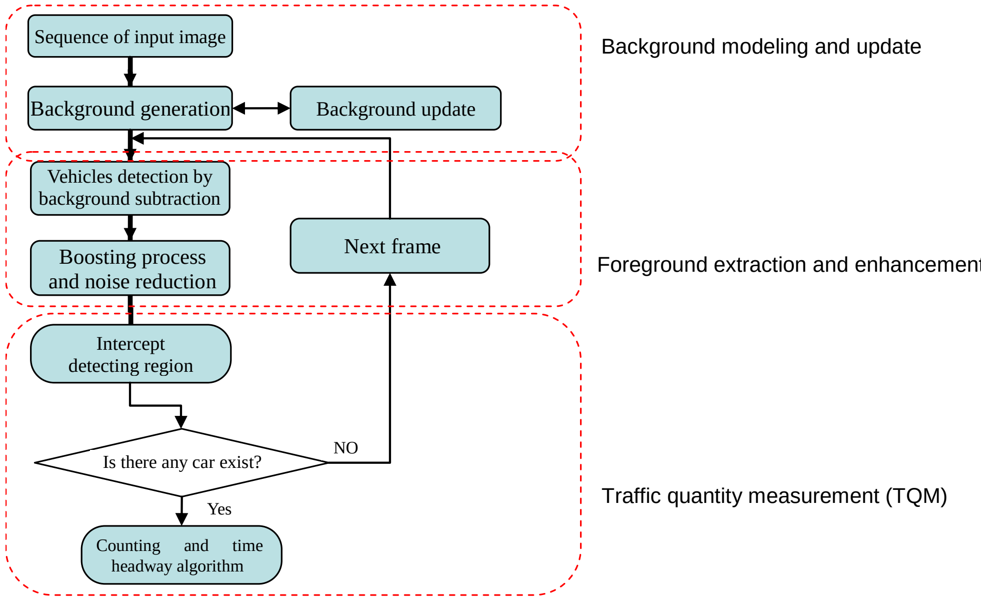


Figure 1. System architecture.

Figure 2. The results of background generation. (a) video sequence in frame 24 (b) video sequence in frame 26 (c) background generation.

VEHICLE DETECTION AND BOOSTING PROCESS

Here, we introduce the method used in this study for vehicle detection and tracking and then the technique for improving the image quality. This step is one of the important parts of algorithm since the final step is related to this step. In final step we want to extract the traffic parameters based on collecting data from the current step. The procedure of this step is shown in Figure 3.

Median filter

Algorithms for noise reduction in video processing, which contains boundary-constrained filtering, low and high-pass filtering, edges masking, generally need high computational power, memory including time (Wu and Reed, 1999). In this research, we employ a simple and powerful technique known as median filter, which is a nonlinear digital filtering technique and frequently used to remove noises. The idea behind this method is to replace the noise pixel with the median values of its neighborhoods pixels (Snoka, 1999) and it can reduce noises faster as well as using low occupancy of memory.

The median filter is perfect for reducing salt and pepper noise which usually happen in image processing procedure. A median filter is shown in Figure 4 and in this example a three by three matrix was used. The neighbor-hood values are shown in the diagram. The pixel value in center point which is 150 is relocating by the median values of its neighborhood which is 124. In addition, larger filter will produce greater smoothing but simul-taneously needs greater computation and time as well which is not preferred.

