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# Vehicle Detection, Tracking and Counting Using Gaussian Mixture Model and Optical Flow

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***Authors' contributions***

*This work was carried out in collaboration among all authors. Author MMA designed the study, performed the statistical analysis, wrote the protocol and wrote the first draft of the manuscript. Authors YL and AA managed the analyses of the study. Author LZ managed the literature searches. All authors read and approved the final manuscript.*

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## ABSTRACT

Vehicle detection, tracking, and counting play a significant role in traffic surveillance and are principle applications of the Intelligent Transport System (ITS). Traffic congestion and accidents can be prevented with an adequate solution to problems. In this paper, we implemented different image processing techniques to detect and track the moving vehicle from the videos captured by a stationary camera and count the total number of vehicles passed by. The proposed approach consists of an optical flow method with a Gaussian mixture model (GMM) to obtain an absolute shape of particular moving objects which improves the detection performance of moving targets.

*Keywords: GMM; vehicle detection; counting; optical flow; tracking.*

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## 1. INTRODUCTION

Because of the increase in population, the use of vehicles is increasing day by day both in developed and developing countries which have led to an increase in the number of vehicles on highways and causing traffic problems such as congestion and severe road accidents. So for the development of the Intelligent Transport System (ITS), traffic monitoring is a significant tool in collecting essential information about the passing vehicles, including the number of vehicles, speed, queue lengths, time occupancy rate, and congestion on the roads. Hence, for detection and tracking of vehicles image processing and computer vision techniques have been applied for the analysis of traffic flow with video sequences as an alternative method require neither camera control by humans nor the placement of sensors [1]. The cameras used for video acquisition in the monitoring of traffic are stationary because it is easier to detect vehicles from stationary cameras and are placed above on the pole to get an optimal view of the passing vehicles. The methods used for the detection/tracking of vehicles in a video sequence using image/video processing are [2]: Matching, Threshold and segmentation, Point detection, Edge detection, Frame differentiation, and Optical flow methods. The frame difference technique is very adaptable to background changes and uses continuous frames of video to perform frame differences for the extraction of moving objects in a video. The optical flow method has the supremacy to detect velocity or motion of target from video frames. In this paper, vehicle detection, tracking, and counting are done using the optical flow and GMM method. Using these techniques together produces good results of detection, tracking, and counting.

The remaining structure of this paper is organized as follows; section 2 gives the details of the related work. In section 3 proposed methods are explained. In section 4, experimental results with input data are mentioned. And section 5 concludes this paper.

## 2. RELATED WORK

Estimation of vehicle speed based on detection and tracking of vehicles with an approach of optical-flow implemented by Hua et al. [3]. Nilakorn [4] proposed video-based vehicle detection and counting method by computer vision technology. Background subtraction technique is used in a video sequence to find the foreground objects (vehicles). Accuracy of the proposed method of vehicle counting depended on the input videos varied from 95-99%. Hyeok [5] proposed an algorithm for the detection and counting of vehicles passing through a defined point in a video sequence. The proposed algorithm calculates the estimated value of speed and passing vehicles which are counted by GMM background modeling, Pyramidal Lucas-Kanade algorithm, and histogram of an object. Amirali [6] proposed a broad approach under several environmental states to localize the targeted vehicles. The geometry features extracted from the video are constantly tracked and consistently projected onto a 1-D profile. For the detection of vehicles, the proposed method relied on the motion behavior and temporal details of features, which compensate for the difficulty in the identification of vehicle types, colors, and shapes. Motion in the range of view with respect to vehicle is modeled probabilistically. Targeted vehicles are separated from the background by the hidden Markov model (HMM) and tracked.

Bhushan [7] introduced a morphological approach for the detection of vehicles based on a video. Investigations of images from traffic video were performed: frames fragmentation, morphological operation on frames, and counting of vehicles. The proposed approach gave an accuracy of 1.02%. Matveev [8] presented a method for the detection of vehicles with colored images acquired by aerial photography. The main solution is that most of the vehicles are painted in one color and have almost the same shape and size. This permits segregating regions engaged by vehicles from the background as areas with certain geometrical properties. By hierarchical clustering regions in images are created as it is induced by spatial neighborhood and color probability. This method was tested with the dataset of rural and urban images as it contains 2226 images of vehicles. Wang [9] proposed a method of speed detection of vehicles using surveillance of video. Background and three frames differencing approach are used to extract the features of vehicles. For tracking and positioning of the vehicles, they implemented the centroid feature extraction technique. In the end, a differencing mapping algorithm is used to estimate the speed of vehicles between actual distance and pixel distance.

