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# Vision based Vehicle Counting for Traffic Congestion Analysis during Night Time

**S. Padmavathi*, C. R. Naveen and V. Ahalya Kumari**

Computer Science, Amrita University, Coimbatore - 641112, Tamil Nadu, India;
s_padmavathi@cb.amrita.edu, crnaveen1994@gmail.com, ahalyaarjun95@gmail.com

## Abstract

**Background/Objectives:** To create an automated system that controls the traffic signals effectively based on the instantaneous calculation of traffic congestion during the given time using image processing techniques. **Methods/ Statistical Analysis:** Vision based Congestion analysis is done based on the vehicles counted from the camera fixed on the signal post. In this paper, the vehicles are detected based on head lights and counted as two wheelers or four wheelers. The congestion is categorized into light, medium and heavy based on this count. **Findings:** The headlights are separated from the illuminated bright spots by considering its circular and elliptical nature. The accuracy of identifying four wheelers depend on the pairing of the head lights. The existing pairing algorithm fails when one head light is hidden by other vehicles. In this paper, a simple pairing algorithm based on the spatial adjacency is experimented. This had less accuracy due to pairing of two wheeler head lights with that of four wheelers. The problem is alleviated by considering a varying scale factor proportional to the perspective projection of the vehicles in the line of sight. The accuracy of counting increased to 98%, where the drop is due to non-elliptical blobs of head lights that were not detected. **Improvements:** To guarantee the robust performance of the system, particularly the accuracy and the real-time processing speed. Limitation: The presence of fog lights in modern 4 wheelers are detected as separate cars which reduces the accuracy. The area of improvement will be to consider them as fog lights of the same car and not to mark them as a separate 4 wheelers.

**Keywords:** Head Light Pairing Algorithm, Night Time Traffic Analysis, Traffic Congestion Analysis, Vehicle Counting, Vehicle Detection, Vision based Traffic Analysis

## 1. Introduction

Traffic congestion analysis in real time is an emerging research area and very needful in the present scenarios. We can match the traffic density of each direction to conditions, such as too low and low and also consider the allotted time for each side as a traffic function of that side in relation to the traffic of other sides of a junction[1]. Several instruments like RFID detectors or radars exist for capturing the real time traffic, the video based identification is the most effective method because of its durability and imperishability[2].The timeline view of videos helps us in identification of vehicles that are moving. Video based method for capturing the real time traffic will be helpful because it doesn't require any additional sensors or tags from the vehicle users, data could be collected from a single point as required by the traffic control people[3].

Traffic surveillance system which is used to detect and track vehicles on the highway utilizes motion detection methods as basic algorithms[4]. However, this approach suffers serious drawbacks while analyzing the traffic congestion in the videos. On the highway there is little or no overlap between the vehicles and the movement of the vehicles is prominent. These are ideal situations for motion detection algorithms which cannot be expected in congestion analysis[5]. These problems motivate us to approach Traffic Surveillance in a systematic methodology which integrates different advanced Computer Vision and Intelligence techniques[3]. Several algorithms have been proposed to weigh the congestion during heavy traffic hours. The effective approach lies in detecting the vehicles that are completely hidden or sometimes partially visible. The data-sets for the real time traffic monitoring systems are obtained from the surveillance cameras installed on top of the traffic signals. These cameras are equipped

* Author for correspondence

with Infra-Red (IR) sensors which provide us a clear vision of the vehicles during night time and bad weather conditions[6]. This helps in eliminating the issue of handling day and night videos with separate cameras. Certain cameras are meant to monitor traffic only during daytime as monitoring of traffic during night time captures images with very high contrast or weak light sensitivity which makes processing of the images a difficult task[7,8].

In this paper, the videos captured during night time using visible light camera is used for traffic congestion analysis. The congestion analysis is done by counting the vehicles present in a particular frame of the video. The vehicles are counted based on the headlights. The block diagram of the entire process is described in Figure 1.