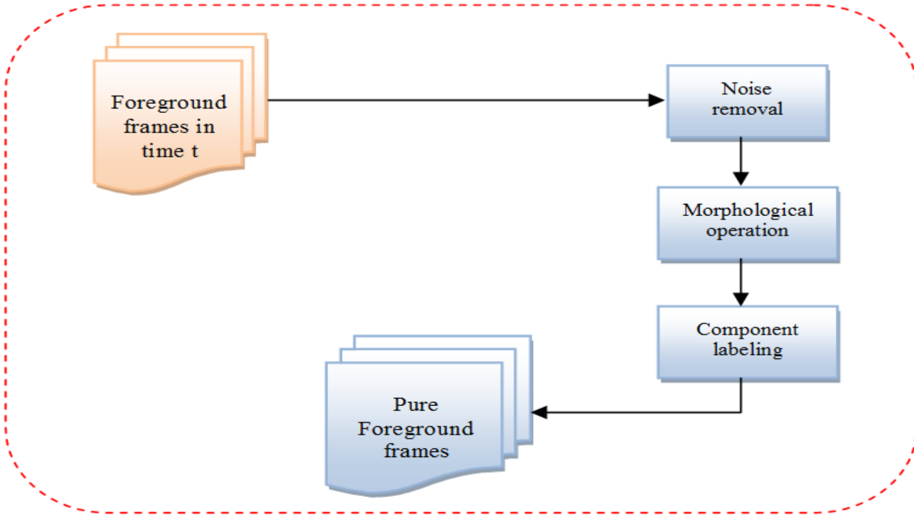


Figure 3. Vehicle detection and boosting process.

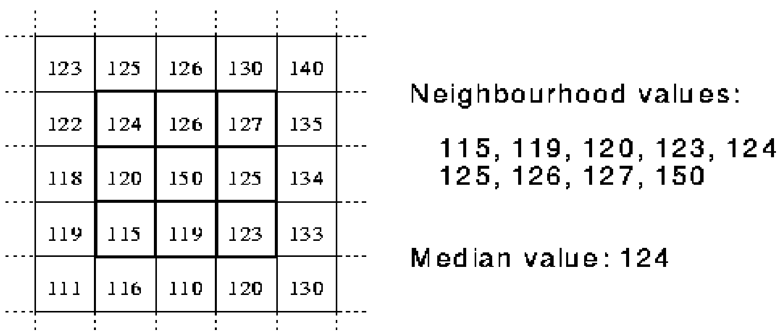


Figure 4. Sample calculation of the median value of a pixel neighborhood.

Morphological operation

Mathematical morphology (MM) is a theory and tech method of performance for the analysis of geometrical structures and usually is used in applications where the object shape and speed are important like image processing or in the analysis of the optical character recognition, document analysis, microscopic images, industrial infection (Ronse et al., 2005).

Morphological operations preserve the image shape and make it simple, and will distinguish the quality of object. Morphological operations are used generally for object structure improvement (convex hull, opening, skeletonization, closing, thinning, object marking), image preprocessing (shape simplification, ultimate erosion, noise filtering), segmentation of object and measurement of area and perimeter (Sonka, 1999).

In this study, we use closing, opening, erosion and dilation technique to fill the hole inside moving objects which commonly happen during the image and video processing and cause disorder and error in the final step which is the obtaining of traffic information.

The dilation is used for examining and expanding the shapes in the input image to extend the border of regions of moving objects. Foreground pixels enlarge while holes within those areas become smaller. In other hand, erosion erodes the border of the foreground pixels and the boundaries of moving objects become smaller in size and shape, and the holes turn into greater size and quantity. An opening is the dilation of the erosion of an object boundary by a chosen structuring element. A closing is the reverse act of an opening and the basic functionality of this operation is noise removal. The main affect of opening is to remove small objects from the foreground which is not really moving object and set it to background, while closing removes small holes inside moving objects.

