Proceedings of the Technical Sessions, 26 (2010) 33-40
Institute of Physics – Sri Lanka

Night Time Detection of Vehicles

Sakunika Perera and Upul Sonnadara
Department of Physics, University of Colombo, Sri Lanka

ABSTRACT

This paper presents results of a study carried out to count and classify vehicles in video sequences of traffic scenes captured from a fixed digital camera under night conditions. The vehicle identification has been carried out using the headlights, which may be the only key feature available to identify vehicles under low light conditions through visible light. Due to lack of features, the vehicle classification was limited to two classes as heavy and light. The development process incorporated a number of pre-processing steps; background subtraction, which was used to extract moving headlights from the static background, followed by grayscalling, thresholding and noise filtering, which were carried out to help with the accurate identification of headlights. The system was build with the assumption that all vehicles switch on their headlights at night-time and all headlights are working properly. The current accuracy of the system for counting vehicles is 89% and that of vehicle classification is 88% for heavy vehicles and 90% for light vehicles. Present accuracy has the potential to improve with further studies.

1. INTRODUCTION

Vision based traffic monitoring systems for motion detection during daytime has been an active research area and variety of well established algorithms has been proposed [1]. But motion detection under night luminance has not yet received an equal attention. During daytime more information about vehicles such as their shape and the type are easily captured in a video sequence taken from a digital camera. In the absence of light the objects are not clearly visible. Hence the algorithms used for daytime motion detection cannot be applied at night.

During night time, the target objects are the pair of headlights, which is the only key feature for extracting moving vehicles in a low light situation. The headlights will illuminate its surroundings, but the bright area will change as the vehicle moves. As a result false moving objects will be detected. False detection can be reduced by considering only the dense bright regions that corresponds to the vehicles headlight only. Shape, size and minimal distance between vehicles are some other aspects that lead to headlight detection with higher accuracy [2].

A recent work carried out by Lee [1] used an infrared camera to capture the video sequence at night and adopted moving vehicle approach to detect the horizontally and vertically moving vehicles in the traffic scene. Headlights and break lights have been used to detect the horizontal motion while headlights and width of the vehicles have been used to detect the vertical motion. Cucchiara and Piccardi [2] used image sequence to extract the headlights of moving objects. They have used luminance to identify the pair of headlights. Reader may refer the review by Piccardi [3] on background subtraction techniques and Dailey and Liv [4] on extracting speeds from real time sequence of images for further information.

The main goal of this research work is to count and classify the vehicles in a video sequence of traffic scenes captured from a fixed digital camera under night conditions. The vehicle identification was carried out using the headlights, which is the only key feature available to identify vehicles under low light conditions.

Following steps were used to process the captured video clips. Video sequence acquired from a digital camera was sampled into multiple frames and the consecutive set of frames which mainly consists of moving vehicle (headlights) were extracted and passed through a series of pre-processing steps. Noise filtering, thresholding and false region removal have been carried out to identify the headlights correctly. Once the pair of headlights was identified, counting and classification of vehicles were attempted.

2. METHODOLOGY AND IMPLEMENTATION

The overall implementation of this system consists of number of processing blocks starting from acquisition of video clips till the end results, which are the vehicle counting and classification.

2.1 Camera Arrangement

The video sequence is acquired from a digital camera (Soney DSC – T100 8.1 Mp) by mounting it at a higher elevation from the road level. The camera should be placed in a way that the vehicles move towards the camera to get the optimum usage from the images. Side views of the vehicle movements will be difficult since both the headlights might not be captured properly in the video. Coverage of a large field of view and minimizing the occlusions of the vehicles can be achieved by mounting the camera at a higher elevation from the road level. When the vehicles are moving due to elevation enough gaps can be observed between the vehicles, so the occlusions will be less. Hence top of the new overhead bridge constructed at Nugegoda was selected as the location for field trials. Several video scenes of vehicles traveling from Nugegoda to Kohuwala at night were collected for further processing.

