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## Vehicle Speed Estimation Using Gaussian Mixture Model and Kalman Filter

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### Abstract

Many countries use traffic enforcement camera to monitor the speed limit and capture over speed violations. The main objective of such a system is to enforce the speed limits which results in the reduction of number of accidents, fatalities, and serious injuries. Traditionally, the task is carried out manually by the enforcement agencies with the help of specialized hardware such as radar and camera. To automate the process, an efficient and robust solution is needed. Vehicle detection, tracking and speed estimation are the main tasks in an automated system which are not trivial. In this paper, we address the problem of vehicle detection, tracking, and speed estimation using a single fixed camera. A background subtraction method based on the Gaussian Mixture Model (GMM) is employed to detect vehicles because of its capability in dealing with complex backgrounds and variations in the appearance due to illumination and scale. Next, the detected vehicles are tracked in each frame by using the Kalman Filter. Finally, an estimate the speed of each vehicle is determined by using the perspective geometry model. The complete system is tested at our university campus and the results are promising.

**Keywords:** Vehicle detection, Gaussian mixture model, Kalman filter, Perspective geometry model, Vehicle speed estimation.

## 1 Introduction

Violation of traffic rules like speed limits, abrupt lane changes, etc., are a global problem and the enforcement agencies in different countries are interested in the development of smart traffic monitoring systems that are capable to detect traffic rules violations on the highways and roads automatically. Determining the vehicle speed is one of the primary tasks in systems which are designed to capture speed limit violations. Hardware-based and software-based methods are commonly employed to estimate the vehicle speed. Hardware based methods involve specialized sensors such as radars which are accurate and highly sensitive, but their assembly is difficult and are usually costly [1]. Software based methods employ complex algorithms to process data from cheap sensors like camera and are the focus of the research community due to the obvious advantage over their counterpart. To estimate the vehicle speed using image sequence obtained from a camera, it is necessary to detect and track the vehicles in the entire sequence. In this paper, we have developed a system that is capable to estimate the vehicle speed reliably using a single fixed camera installed on a bridge on the road. Vehicles are detected by using a background subtraction scheme based on Gaussian Mixture Model (GMM) which is efficient against changes in the appearance, scale, and background. Tracking is performed by employing the Kalman filter with constant velocity model assumption for each detected vehicle. Perspective geometry model is then employed to estimate the vehicle speed. We have performed several tests at our university campus and the results are encouraging.

The rest of the paper is as follows: a concise literature review is presented in the second section. Our proposed system for vehicle speed estimation is described in the third section. Experimental setup and results are presented in the fourth section. Finally, conclusions and future works are presented in the last Section.

## 2 Literature review

To identify moving objects in a frame, foreground is separated from the background by employing background subtraction methods. Several methods such as frame difference, approximate median filter, running gaussian average, optical flow, visual background extractor and gaussian mixture model, etc., have been proposed in the literature for this purpose [2]. Once detected, the moving objects are tracked in the entire image sequence with the help of trackers. Point tracking, kernel tracking and silhouette tracking are the most used techniques for tracking [3]. For speed estimation, the Euclidean distance between centroids of the bounding boxes of the detected vehicles is generally employed [4, 5].

In [4], moving vehicles are detected by gaussian mixture model based background subtraction technique. To remove noise in the foreground due to misclassification of the background, a median filter is employed followed by shadow removal and morphological operations. The speed of a vehicle is estimated by calculating the distance travelled by the detected vehicles and the time difference in consecutive frames. In a similar work [6], the author used background subtraction based on gaussian mixture model for vehicle detection followed by noise removal technique to account for misclassification of the background. Tracking is done by computing the Euclidean distance between the bounding boxes of the detected vehicles. Vehicle speed is calculated using the distance travelled by the detected vehicles in a certain number of frames and frame rate.

The author in [5] proposes to use background subtraction based on frame difference of three frames for detecting the moving vehicles. Centroids of the bounding boxes of a detected vehicle in consecutive frames are used to compute the distance travelled by the vehicle. Finally, vehicle speed is estimated by using the relationship between pixel distance and actual distance. In [7], background subtraction based on the gaussian mixture model is employed to detect the foreground. In order to remove noisy pixels which are caused by misclassification in the background subtraction, the density-based spatial clustering of application with noise (DBSCAN) algorithm is employed to cluster the foreground pixels related to a single vehicle and the bounding box is determined. Kalman filter and optical flow are used to track the vehicle in the image sequence. Average velocity computed by the optical flow inside a bounding box representing a vehicle is used to compute the vehicle speed. In a similar work [8], the authors employ gaussian mixture model for background subtraction and Kalman filter for tracking for

vehicle speed estimation. The results of vehicle speed estimation in light and heavy traffic conditions are presented.