Connected component labeling

Connected components labeling is the basic role in

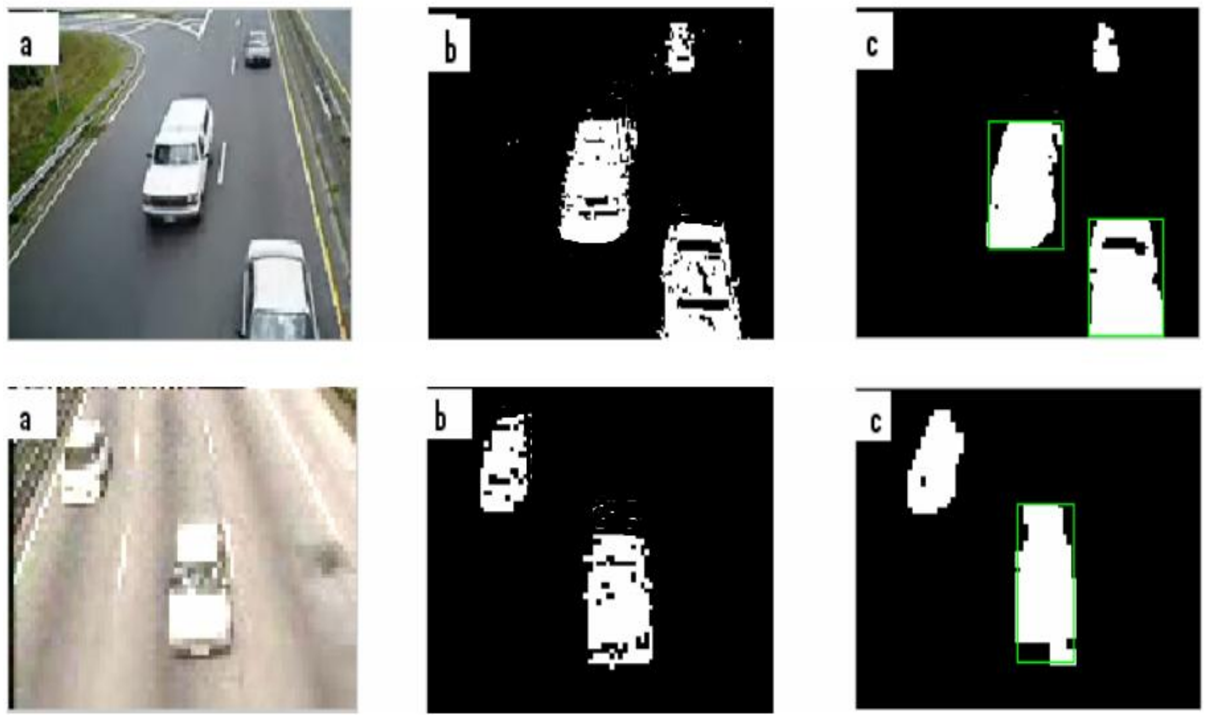


Figure 5. Result of vehicle detection and boosting process: (a) Video frames in time t in Matlab demo; (b) Video frames before boosting process, and (c) Video frames after boosting process.

image processing to classify a groups of pixels into components. Rosenfeld (1970) and Samet (1981) proposed and developed it as the procedure of recognizing the elements which have no common and are separated from each other in an image. It is one of a fundamental operation in video and image processing and is practical for object segmentation (e.g., the separation of vehicles in the scene from one another) and also can be used for thresholding and classification. The basic activation in the connected component labeling is by pixel-by-pixel scanning an image (from left to right and top to bottom) to find out connected pixel regions and then separate each region from another by using distinguished index on each region. The results obtained are shown in Figures 5 and 6.

Traffic quantity measurement (TQM)

The traffic flow is defined by a number of vehicles passing a specified point during certain time period which is usually one hour. Here, the extraction of traffic data like the number of passing vehicles, road-occupancy rate and time headway between vehicles in traffic scenes is explained. 'TQM' consists of three parts, defining detecting regions, tracking the vehicle on detection regions and calculating the vehicle and time headway in duration of the vehicle passing the detection regions and save the data. In the following part, we will explain each of these steps. The flowchart of these steps is shown in Figure 6.