2.2 Frame Extraction

A video sequence needs to be sampled into multiple frames before applying the image processing techniques and those set of frames are the inputs to the subsequent stages of the system. Hence external software called ‘Adobe Premier Pro’, which is a real-time, timeline based video editing software application, was used to extract the frames. The built-in function ‘imread ()’ in Matlab was used to read and convert the extracted frames into readable form. From the extracted frames, 200 consecutive frames were chosen to develop the system and rest of the frames were used for testing.

2.3 Grayscalling

Converting colour images into greyscale images is the first step of the pre-processing. Grayscalling removes the colour values of an image and simplifies computation drastically compared to a colour RGB image. There are several algorithms to convert a colour RGB image to a greyscale image. The function called ‘rgb2gray ()’, which is a built in function in Matlab is one such method, which eliminates the hue and saturation information of the true colour RGB image while retaining the luminance. Luminance model is another method that can be used for colour to greyscale conversion and it gives better greyscaling results than the above mentioned built-in function. Colours in an image are converted to a shade of grey by calculating the effective brightness or luminance of the colour and this value is used to create shade of grey that matches the desired brightness. In this work the luminance model was chosen as the technique for this colour to greyscale conversion as it gives better results than the built in-functions in Matlab.

2.4 Noise Filtering

After grayscalling the images had to go through the filtering process to filter out any noise in the image. A wide variety of filtering algorithms are available to detect and remove noise, leaving as much as possible the original signal. The filter used in this work is a median filter, which has a nonlinear operation and often used to reduce "salt and pepper" noise. Median filter is more effective than convolution when the goal is to simultaneously reduce noise and preserve edges. The function, 'medfilt2 ()' is a built-in function, which performs the median filtering operation in Matlab. The output images from the previous operation are passed through the filter to obtain the noise free images.

2.5 Background Subtraction

The simplest mechanism for detecting foreground objects from a sequence of frames from stationary camera is by obtaining the difference between the current frame and an image of a static background [3]. But it is difficult to obtain such a complete static background due to constant flow of traffic. In this work an assumption has been made that if the camera is fixed, the background of the images captured under night conditions is almost static. Hence instead of obtaining a static background image, the frame difference technique was applied to estimate the background image.

Since the frame rate is high (30 fps) the consecutive images are more or less the same and the difference is negligible. Hence the shape of the vehicle headlights will not be filtered out properly. So the selected frames should have a reasonable gap between them. In this work the gap between two such frames were fixed at 7 frames.

2.6 Thresholding

By applying the frame difference technique most of the background objects could be removed and the resultant images were a set of bright spots on a dark background. However, all bright spots may not be clearly separated from the background and hence the feature extraction could be difficult. Thus, filtering out the bright spots should be attempted as the next step in the chain of processes. This was done through thresholding which segments the images into two regions: object region and the background region. This step is also called binarization. Instead of drawing histograms and manually finding the threshold value, the in-built functions in Matlab were used to find the required threshold value and convert the images into binary images. In each iteration the function, 'graythresh()', calculates the most suitable threshold value for the image and passes that value to the function called 'im2bw()' to segment the image it into regions.

2.7 Removing False Bright Regions

To remove the false bright spots, number of features has to be extracted from the image and several methods had to be tested to choose a proper method to eliminate the unwanted white pixels. The areas of the bright spots, distance between the light pairs, and shape of the headlights are some of such parameters that were considered to identify false regions. Compared to the areas of the real headlights, the false light spots are very small in area. But this might not true for all cases since some vehicles like three-wheelers also have such small lights, which might be treated as false light spots during the analysis process.

The real vehicle headlights are almost rounded in shape but spots due to reflections are not; most of them are vertical or horizontal lines. This shape difference was taken into account to eliminate the reflection effect from the image. The method was initiated by calculating the height-to-width ratio of every bright spot and eliminating the unlikely candidates.