Initially the video from the surveillance cameras are taken as input. The frame is extracted at the time when congestion analysis is required. Headlights of the vehicles are detected based on the bright spots using color segmentation techniques[9–11]. The reflections and other illumination spots are eliminated by using thresholding. Based on this, the vehicles are identified as 2-wheelers or 4-wheelers which are later counted and specified as the output.

Section 2 provides the various methods available for vehicle detection. Sections 3 gives an insight into the proposed methodology, vehicle detection and pairing algorithms utilized for congestion analysis. Section 4 discusses the experimental results and Section 5 elucidates the conclusion and future enhancements.

## 2. Night Time Vehicle Detection

The major methods taken into consideration for detecting the vehicles during night time are: Feature identification[12,13] such as Wind shield based Identification & Headlight based identification[14]. Modern windshields are generally made of laminated safety glass, which consists of two curved sheets of glass with a plastic layer laminated between them for safety, and are bonded into the window frame. Motorbike windshields are often made of high-impact acrylic plastic. The windshields can be identified as the upper part of the headlights i.e. above two bright blobs. Once the bright blobs are identified, the identification of windshields is not too complex[12]. Based on the size of the windshields identified using edge detection techniques[13,15,16], the vehicles can be classified either as Heavy motor vehicles or light motor vehicles[17,18]. Since a few 2 wheelers do not have wind-shields, they remain undetected, which fails the effectiveness of an algorithm. In order to identify even 2 wheelers, we have to adapt to the technique of vehicle identification using head lights detection[10,11,19].

The headlights are identified as bright pixels from the extracted frame[20]. But unfortunately not all bright pixels are assumed to be headlights. They can be streetlights, reflection of the headlights, and other several false alarms[6,21]. In order to extract only the headlights from several other bright spots. The algorithm for vehicle detection during night time is presented under Section 3 in detail.

## 3. Proposed Methodology

### 3.1 Color Segmentation by Delta-E Color Difference

The headlights seen are white spots (Bright) or yellow, blue tinted white spots. The RGB image is converted to LAB color space to handle the color components efficiently. The average values are calculated as LMean, aMean and bMean. Uniform standard image of only that mean LAB color is obtained by multiplying the MeanLAB arrays with a 2D all-one array. Then delta image channels are calculated as the difference between the actual values and the mean values as deltaL, deltaa, deltab.

deltaL = LChannel – Lstandard
deltaA = aChannel – aStandard
deltaB = bChannel – bStandard

Where LChannel, aChannel and bChannel are the LAB channels of the actual image and Lstandard, aStandard and bStandard are the LAB channels of the uniform image.

The Delta-E image represents the difference of LAB color values from the mean value and is calculated for each pixel using the formula,

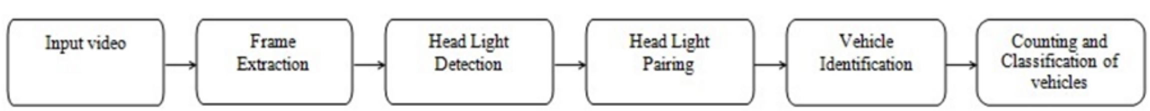


**Figure 1.** Architecture diagram of the proposed method.

Delta-E= sqrt (delta $L^2$ + delta $A^2$ +delta $B^2$)

From the Delta-E image a sample headlight region is chosen by the user which is marked as the masked region. The intensity values from the masked region are used to decide the threshold (T) for segregating the headlight regions in the entire image. Using the threshold, the image is converted to binary image with the headlight regions as 1.

### 3.2 Head Light Detection:

Blob Analysis is done on the binary image and parameters such as orientation (θ), Diameter, Eccentricity (e) and centroid of each blob are extracted. The orientation of the blob region represents the angle made by the major axis with the x-axis. The headlights are approximately horizontal or inclined due to the design of the car or due to perspective projection. Blob regions which satisfy this criterion are possibly the headlights while others are rejected as reflections. Hence the blob regions with orientation between 0 and $\theta_t$ are accepted as headlights.