In contrast to the above-mentioned research works, the authors in [9] propose a different approach for vehicle detection and speed estimation in low-light conditions. They employ normalized cross-correlation technique and centroid-area-difference to detect the headlights of a vehicle. Tracking is performed in successive frames using the distance between the centroids of the bounding boxes of the headlights. Finally, the pinhole camera model and Euclidean distance are employed to determine the vehicle speed. Stereo cameras have been used in [10] to estimate the vehicle speed on the highways. The vehicles are detected using a reference image and a background subtraction method based on the frame difference. A sparse depth map is computed using the stereo images where the correspondence between images is established by matching Speed Up Robust Features (SURF) descriptors in the left and right images. The depth map is used to compute the distance travelled by the vehicle in successive frames. The vehicle speed is estimated using distance travelled by the vehicles and frame rate.

### 3 Methodology

Our approach for vehicle speed estimation is composed of three stages as shown in Figure 1. In the first stage, background subtraction is performed with the help of Gaussian Mixture Model (GMM) to detect and extract moving vehicles. In the next stage, the vehicles are tracked using the Kalman filter. Finally, speed estimation is performed using the perspective geometry model and is reported for each vehicle in the view. Each stage of our proposed method is described in detail in the following sub-sections.

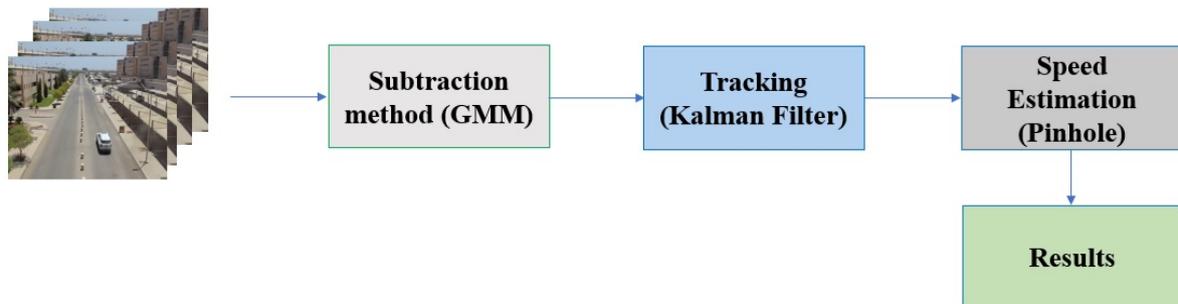


Figure 1: Block diagram of the system.

#### 3.1 Vehicle Detection

Detecting moving objects i.e., vehicles in the image sequences is the preliminary step for speed estimation. The objective is to localize each object (vehicle) in the image and represent it by a bounding box. In the last two decades, various approaches for detection of moving objects have been presented. Frame difference, optical flow and background subtraction are the commonly employed for the task of detection of moving objects [11].

In this work, background subtraction based on the Gaussian Mixture Model (GMM) is employed for vehicle detection following the work of Stauffer and Grimson [12]. It is a wellknown fact that GMM is robust to deal with cluttered background and appearance changes due to illumination, scale, etc. Each pixel in the image is modelled by a GMM which employs  $K$  Gaussians to track the changes in the appearance of the pixel. Typically,  $K$  ranges from 3 to 5 to achieve real time performance. Each Gaussian in the mixture is initialized with the gray value (or RGB color) of the pixel as the mean vector and the covariance matrix is assumed to be an identity matrix with an initial variance set by experimentation [13]. Let  $z_t$  denotes the pixel (gray value or RGB color) in a frame at instant  $t$  of

the video, we can write the mixture model representing the background as:

$$p(\mathbf{z}_t) = \sum_{j=1}^K w_j \eta(\mathbf{z}_t, \boldsymbol{\mu}_j, \boldsymbol{\Sigma}_j) \tag{1}$$

where  $w_j$  is the weight of the  $j^{th}$  Gaussian ( $\eta$ ) in the mixture with  $\boldsymbol{\mu}_j$  as the mean vector and  $\boldsymbol{\Sigma}_j$  as the covariance matrix.