Seenouvong et al. [10] presented a method based on computer vision for the detection and counting of the vehicles in a video. The background subtraction algorithm is used to extract the foreground objects. To identify the moving vehicles, different computer vision techniques are applied such as thresholding, morphological operation, and hole filling, etc. Arash [11] presented a method that estimates the velocity of vehicles. A stationary camera is placed above the road which is used to record the video of traffic and it is adjusted based on geometrical parameters. Camera calibration for a precise calculation can be possible, but the estimation of accurate speed would be difficult to achieve. Y. L. Ma [12] proposed an improved GMM model for the detection of vehicles as it identifies background for the foreground in different environmental conditions. The improved version of GMM is obtained when combining the frame difference method with GMM. Due to the increase of the demarcation point between foreground & background, the moving vehicles are detected.

## 3. PROPOSED METHOD

The proposed method is based on the Gaussian mixture model (GMM) and optical flow. The background is subtracted by GMM and parallel estimated the optical flow whose vectors are in complex form. In optical flow, binary thresholding is performed using the average value of moving intensities which is calculated as modulus of each complex value connected to all pixels. Noise is removed by using a median filter and morphological operators and the foreground obtained from GMM are fused with the optical flow field to get better results of moving vehicles which are then detected by bounding boxes. Fig. 1 shows the flow diagram of the proposed method.

### 3.1 Gaussian Mixture Model (GMM)

Gaussian mixture model consists of a mixture of K Gaussian distribution illustrated by these parameters: mean (μ), weight (w), and variance (σ2). In every frame, each pixel on an image has non-identical parameters. This method gives good results when using for background extraction [13]. Pixels whose weight factor is low and the standard deviation is high are considered as foreground pixels, whereas pixels whose weight factor is high and has the same value of standard deviation are considered as background pixels [14]. The Gaussian mixture model was proposed by Friedman & Russel in [15]. Equation (1) gives the probability of a particular pixel of K Gaussian Distribution with intensity and time.

$$P(x_t) = \sum_{n=1}^{k} \omega_n * \eta(x_t, \mu_n, \sum\nolimits_n) \tag{1}$$

The grayscale model of background varies from 0 to 255 by applying the weight and mean of the Gaussian model and is expressed in equation (2).

$$B_t = \sum_{i=1}^{K} \omega_{n,t} \cdot \mu_{n,t} \tag{2}$$

### 3.2 Optical Flow

Optical flow is the detectable motion of any objects between the back-to-back sequence of frames, and in a video, it is caused by the motion of an object in a scene with respect to the camera. Optical flow defines a scattered and thick vector field that can be used for the segmentation of a moving object. A displacement vector is allocated to every pixel position which is used to estimate the position of a particular pixel in another frame.

Consider we have two frames $F(a,b,t_n)$ and $F(a,b,t_{n+1})$, so the optical flow is defined as:

$$F(a,b,t) = F(a+\delta a, b+\delta b, t+\delta t) \tag{3}$$

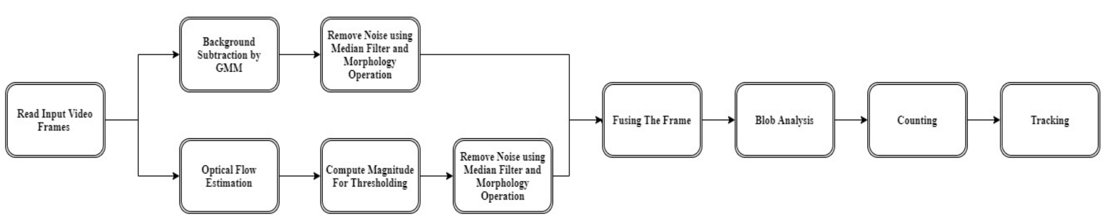


**Fig. 1. System flow diagram**

**Fig. 2. Grayscale of input video frames**

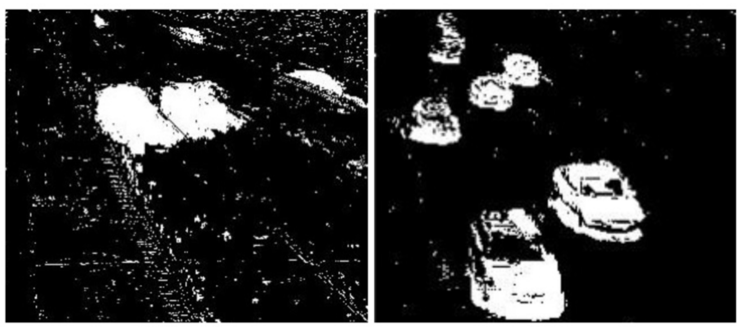

**Fig. 3. Background subtraction by GMM**

*da* and *db* define the motion vector over time *dt*. Fig. 4 shows the position of a vehicle at point x and time t. When it moves the value of the position changes and this is displayed in Fig. 5. The motion vector in Fig. 8, shows the moving objects in an input video sequence.

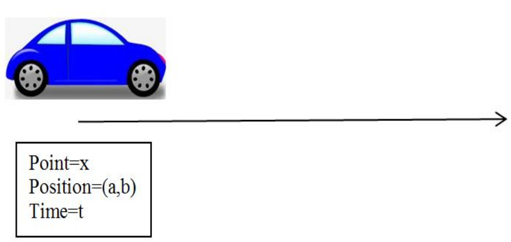


**Fig. 4. The position of the vehicle at point x**

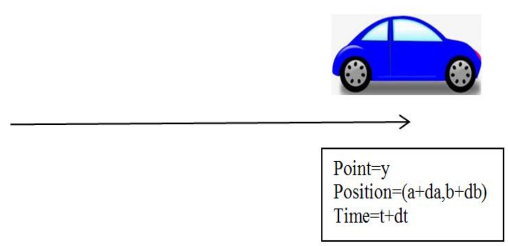


**Fig. 5. Position of a vehicle at point y after certain motion**

The video is taken using a stationary camera over the road mounted at the pole above. By applying the Horn-Schunck algorithm (1981), the optical flow approximates the direction of motion of the object and its speed from the back-to-back frame of a video sequence. Several techniques of image processing such as image segmentation, median filtering, and morphological operators are applied consecutively to acquire our required result for the examination. The simplest technique of segmentation is thresholding which differentiates the moving object (foreground) and unchanged background. The foreground is represented by white and background is represented by black as shown in Fig. 6.

### 3.3 Denoising

The detection process of moving vehicles is not absolute due to the presence of noise (i.e salt and pepper). Different filters and morphological operations are used to remove noise, which improves the accuracy of detection. A median filter is applied, a non-linear digital filtering method which is used to eliminate noise from an image though maintaining edges. It is certainly used to remove 'salt and pepper' noise. The median filter operates pixel by pixel and changes each pixel value with the median of neighboring pixels and creates notable outcomes for the identification of objects. Equation (4) shows a non-median filter with output *y(n)* and input *x(n)*.

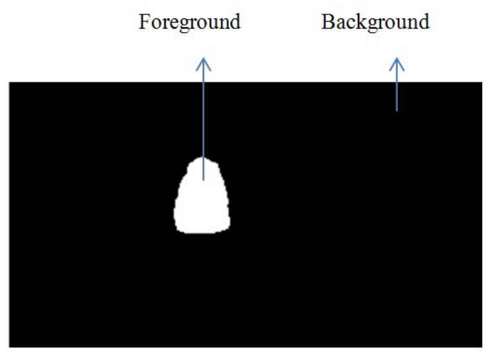


**Fig. 6. Background and foreground**

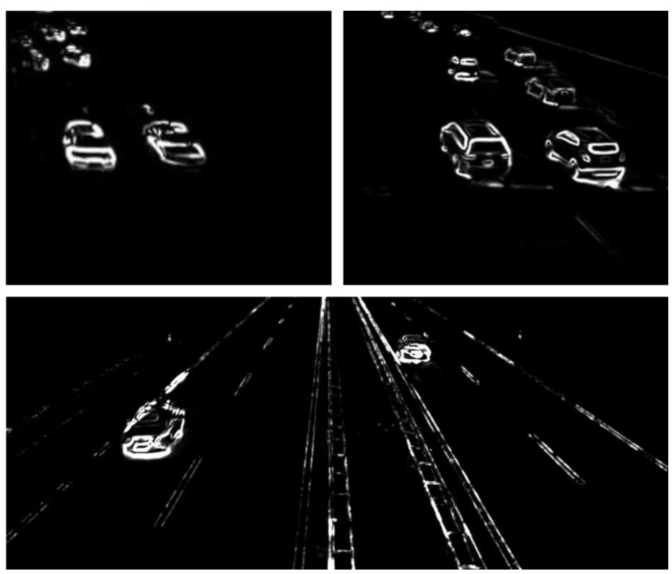

**Fig. 7. Optical flow field**

$$y(n) = median[x(n-k), x(n-k+1), ..., x(n), ..., x(n+k-1), x(n+k)] \tag{4}$$

Then morphological closing is used to remove small holes from moving target to make the detection more ideal. The close operation performs dilation followed by erosion and uses the same structuring element (SE). Equation (5) depicts the close operation, where dilation and erosion are represented by $\oplus$ and $\ominus$.