Intercept detecting region

Here, we choose the best place for detection region which depends on the road line. For example, road with one line has one detection region and road with two lines has two detection regions and so forth. We found the best place for detection region is in the middle of the lines which depends on the frame size and are calculated by the following equation:

$$D = \frac{L \times 70}{100}$$

where D is detection region and L is distance between each line and the detection region starting from 15% of left side of each line and two third of bottom scene. Detection regions for two line road and threes line road are shown in Figure 7.

Vehicle counting and time headway measurement

Here, we proposed new and robust algorithm for vehicle counting and time headway measurement which is simple and also powerful to count vehicle carefully and extract time headway among passing vehicles.

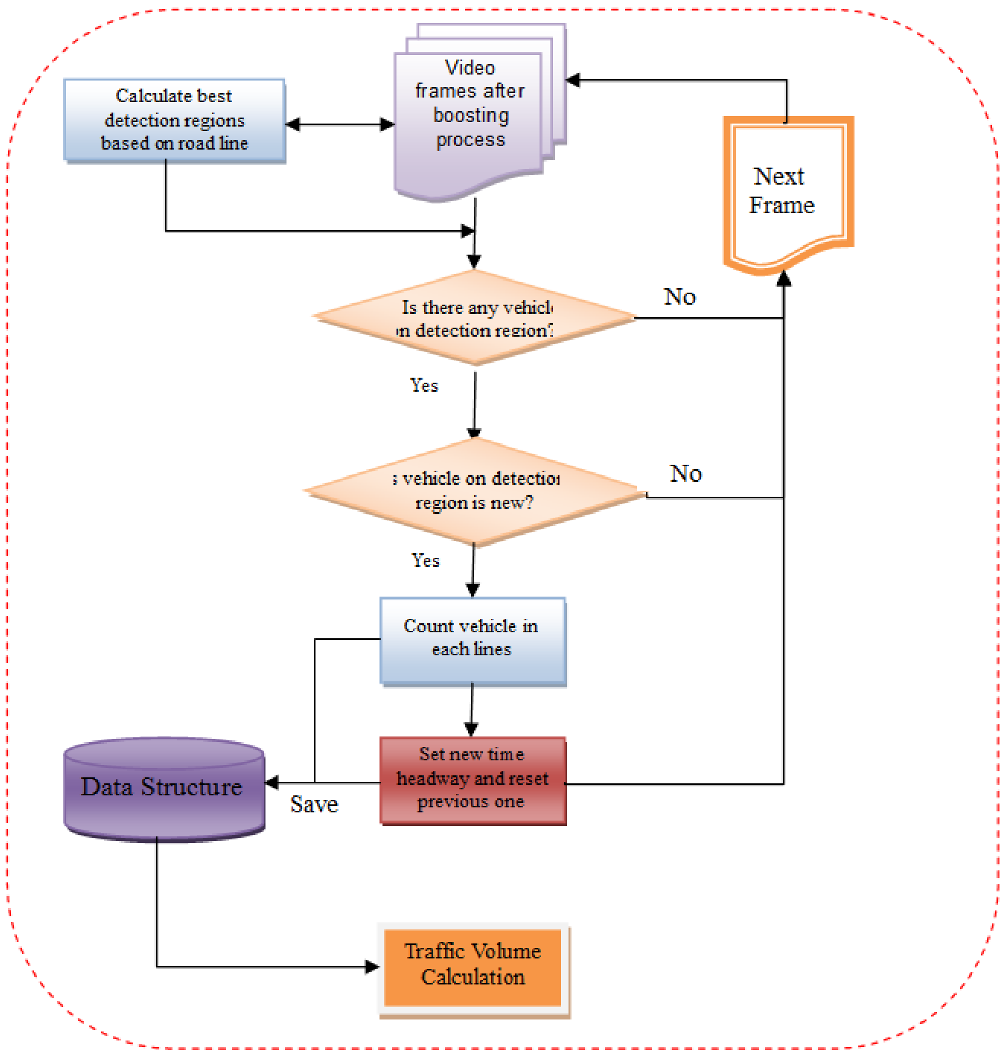


Figure 6. Traffic quantity measurement (TQM). Flow chart of traffic quantity measurement process.