The  $j^{th}$  Gaussian for single dimensional feature i.e. gray value of the pixel in the mixture has the following form:

$$\eta(z_t, \mu_j, \sigma_j^2) = \frac{1}{(2\pi\sigma_j^2)^{\frac{1}{2}}} \exp\left(-\frac{z_t - \mu_j}{2\sigma_j^2}\right) \tag{2}$$

In case where a  $d$ -dimensional feature vector (e.g., RGB color images) is employed, a Gaussian in  $d$ -dimensions has the following form:

$$\eta(\mathbf{z}_t, \boldsymbol{\mu}_j, \boldsymbol{\Sigma}_j) = \frac{1}{(2\pi)^{\frac{d}{2}} |\boldsymbol{\Sigma}_j|^{\frac{1}{2}}} \exp\left(-\frac{1}{2} (\mathbf{z}_t - \boldsymbol{\mu}_j)^T \boldsymbol{\Sigma}_j^{-1} (\mathbf{z}_t - \boldsymbol{\mu}_j)\right) \tag{3}$$

Once initialized, the mixture model tracks the appearance of a pixel over the entire image sequence by continuously adapting the parameters of the Gaussians of the mixture. Generally, the pixels related to the background do not have fast appearance variations as opposite to the pixels representing moving objects also known as the foreground. To adapt the appearance changes in the background, the  $K$  Gaussians in the mixture model are ranked according to their weights and the top  $B$  Gaussians fulfilling the following condition constitutes the mixture model for the background.

$$B = \underset{K}{\operatorname{argmin}} \left( \sum_{j=1}^K w_j > \gamma \right) \tag{4}$$

where  $\gamma$  is the threshold on the cumulative weights of the Gaussians in the mixture model.

To classify the pixels in the next frame as foreground or background, each pixel in the frame is matched with every Gaussian in the mixture model of the respective pixel. A pixel is matched with the specific Gaussian in the mixture model if it lies within 2.5 standard deviation of that distribution. If a match is found, the parameters of the Gaussian in the mixture model are updated in the following manner:

$$w_j = w_j + \alpha(1 - w_j) \tag{5}$$

$$\boldsymbol{\mu}_j = \boldsymbol{\mu}_j + \alpha \mathbf{z}_{t+1} \tag{6}$$

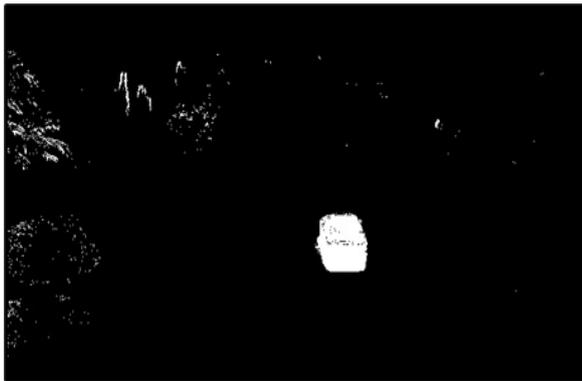
$$\boldsymbol{\Sigma}_j = \boldsymbol{\Sigma}_j + \alpha \left( (\mathbf{z}_{t+1} - \boldsymbol{\mu}_j) (\mathbf{z}_{t+1} - \boldsymbol{\mu}_j)^T - \boldsymbol{\Sigma}_j \right) \tag{7}$$

where  $\alpha$  is the learning rate.