The eccentricity is calculated using the formula,

e = majorAxis/minorAxis

The eccentricity value is 1 for a perfect circle since the headlight of the cars varies from elliptical to a circular region. The eccentricity values greater than or equal to 0.6 is used for filtering the headlights. The blobs filtered out using the above two criteria are taken as the headlight region. The diameter, radius and centroid or these filtered regions are calculated.

The headlights of 4-wheelers appear in pairs and the headlight if the 2-wheelers appear as a single blob. Hence a pairing algorithm is used to identify the 2 blob regions belonging to a 4-wheeler. After the pairing algorithm, the paired headlights are counted as 4-wheelers and the blobs that are not paired are identified as 2-wheelers. When the 4-wheelers are partially hidden in the traffic, only one headlight will be seen due to the vehicles in front of it. Such partially hidden headlights are identified by looking for the presence of connected components and vertical lines close to the headlights. This reduces the chance cars being falsely identified as bikes.

### 3.3 Pairing Algorithm

The centers of all qualified circular white spots which represent the headlight of vehicles are considered for the pairing algorithm. The headlights of the 4-wheelers will be horizontally nearby or with a slight difference in the vertical distance due to the variation in the line of sight and the alignment of the vehicles. Hence the blobs are paired with the neighboring blob that has the minimum horizontal distance to its right and with the small difference in their vertical distance. For every blob center from left to right, all centers at minimum horizontal distance are found and the difference of their vertical distance is calculated. The minimum of the vertically distant center is considered the best pair if its value is less than $T_h$ and also if it has not been previously paired with any of the headlights. All such matches are classified as 4-wheeler and if no such match is found, it is classified as two-wheeler. The headlights of the 2-wheelers standing close by the 4-wheelers are paired by the above mentioned algorithm. Hence giving incorrect results.

To avoid this problem, virtual line of sight is considered with the perspective projection on the image and appropriate scaling factor which is varied along the line of sight. The distance between the headlights is larger for vehicles nearby and smaller for vehicles that are far away. The nearby vehicles typically lie in the lower half of the image and vehicles far away are lying on the upper half of the image. This variation is taken into consideration for the paring algorithm as a scaling factor that is proportional to the y co-ordinate of the headlights position. The centroids of all headlights are considered for calculating virtual reference line which is a horizontal line with y-value calculated as mid-y in equation,

midy = (max(y) + min(y))/2

where, min y and max y represent the minimum and the maximum y co-ordinates of the blob regions extracted from the image.

The scaling factor is calculated using

sc = (y/midy)*2

As earlier, the blobs are traversed from left to right and for every center a left best match and right best match are found, and the best of two is found considering the scaling factor and the minimum of vertical distance. If the right blob is the best match, pairing is done but if the left is a best match it means that it could have been paired already with another blob. Hence the car count is kept the same and the left out blob is marked as missed bike. The paired headlights are marked with a line joining the centers which are then utilized for counting the cars. The count of the vehicles in the image is calculated using the formula,

Cars_count = number-of-pairs
Bike = actual_found_bikes + missedBike – cars
Actual found bikes = spots with no pair
missedBike = spots with no best pair UNION end-point-of-cars.

## 4. Experimental Analysis

The traffic surveillance camera videos are obtained for Coimbatore, Tamil Nadu roads. The total number of videos obtained approximately equals 1TB storage which is of the format.avi.Traffic congestion analysis algorithm is tried on samples having duration less than 15 minutes.

Figure 2 is the exact image extracted from the surveillance camera video prior performing any enhancement. Figure 3 is the Delta-E color segmented image.