First, we calculate the vehicles width based on the frame size which is based on the pixels. The equation is shown in below:

$$W \cong \left(\frac{2}{3}\right)\left(\frac{F_{wd}}{L_N}\right)$$

where W is vehicle width based on pixels, F_{wd} is the frame width based on pixels and L_N is the number of the road line.

Second, video frames after boosting process is the binary value which is contain of pixels with zero and one value and the vehicles represent by one and background with zero. This helps to count the vehicles and measure the time headway duration of passing the vehicle from detection region with measurements of changing value in detection regions. The procedures of counting and measurement of time headway is described in the following steps:

Step1: The value of detection regions is zero means no vehicle exists.

Step 2: More than 50% value of vehicle width, on detection regions become one which means the vehicle on the detection region, start vehicle counter and time headway counter start to count the frame number.

Step 3: The value of detection regions is one which means previous vehicle still on detection region, no counting vehicle but time headway counter still counting .

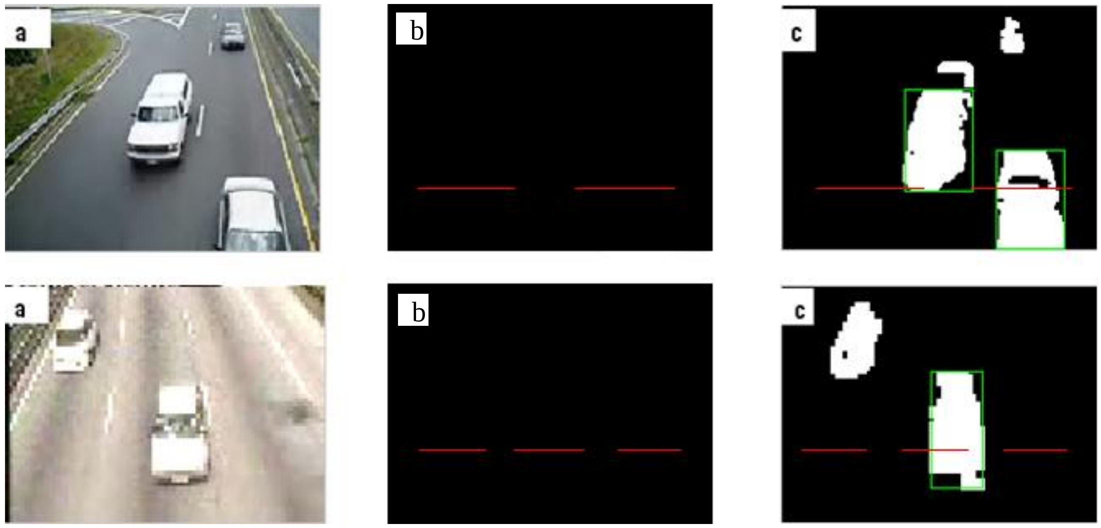


Figure 7. Result of region detection identification. (a) Video frames in time t in Matlab demo and hand capture move; (b) Video frames before boosting process, and (c) Video frames after boosting process.

Step 4: The value of detection regions become zero vehicle pass the detection region, headway counter still counting.

Step 5: The 50% value of vehicle width, on detection regions become one which means the vehicle is on the detection region, vehicle counter add one number and time headway counter stop previous counting and save that number to data structure and start new counting and jump to step 3.

We choose 50% changes in value of vehicle width, on detection regions because that help to increase the accuracy of detection. During this process, we can have access to data structure and access to the data which is time headway and number of vehicle passed the detection region. Time headway is obtains from following equation:

$$T = F_N \times F_R$$

where, T is the time headway between two successive vehicles, F_N is the amount of frame number and F_R is the frame rate which is the number of frames that are displayed per second.
Finally we can define traffic flow by following equation:

$$q(Time, x) = \left(\frac{N}{Time}\right) = \frac{1}{\overline{\overline{h(x)}}}$$

where, q is traffic flow passing a detection region (x) during an interval time (Time) and N is the number of vehicles in interval time and it is equal to the reversed of the average headway.