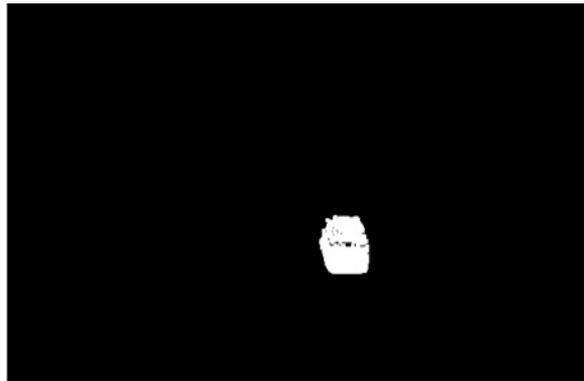
On the other hand, if a match is not found with any Gaussians in the mixture model, the one with the smallest weight is replaced with a new Gaussian with the pixel value as the mean, variance is set to pre-defined high initial value, and a small weight is assigned to it. Finally, a pixel is classified as a background pixel if it matches with the  $B$  Gaussians in the mixture model that are responsible to represent the background, otherwise it is classified as a foreground pixel. Figure 2 shows a single frame captured from the fixed camera. Figure 3a shows an example of the GMM based background subtraction described above where white and black pixels represent the foreground and background, respectively. It can be seen that the background-foreground classification process results in some classification errors and holes in the detected objects. They can easily be removed by applying simple morphological operations such as dilation, erosion, etc as can be seen in Figure 3b. In order to determine bounding boxes for the detected vehicles, connected component analysis is performed [14, 15]. Figure 4 shows an example of a detected vehicle and the associated bounding box.



Figure 2: Single frame captured from the fixed camera.



(a)



(b)

Figure 3: Vehicle detection (a) Noise due to classification errors (b) Morphological filtering and hole filling.



Figure 4: Vehicle detection and the associated bounding box.

### 3.2 Vehicle Tracking

After detecting the vehicles, the next task is to track them in the entire image sequence. Generally, the object tracking aims to generate trajectory over the time to find the position and location of a moving object in each frame. Tracking methods are generally divided into three main categories: point tracking, kernel tracking and silhouette tracking [16]. Point tracking based methods are generally faster and are suitable for real time operations.

In this work, point tracking based on Kalman filter is used to track the bounding boxes of the vehicles in the image sequence. The tracking problem is represented by the state-space equations. The Kalman filter is required to consider the current bounding box, makes a prediction on the location of the bounding box in the next frame and corrects the prediction by incorporating the new bounding box generated by the vehicle detection step applied to the next frame. To simplify the model, we assume the object moves in two dimensions and can be described as a dynamic system using the

following state-space equation:

$$\mathbf{x}_t = \mathbf{A}\mathbf{x}_{t-1} + \mathbf{B}\mathbf{u}_{t-1} \tag{8}$$

$$\begin{bmatrix} x_t \\ y_t \\ \dot{x}_t \\ \dot{y}_t \end{bmatrix} = \begin{bmatrix} 1 & 0 & T & 0 \\ 0 & 1 & 0 & T \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x_{t-1} \\ y_{t-1} \\ \dot{x}_{t-1} \\ \dot{y}_{t-1} \end{bmatrix} + \begin{bmatrix} \frac{1}{2}T^2 \\ \frac{1}{2}T^2 \\ T \\ T \end{bmatrix} a \tag{9}$$

where  $\mathbf{x}_t$  and  $\mathbf{x}_{t-1}$  are the state vectors at time instants  $t$  and  $t - 1$  respectively. Each state vector is composed of two components: position  $(x, y)$  and velocity  $(\dot{x}, \dot{y})$ ,  $u$  is the control input,  $a$  is the acceleration, and  $T$  is the time difference between two frames.

For tracking the vehicle, we assume a constant velocity model in this work. Therefore, the term  $\mathbf{B}\mathbf{u}_{t-1}$  in Eq. 8 is considered as the noise in the process. Let  $\mathbf{S}$  and  $\mathbf{Q}$  denote the covariance matrices denoting the uncertainty associated with the state vector and noise, respectively. The covariance matrix associated with the prediction  $\mathbf{x}_t$  in Eq. 8 is determined as follows:

$$\mathbf{S}_t = \mathbf{A}\mathbf{S}_{t-1}\mathbf{A}^T + \mathbf{Q} \tag{10}$$

Moreover, in this work, we are observing the position of the bounding box in a frame only and therefore, the output process can be written in the following form:

$$\mathbf{y}_t = \mathbf{H}\mathbf{x}_t + q_t \tag{11}$$

$$\begin{bmatrix} x_t \\ y_t \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix} \begin{bmatrix} x_t \\ y_t \\ \dot{x}_t \\ \dot{y}_t \end{bmatrix} + q_t \tag{12}$$

where  $q_t$  accounts for the measurement noise.