**Figure 2.** Original image prior performing enhancement technique.

**Figure 3.** Delta-e color segmented image.

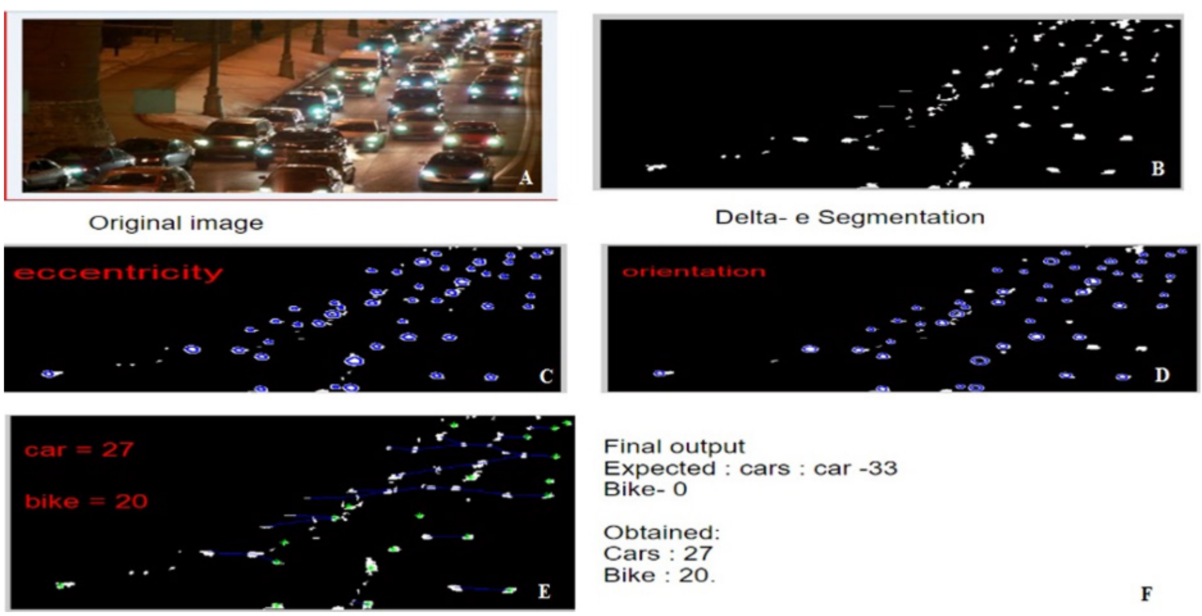


**Figure 4.** A. Original image, B. Delta-E Segmented Image, C. Filtered based on eccentricity D. Filtered based on orientation, E. Image showing expected count vs. obtained count of the vehicles, F. Final output.