The results are obtained (Figure 8) from 4 different videos corresponding to different lanes to test the accuracy of our system.

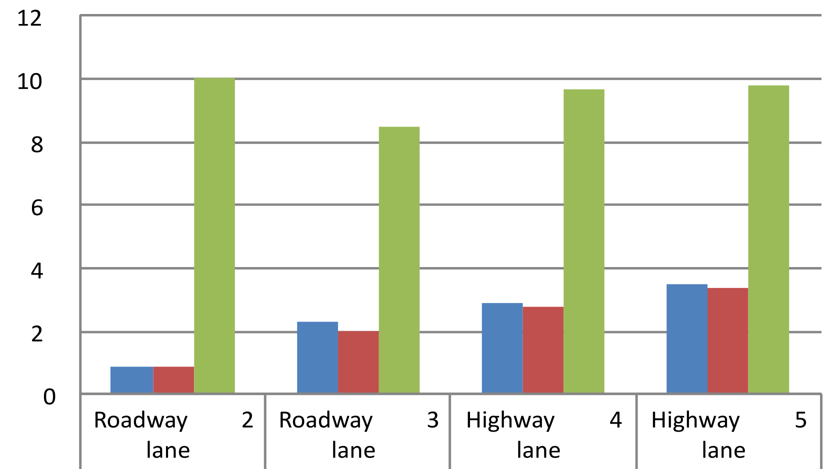
DISCUSSION

Our purposed quantity measurement system works fairly accurately to count the vehicles and time headway among them. The only things that have to be considered more carefully are the placement of detection region. The error happens because of two reasons, first the change of the lane by vehicles and second, the low quality of binary images used in this study. In Figure 9, the results averaged over five trials obtained from 4 different videos corresponding to different lanes are shown.

The results are obtained from 4 different videos corresponding to different lanes averaged over five trials.

Figure 10 shows two different video frames which are used in this study: Video frames from hand capture movies and video frames from live traffic cameras which are available through the internet.

In this study, the relationship between average time headway and traffic condition is tasted. Traffic condition based on average time headway consists of three parts, average time headway less than 1 s shows the heavy traffic, average time headway between one to three second shows moderate traffic, and average time headway more than three second shows light traffic. In



	Roadway lane 2	Roadway lane 3	Highway lane 4	Highway lane 5
Real	9	2	2	3
Detected	9	2	2	3
Accuracy	10	8	9	9

Figure 8. The obtained results from 4 different videos.

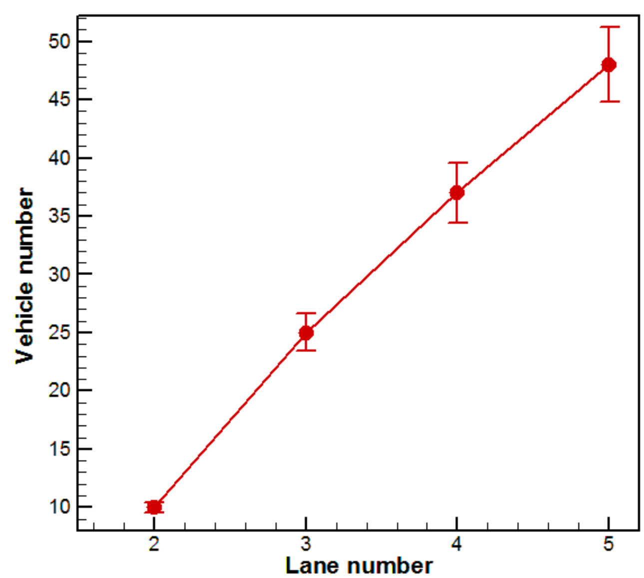


Figure 9. The obtained results from 4 different videos corresponding to different lanes.

addition, because of high computation power, in this study the effect of shadow is ignored.