$$A \cdot B = (A \oplus B) \ominus B \tag{5}$$

**Fig. 8. Moving vehicles with the motion vector**

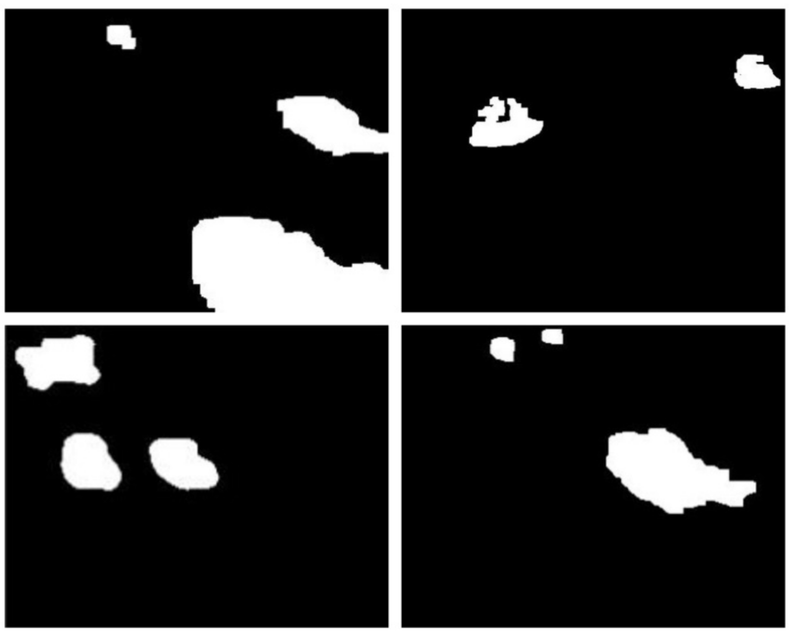

**Fig. 9. Segmented image obtained after the fusion**

### 3.4 Vehicle Detection

After the segmentation of an image and the noise is removed by using a median filter and morphological operations the image obtained from GMM and optical flow methods are fused for better detection of moving vehicles in the video sequences. The ratio between the area of blob and bounding box is computed if it is greater than 0.4, then the vehicle is detected. Fig. 9 depicts the extracted foreground which is then detected by blob analysis.

### 3.5 Counting and Tracking of Vehicles

Counting the total number of vehicles passing by plays an important role in an intelligent transport system. Vehicle detected by bounding box through blob analysis is used to count the number of vehicles. The image is traversed and each vehicle entering into the frame and is registered with a specific ID. If the vehicle is registered in the counter with that ID the counter is not incremented whereas if a new vehicle enters in a frame then the counter is incremented and the vehicle is registered. Fig. 10 shows the counting result of different video frames for which the vehicle is detected by using the bounding box. The specific ID assigned to a vehicle is also used to track that vehicle from a point when it is entered into the video until it vanishes. And this is done by assigning that ID also to the trajectories of each bounding box.

## 4. EXPERIMENTAL RESULTS AND DISCUSSION

5 different traffic videos are used for this experiment and all the input videos are of the day time. The simulation results are given in Table 1: Where the 1st column shows the input video, the 2nd column shows the actual number of vehicles in each video, 3rd column shows the detected number of vehicles in each video, and finally, the last column shows the percentage accuracy of each video. Fig. 11 shows the simulation results of each video graphically: where the input videos are shown on the horizontal axis and the actual number of vehicles, detected number of vehicles, and the percentage accuracy are shown on the vertical axis. In a few cases, occlusion occurs and two vehicles are counted as one which creates a little difference between the actual number of vehicles and the detected number of vehicles.