2.8 Headlight Pairing

After clearing out the unwanted cluster pixels, the process was moved towards the most important and the critical step of headlight pairing. The shape and size of the light, distance between the lights in pairs and the minimal distance between the vehicles were considered as parameters to match with the light clusters. It is not practical to identify a particular vehicle by matching all the parameters together. Identifying the most prominent feature first and then trying to match with other features was more effective. Since it is not necessary to find the exact type of the vehicle, just having a few sets of parameters was enough to find such groups.

2.9 Vehicle Counting

In counting vehicles, first a region of interest was defied. Vehicle counting was commenced as soon an object appeared from the upper boundary of the region of interest. In order to check the accuracy, the number of vehicles were counted manually from the video and compared with the automated counting given by the developed system within fixed time segments. In the selected traffic junction the vehicles were counted in 20 second time segments.

2.10 Vehicle Classification

Vehicle classification was performed by categorizing them into two categories; heavy and light according to their headlight patterns. The vehicles having two parallel headlights were categorized as heavy vehicles and the ones having single headlight or three light pair were categorized as light vehicles. It was assumed that all vehicles have their headlights switched on. The following table shows the vehicles that fall into these two categories.

Table 1: Classification scheme of vehicles

Heavy	Car, Van, Lorry, Bus etc.
Light	Motorbike and Three-wheelers

3. RESULTS AND DISCUSSION

A set of two hundred consecutive frames was used to develop the system. The frame number one is shown below (see Figure 1(a)) as an example to get an idea about the complexity involved in the identification. Since only headlights are tracked, vehicles moving from top of the image frame to the bottom of the image frame are the candidates.

(a)

(b)

Figure 1: (a) Original image frame (b) Difference image (frame 8-1)

3.1 Pre-Processing

The original frames in RGB colour format were converted into greyscale format to reduce the complexity of the images. To remove the noise due to camera effects**,** a median filter was applied. To identify the moving vehicles (headlights) the background has been subtracted from the image using the frame difference method. Figure 1(b) is the resultant image after subtracting the frame number 8 from the current frame (frame number 1). In the selected frame difference technique the gap between the two frames was set as 7 frames.

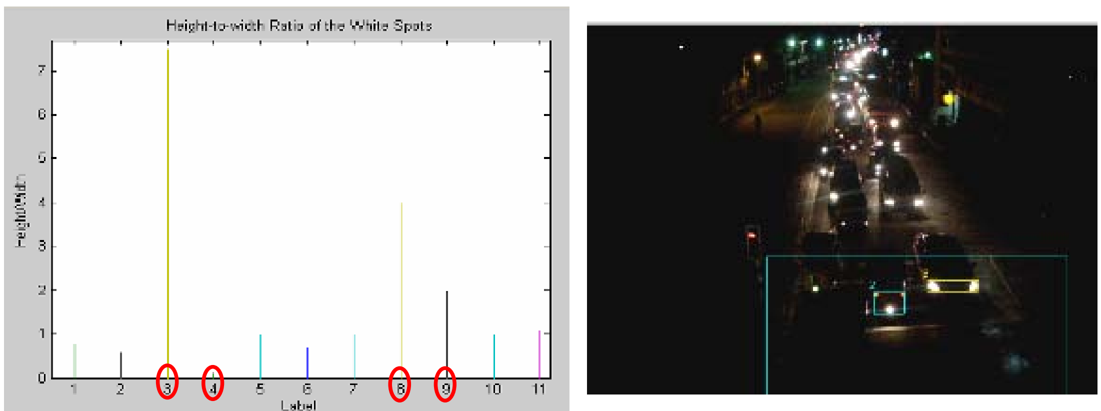
Then the thresholding technique was applied to the resultant images from the previous step. The headlights in the bottom region of the image have been successfully filtered and their shapes remain as in the original image. However, the headlights in the top region of the image were not filtered properly hence difficult to use in headlight paring. This is due to the occlusions among vehicles in the top region of the image which are the distance vehicles. Even if there are no occlusions and the entire set of headlights was filtered out to the output, it will be too complex and time consuming to pair a huge set of light spots at all times. Therefore, it is much more effective to select and analyze a limited region, where headlight pairs can be reliably detected.