Conclusion

Traffic parameters extraction is an important mission in ITS. There are three steps to realize such processing, namely, background subtraction, object detection and traffic data extraction. In the first step, background generation and update was used. In the second step, a novel algorithm which performs background subtraction for moving object detection and the boosting technique, which is employ to enhance the quality of foreground was used. And in final step, the detection region was identified, and then robust algorithm was introduced to obtain the traffic data such as vehicles counting, time headway and traffic flow. Traffic parameters extractions have been implemented using MATLAB software. the The prototype can process around 15 frames per second

Figure 10. The images studied to find the traffic flow. (a) Video frames from hand capture movies (b) Video frames from live traffic cameras available through the internet.

on a core2Duo processor at 2 GHz.

REFERENCES

Asaad AM, Syed IA (2009). “Object identification in video images using morphological background estimation scheme.” 22: 279-288.

Bailo G., Bariani M, Ijas P, Raggio M (2005). ”Background estimation with Gaussian distribution for image segmentation, a fast approach,” Proc. IEEE Int. workshop on Measurement Systems for Homeland Security, Contraband Detection and Personal safety, 2-5.

Coifman B, Beymer D, McLauchlan P, Malik J (1998). “A real-time computer vision system for vehicle tracking and traffic surveillance,” Transp. Res. Record Part C, 6: 271-288.

Hsu WL, Liao HYM, Jeng B, Fan K (2002). “Traffic parameter extraction using entropy measurements,” Proc., IEEE 5th Int. Conf. Intell. Transp. Syst., 106-111.

Lee DH, Park YT (2006) “Robust vehicle detection based on shadow classification” Proc. 18th Conf. on Pattern Recognition 3: 1167–70

Rad AG, Abbas D, Mohamed RK (2010). “Vehicle speed detection in video image sequences using CVS method”. Int. J. Phys. Sci., 5(17): 2555–2563.

Ridder C, Munkel O, Kirchner H (1995). Adaptive background estimation and foreground detection using kalman-filter, Technical report, Bavarian Research Center for Knowledge-Based Systems.

Ronse C, Laurent N, Etienne D, (2005) “Mathematical Morphology: 40 Years On: Proceedings of the 7th International Symposium on Mathematical Morphology, April 18-20, (Computational Imaging and Vision) ISBN 1-4020-3442-3 (2005)

Rosenfeld A (1970). Connectivity in Digital Pictures, J. ACM (JACM), 146 - 160

Samet H (1981), “Connected Component Labeling Using Quadtrees”, J. ACM (JACM), pp. 487–501.

Stauffer C, Grimson W (1999). “Adaptive background mixture models for real-time tracking”.In Proc.IEEE Conference on Computer Vision and Pattern Recognition.FortCollins. Colorado. pp. 246-252.

Shi P, Jones EG, Zhu Q (2002). “Adaptive Median Filter for Background Generation - A Heuristic Approach,” Proceed. Int. Conf. Imaging Sci. Syst. Technol., CISST '02: 1, CSREA Press, 173-179.

Sonka M, Vaclav H, Roger B (1999). ”Image Processing, Analysis, and Machine Vision” Second. Edition. PWS Publishing, 370-375.

Viarani E (1999) “Extraction of traffic information from image at DEIS,” Proceedings, Int. Conf. Image Anal. Processing, pp. 1073-1076.

Wu GK, Reed TR (1999). ”Image sequence processing using spatiotemporal segmentation” Circuits and Systems for Video Technology, IEEE Trans., pp. 798 – 807.

Zhu Z, Xu G, Yang B, Shi D, Lin X (2000) “a real-time vision system for automatic traffic monitoring Image.” pp. 781–794.