To refine the estimate the vehicle position and velocity, Kalman filter employs a correction step by taking into the consideration measurement noise, predictions, and state covariance matrix [17, 18]. Let  $\mathbf{K}_t$  and  $\mathbf{R}$  denote the Kalman filter gain and measurement noise covariance respectively, the correction step of the Kalman filter is written as:

$$\begin{aligned} \mathbf{K}_t &= \mathbf{S}_t\mathbf{H}^T(\mathbf{H}\mathbf{S}_t\mathbf{H}^T + \mathbf{R})^{-1} \\ \mathbf{x}_t &= \mathbf{x}_t + \mathbf{K}_t(\mathbf{y}_t - \mathbf{H}\mathbf{x}_t) \\ \mathbf{S}_t &= (\mathbf{I} - \mathbf{K}_t\mathbf{H})\mathbf{S}_t \end{aligned} \tag{13}$$

The updated state vector in Eq. 13 provides the corrected position of the bounding box of a detected vehicle.

### 3.3 Vehicle Speed Estimation

To estimate the vehicle speed, the perspective distortion in the scene Figure 2 must be considered. We have used the modified pinhole camera model in [19] which is shown to achieve the smallest average error. The pinhole camera model establishes the relationship between the world scene and its projection in the image plane. Figure 5 shows an example of perspective projection of world scene to the image plane. It can be seen that the vehicle is at a distance of  $d_O$  meters from the base of the camera. Let  $y_t$  be the corresponding vehicle position in the y-direction in a frame of size  $M \times N$  pixels. Let  $h$  be the height of the camera from the ground in meters,  $f$  be the focal length of the lens and  $\theta$  be the angle accounting for the orientation of the camera with respect to the perpendicular. The relationship between vehicle position in the image  $y_t$  and the world  $d_O$  can be written using the simple geometry equations:

$$d_O = h \tan(\phi + \theta) \tag{14}$$

where

$$\begin{aligned} \theta &= \tan^{-1} \frac{d\theta}{h} \\ \phi &= \tan^{-1} \left( \frac{N}{f} \right) - \tan^{-1} \left( \frac{y_t - \frac{N}{2}}{f} \right) \end{aligned}$$

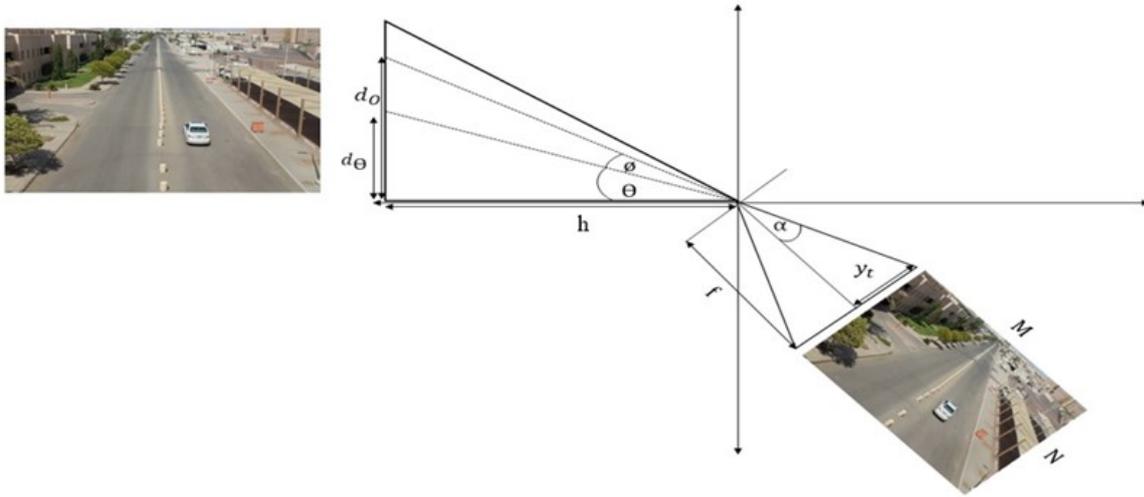


Figure 5: Perspective projection of world scene to the image plane.