The next step was to remove the false bright regions from the image. From the false bright regions the spots due to reflections were removed first. The ratio values can be analyzed with the shapes of the spots. Most of the real headlights spots are rounded in shape hence give a ratio which is close to one. The horizontal or vertical line shaped regions give a significant deviation from the value one (see Figure 2(a)).

3.2 Headlight Pairing

The next step was paring the set of bright clusters to identify headlight pairs on the image. After applying the headlight pairing mechanisms, the system has identified three headlight groups (see Figure 2(b)). There is a single cluster to the left of the image, which has not been identified as a vehicle headlight but considered as a false bright region on the image.

In the original image frame, the first two vehicles are three-wheelers, but in Figure 2(b), only the 2nd group of cluster indicates the true light arrangement of a three-wheeler and the 1st group indicates just a single light and has identified as a vehicle without considering its type. Hence it is not practical to match with 100% accuracy.



(a) (b)

Figure 2: (a) Height-to-width ratio of light spots (b) Image after headlight pairing

3.3 Vehicle Counting Results

The counting of identified vehicles were carried out through the developed system and also by manually in each 20 sec time period of the video clip. The manual counting was also done from the video sequence by selecting the same region. The results obtained through the manual (circles) and automatic counting (squares) are shown in Figure 3.

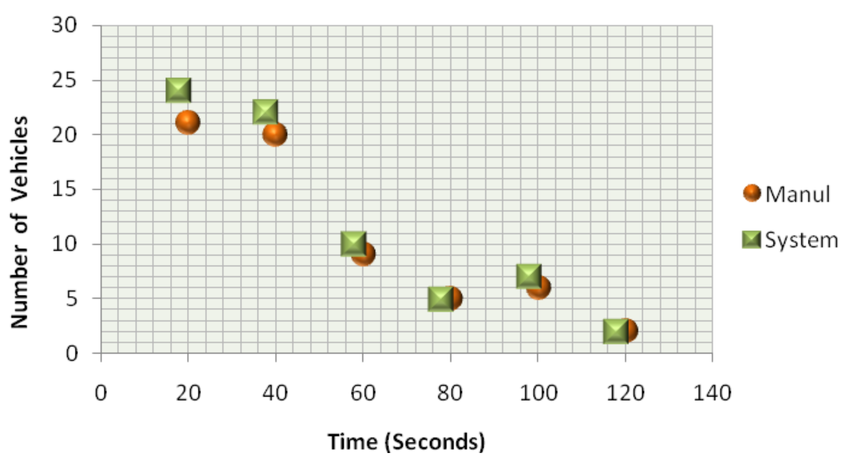


Figure 3: Comparison results of vehicle counting.

The system has given a positive deviation from the actual count. This can happen most of the time due to false bright regions in the image. The system has given an average error of 11% for the vehicle counting. Hence the accuracy of the system can be given as 89%, which indicates that the system performs quite reasonably.

3.4 Vehicle Classification Results

The vehicle classification results obtained from the developed system and by manually in each 20 sec of time period are given in the Figure 4. The classification was done for two categories of vehicles defined as heavy and light. Here also the manual counting was done from the video sequence by selecting the same region.