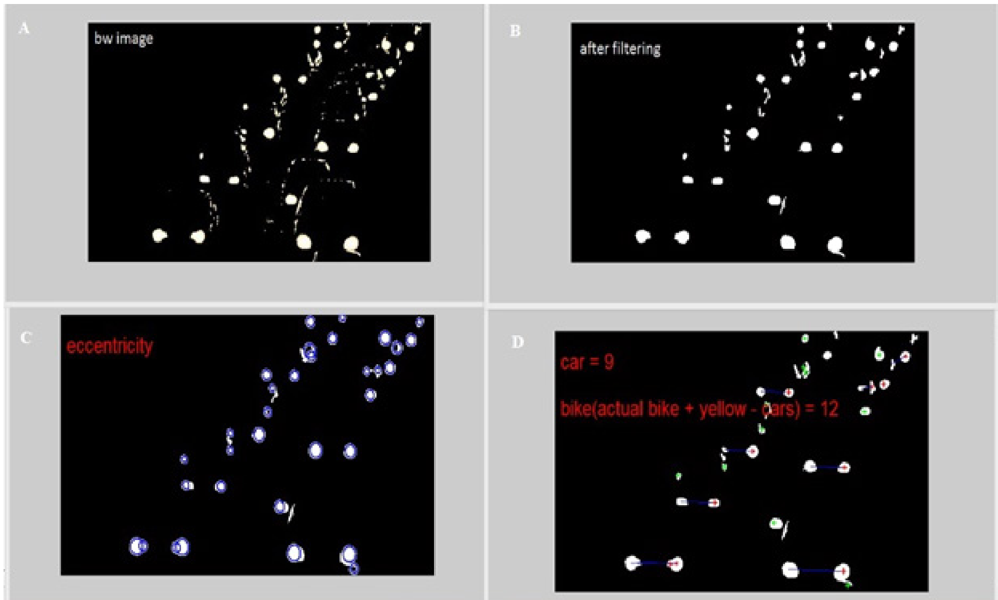


**Figure 5.** A. Black & white image, B. Image obtained after filtering, C. Filtered based on eccentricity, D. Image showing the exact count of vehicles.

Figure 4a shows a particular frame extracted from the night time video. Default tolerance (T) to identify the bright spots in the Delta-E image is set to be the mean delta E in the masked region plus two standard deviations. Once the bright blobs are identified as shown as white spots in Figure 4b they are further segregated as headlights using region properties such as eccentricity as shown in Figure 4c and orientation as shown in Figure 4d. The orientation threshold $\theta_t$ is set as 60 to qualify the blob as possible headlight while the other regions would be reflections.

Eccentricity values greater than or equal to 0.6 are filtered out to account for elliptical headlights. The count of the vehicles after applying pairing algorithm without the scaling factor is shown in Figure 4d. The actual number of cars and bikes in the frame are 33 and 0 respectively whereas the algorithm listed 27 cars and 20 bikes which gives an accuracy of 82%.

From Figure 5a when only one headlight is visible, if it possesses certain characteristics such as connected components or vertical line above the bright blob it is classified as car. The connected components are blacked out and only the bright blobs are prominent in Figure 5b. After introducing the scaling factor (sc) the car and bike obtained according to the algorithm are 9 & 12 respectively which is the same as the count obtained from the original image. The accuracy has increased to almost 98%. This is introduced in consideration with the perspective projection portrayed by the images.

Table 1 displays the various scenarios taken into consideration for calculating the accuracy. From several videos analyzed, with respect to the number of vehicles identified, the scenarios are classified and tabulated.
The accuracy rate is calculated using the formula,

Accuracy = (number of true positives + number of true negatives) / (number of true positives + false positives +false negatives + true negatives)

**Table 1.** Performance analysis

| Congestion rate | Actual no. of vehicles | Detected & classified | True Positive | True Negative | False positive | False negative | Accuracy |
|---|---|---|---|---|---|---|---|
| Low | 6 | 6 | 6 | 5 | 0 | 0 | 100% |
| Medium | 10 | 9 | 9 | 3 | 0 | 1 | 92.3% |
| High | 23 | 26 | 23 | 5 | 3 | 0 | 90.3% |
| Cloudy/Rainy day | 12 | 10 | 9 | 11 | 1 | 1 | 90.6% |

## 5. Conclusion and Future Enhancements

Vehicle detection from night time videos is a challenging task due to the presence of non-uniform illumination. Headlight based vehicle detection algorithm has less accuracy due to the presence of reflection from various surfaces. In this paper the headlights are identified based on elliptic bright spots. A pairing algorithm is proposed which segregates the headlights of 4-wheelers from that of 2-wheelerls. The size of the headlight varies based on the distance from the cameras. A suitable scaling factor is suggested based on perspective projection. The 4-wheelers today possess more than a pair of headlights. The headlights close to each other is identified as single blob region and counted accurately. However, the fog lights and the headlights with sufficient gap between them are identified as separate 4-wheeelers which are not effective in calculating the number of vehicles during night time. The future enhancement of the project is to calculate the relative distance between the headlights and fog lights and not mark them as separate vehicles.

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