The actual displacement  $d_y$  covered by a vehicle in the y-direction over a certain time interval can be computed by the application of Eq. 14 to the vehicle positions in the corresponding frames of the image sequence. Thus, for two such vehicle positions  $d_{O1}$  and  $d_{O2}$ , we can write:

$$d_y = d_{O1} - d_{O2} \tag{15}$$

To compute the vehicle displacement in the x-direction ( $d_x$ ), the displacement in the horizontal direction in two frames is converted to the actual displacement by considering the ratio of actual road width ( $w_R$ ) and its projection in the image plane. Now, both horizontal and vertical displacements are combined to compute the vehicle displacement ( $d_v$ ) in the following way:

$$d_v = \sqrt{d_x^2 + d_y^2} \tag{16}$$

Finally, the vehicle speed ( $v$ ) can be estimated by the following equation:

$$v = \frac{d_v \times FR \times 3.6}{Frame_t - Frame_{t-1}} \left( \frac{km}{h} \right) \tag{17}$$

where  $FR$  is the frame rate of the video and  $Frame_t, Frame_{t-1}$  are the indices of the current and previous frames respectively.

## 4 Experimental Results

At first, we describe our experimental setup which is shown in Figure 6. The camera is mounted on a tripod at the center of a walkway bridge that connects the parking garage and the college of engineering building at Al-Oloum street. The height of the bridge is five meters. Two markers are placed on each side of the street and are used to mark the region of interest in the image obtained using the camera. The street is 15 meters wide. The distance between the two markers on one side, denoted as  $\Delta d_{RO}$ , is 27 meters. The distance of the first marker and the base of the camera is 28 meters.

As mentioned earlier, the mixture model for vehicle detection is composed of  $K$  Gaussians. In this work,  $K$  is set to 3. Moreover, the threshold on the cumulative weights of the Gaussian  $\gamma$  is set to 0.7 which is used to determine the number of Gaussians modelling the background. The learning rate ( $\alpha$ ) is set to 0.005 determined through experimentation. Please note the parameters are fixed for all the experiments. For tracking, the process noise covariance matrix  $\mathbf{Q}$ , state covariance matrix  $\mathbf{S}$  and measurement noise covariance matrix  $\mathbf{R}$  are assumed to be Gaussian.

In all experiments, Canon cameras (EOS 600D and EOS 700D) are used to capture the videos. The tests are conducted between 10AM and 4PM at the University campus. Moreover, the tests are



Figure 6: Experimental setup.

performed with two different video resolutions:  $640 \times 360$  and  $1920 \times 1080$ . Different scenarios such as single car, multiple cars and lane changing are considered during the experiments. The experiments are conducted by driving the test car with a known speed and compare it with the estimated speed and results are shown in Tables 1 and 2. It can be seen that average error in speed estimation is below 2 km/h in all the scenarios while the maximum error is 4 km/h. The experimental results show that the proposed system is robust in different scenarios and is quite accurate. The qualitative results are also presented in Figure 7. The implementation is based on MATLAB® running on a PC with Intel-i7 processor with 64GB RAM. The proposed system can process 37 frames per second for a video resolution of  $640 \times 360$  and 11 frames per second when video resolution is  $1920 \times 1080$ .