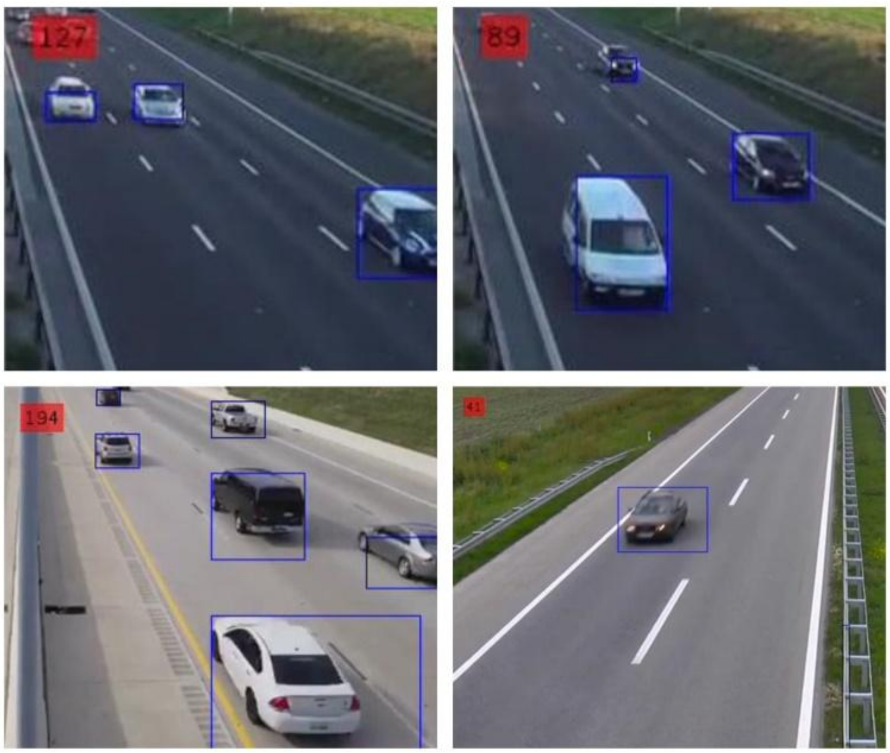


**Fig. 10. The output result of different input video frames**

**Table 1. Accuracy of detection and counting of vehicles**

| Input video | The actual number of vehicles | Detected no. of vehicles | Percentage accuracy (%) |
|---|---|---|---|
| Video 1 | 185 | 181 | 97.83 |
| Video 2 | 123 | 121 | 98.37 |
| Video 3 | 207 | 199 | 96.13 |
| Video 4 | 93 | 92 | 98.92 |
| Video 5 | 155 | 153 | 98.71 |

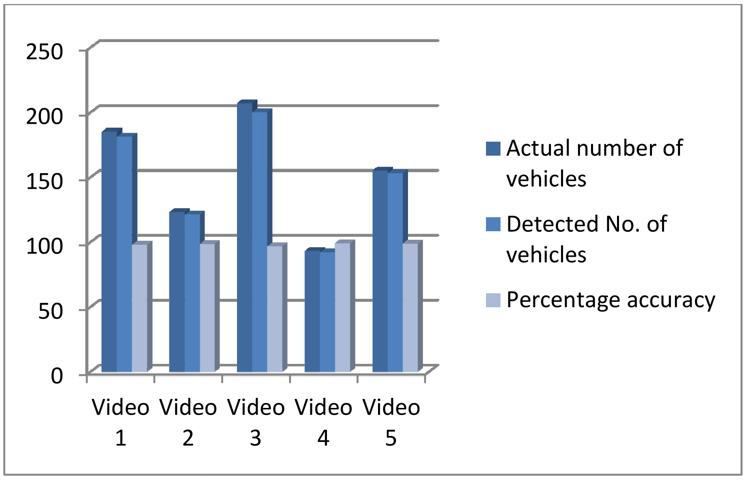


**Fig. 11. Graphical results of the accuracy table**

## 5. CONCLUSION

In this paper software-based low-cost techniques of vehicle detection, counting and tracking have been discussed using Optical Flow and Gaussian Mixture Model in video sequences. Optical flow calculates the intensities of moving pixels and computes the optical field flow which is fused with foreground object after the background subtraction by GMM to obtain better results. Finally bounding box generated by Blob analysis detects the moving vehicles. And then counting is done using the location of the bounding box on each pixel. The proposed method resulted in almost 97% accuracy for the counting and detection of moving vehicles, which is calculated from detected vehicles with respect to the observed vehicles.

## COMPETING INTERESTS

Authors have declared that no competing interests exist.

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