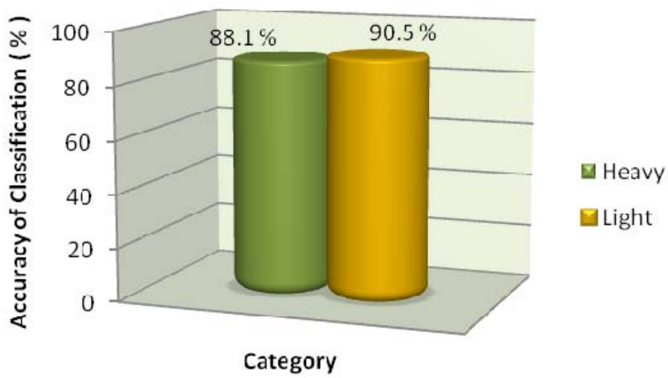


Figure 4: Vehicle Classification

The system classifies heavy vehicles with an average error of 12% and light vehicles with an average error of 10%. Results indicate that the system performs better in light vehicle classification with the accuracy of 90% which is approximately 2% higher than the heavy vehicle classification (which shows an accuracy of 88%).

3.5 Failure Cases

When all headlights of a vehicle are not illuminated or due to occlusion, the vehicle could be wrongly classified. For example, a three-wheeler having only the two side lights illuminated will be categorized as a heavy vehicle (Figure 5(a)). A bus in front of a car with only one headlight is visible will be classified as a light vehicle (Figure 5(b)).

(a) (b)

Figure 5: Vehicle identification errors

4. CONCLUSIONS

This paper presents the results of counting and classifying vehicles in video sequences of traffic scenes captured from a fixed digital camera under night conditions. Vehicle identification was carried out through the headlights; hence there were many challenges in pairing vehicle headlights correctly. At the initial stage of this work, it was assumed that the headlights of all vehicles are switched on and all headlights in vehicles were working properly. But this may not be true in some instances which creates automatic counting and classification a real challenge.

By analyzing the results obtained from the developed system it was found that the system performs with high accuracy for vehicle counting. Most of the time system shows a positive deviation from the actual count due to false bright regions in the study environment. In vehicle classification, a reasonable accuracy for both heavy and light vehicle identification was seen. On average the system was able to track the vehicles under night conditions. Especially, when the vehicles flow rate is small, the system can count and classify vehicles with almost 100% accuracy.

Although not discussed here, field trials were also carried out to study the possibility of estimating the speeds of vehicles under night conditions. Preliminary results indicated that speed detection can be carried out through the same video frames under night conditions. Hence as a future work, the system can be further developed by integrating the speed estimation methods to the developed system to track high speed vehicles at night.

Acknowledgements: This research is supported by the National Science Foundation (NSF) grant RG/2007/E/03. Authors wish to acknowledge NSF for providing financial assistance in carrying out this work.

5. REFERENCES

[1] C.C. Lee, Moving object detection at night, Department of Electrical-Electronic Engineering, University of Technology, Malayasia (2007)
[2] R. Cucchiara, M. Piccardi, Vehicle detection under day and night illumination, Proc. 3rd ICSC on Intelligent Industrial Automation and Soft Computing, Italy (1999)
[3] M. Piccardi, Background subtraction techniques: A review, IEEE conference on Systems, Man and Cybernetics, 4 (2004) 3099-3104
[4] J. Dailey, L. Liv, Video image processing to create a speed sensor, Department of Electrical Engineering University of Washington Seattle, Washington (1999)
[5] C.J. Setchell, Application of computer vision to road-traffic monitoring, Department of Electrical and Electronic Engineering, University of Bristol (1997)
[6] L. Grammatikopoulos, G. Karras, E. Petsa, Automatic estimation of vehicle speed From uncalibrated video sequences, Modern Technologies, Education and Professional Practice, in Geodesy and Related Fields (2005)
[7] L.G.C. Wimalaratna, D.U.J. Sonnadara, Estimation of speeds of moving vehicles from video sequences, IPSL, Proc. 24th Technical Session, Sri Lanka (2008)
[8] http://en.wikipedia.org/wiki/Grayscale
[9] http://www.cs.washington.edu/research/metip/tutor/tutor.Filtering.html