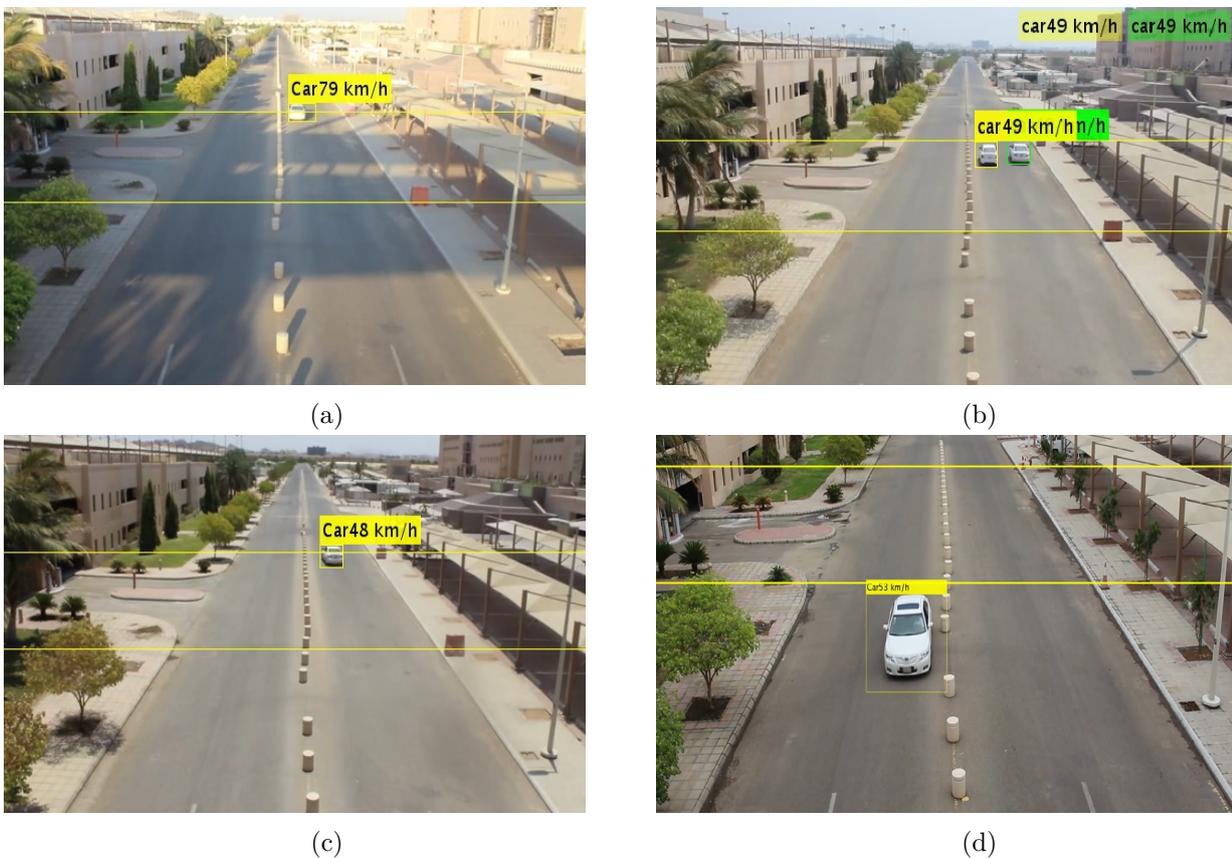


Figure 7: Qualitative results of vehicle speed estimation.

Table 1: Vehicle speed with single Vehicle.

Test No.	Actual Speed (Km/h)	Speed Estimation (km/h)	Error (Km/h)
1	80	77	3
2	80	79	1
3	80	79	1
4	80	77	3
5	80	79	1
6	60	61	1
7	60	61	1
8	60	61	1
9	50	48	2
10	50	53	3
11	50	47	3
12	50	48	2
13	50	48	2
Average error (Km/h)			1.8

Table 2: Vehicle speed estimation with multiple vehicles.

Test No.	Actual Speed (Km/h)	Speed Estimation (km/h)	Error (Km/h)
1	50	51	1
	50	53	3
2	50	49	1
	50	49	1
3	70	66	4
	50	51	1
	40	39	1
4	70	69	1
	50	57	3
	40	42	2
5	70	71	1
	50	50	0
	40	42	2
Average error (Km/h)			1.6

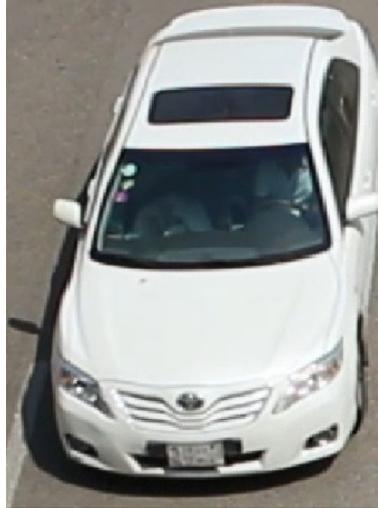


Figure 8: Example image of an over speeding vehicle for license plate recognition.

## 5 Conclusions

In this work, we have presented a system that is capable to estimate the vehicle speed reliably using a single fixed camera installed on a bridge on the road. Gaussian mixture model (GMM) based background subtraction is used to detect the moving vehicles. Tracking is performed by employing the Kalman filter for each detected vehicle. Perspective geometry model is then employed to estimate the vehicle speed. Several tests are conducted at our university campus and the results are quite promising. We plan to extend the work to detect the speed limit violations in an automated manner in future. For this purpose, we will develop a license plate recognition module to read the license

plates of over speeding vehicles. It can be seen in Figure 8 that the task is challenging due to poor quality of vehicle image owing to factors like low resolution, motion blur and perspective distortion.

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