

Vehicle Detection for Traffic Management System by Using Gaussian Mixture Model

Jackson Tan Zhen Hor¹, Siti Suhana Jamaian^{1*}

¹Department of Mathematics and Statistics,
Faculty of Applied Sciences and Technology,
Universiti Tun Hussein Onn Malaysia (Pagoh Campus)
84600 Pagoh, Muar Johor, MALAYSIA

*Corresponding Author Designation

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Abstract: Nowadays, vehicle density has increased significantly around the world. Therefore, Intelligent Transportation Systems (ITS) play an essential role in the traffic management system, and vehicle detection system is significant in this system. The aim of this research is to investigate the efficiency of the vehicle detection system by using Gaussian Mixture Model (GMM). In this research, our objectives are to propose a vehicle detection algorithm based on GMM using MATLAB programming and examine the performance of the vehicle detection model by using real-life datasets. Since ITS is still not widely pervasive in the traffic network, there is a good chance to study the current vehicle detection system. GMM provides background subtraction for object detection in machine learning such as MATLAB and Python. The video samples are taken from SENA Traffic Systems Sdn. Bhd. and had been tested by using the GMM package provided in the MATLAB software. The results had been tested with 4 types of road video condition which are Normal Day, Normal Night, Raining Day and Raining Night in the same location to determine the efficiency of the vehicle detection system. In the conclusion, the system had come out different results according to the different condition of road.

Keywords: Intelligent Transportation Systems (ITS), Vehicle Detection, Gaussian Mixture Model (GMM), MATLAB

1. Introduction

In recent years, vehicle usage has increased around the world. Inefficient traffic management and excessive demand cause traffic congestion in urban countries [1]. Vehicle detection in this feedback control is essential because the feedback that received from the detection system had to be informative and clearly to help the analysis of the situation where the incident happened. By referring to Victoria

Transport Policy Institute's Urban Mobility Report (UMR) published on 18 December 2014, lots of time and money have been wasted. For example, 5.5 billion hours and fuel were wasted: 2.9 billion gallons in urban areas of the United States because of the traffic congestion between 2000 and 2010 [2]. Traffic management systems are made up of a set of applications and management tools that function together to improve the overall efficiency and safety of transportation systems [3]. Therefore, Intelligent Transportation Systems (ITS) play an essential role in the traffic management system, and vehicle detection system is significant in this system.

In the traffic networks such as the development of a driving system, real-time surveillance systems, and ITS, real-time vehicle detection is a key component of the challenge. Vehicle detection plays an important role in the traffic management system to solve the problem of traffic congestion nowadays. Effective vehicle detection can help to find out the problem source that caused traffic congestion. In the other hand, vehicle detection in complex scenes with different obstacles is also a challenging task due to the heavy traffic densities [4].

Due to its wide range of applications in traffic monitoring, detecting moving objects is one of the most important research topics in computer vision [5]. Foreground detection, often known as moving object detection, plays a vital role in video surveillance systems [6]. GMM uses a Gaussian mixture to model the values of a single pixel over time. Gaussians are classified as background or foreground based on their persistence and variance [7]. Background subtraction by using GMM is a widely used technique for foreground detection. GMM is usually utilized to detect vehicles from the denoised images from the video surveillance [8]. In addition, GMM has satisfying performance in different traffic situations, but the algorithm's accuracy depends on the quality of captured video of the camera [9]. Therefore, in this research, GMM is used for the investigation of vehicle detection model in MATLAB software.

2. Methodology

In this research, MATLAB software had provided Gaussian Mixture Model (GMM) packages for background subtraction in vehicle detection. Background subtraction will differentiate the case of two different images, which are the background image and the current image, based on the video sequences. Besides, GMM will model the values of a pixel over time as a mixture of Gaussians. Based on the parameters concerned, the pixel in the video sequences will be classified as background and foreground, and Gaussian will include them and support with consistent evidence.

2.1 Video Samples

The video samples were provided by SENA Traffic Sdn. Bhd. The location in the video is Lebuhraya Bukit Jalil, Puchong with four different road conditions. The video road conditions that considered in this research are Normal Day, Normal Night, Raining Day, and Raining Night.

2.2 Gaussian Mixture Model and EM(Expectation-Maximization) Algorithm

Gaussian Mixture Model (GMM) uses a Gaussian mixture to model the values of a single pixel over time. Gaussians are classified as background or foreground based on their persistence and variance [7]. The following probability distribution function (PDF) will verify the random variable X if the variable is Gaussian:

$$p_X(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-(x-\mu)^2/2\sigma^2}, \quad \text{Eq. 1}$$

where μ is mean and σ^2 is variance and σ is standard deviation.

From the observation X_1^n of a Gaussian distribution with unknown parameters, mean μ and variance σ^2 , we need to find the maximum likelihood estimate the parameter μ with log-likelihood and differentiate, and set the value to 0.

$$p_{X_1^n}(x_1^n) = \prod_{i=1}^n \mathcal{N}(x_i; \mu, \sigma^2) = \prod_{i=1}^n \frac{1}{\sigma\sqrt{2\pi}} e^{-(x-\mu)^2/2\sigma^2},$$

$$\ln p_{X_1^n}(x_1^n) = \sum_{i=1}^n \ln \left(\frac{1}{\sigma\sqrt{2\pi}} \right) - \frac{1}{2\sigma^2} (x_i - \mu)^2, \tag{Eq. 2}$$

$$\frac{d}{d\mu} \ln p_{X_1^n}(x_1^n) = \sum_{i=1}^n \frac{1}{\sigma^2} (x_i - \mu). \tag{Eq. 3}$$

x_i in Eq. 3 is the pixels calculated in the video frame.

The maximum likelihood estimate is $\hat{\mu} = \frac{1}{N} \sum_i x_i$, it is the average of our observed samples.

From the observation of pixel values, find maximum likelihood (ML) estimates for parameters μ_B and μ_F based on the labels. First, joint density of all the data points $p_{Y_i, \dots, Y_n}(y_1, \dots, y_n)$ in terms of $\mu_B, \mu_F, \sigma,$ and q will be computed:

$$\begin{aligned} p_{Y_i}(y_i) &= \sum_{c_i} p_{c_i}(c_i) p_{Y_i|c_i}(y_i|c_i) \\ &= \sum_{c_i} \pi_c \mathcal{N}(y_i; \mu_c, \sigma^2) 1_{(c_i=c)} \\ &= q \mathcal{N}(y_i; \mu_B, \sigma^2) + (1 - q) \mathcal{N}(y_i; \mu_F, \sigma^2) \end{aligned} \tag{Eq. 4}$$

y_i is density of all the data points of pixel values.

The log-likelihood of the parameters:

$$\ln p_{Y_1^n}(y_1^n) = \sum_{i=1}^n \ln(q \mathcal{N}(y_i; \mu_B, \sigma^2) + (1 - q) \mathcal{N}(y_i; \mu_F, \sigma^2)). \tag{Eq. 5}$$

By differentiating the means [10]:

$$\begin{aligned} \frac{d}{du} \mathcal{N}(y_i; \mu, \sigma^2) &= \frac{d}{du} \left[\frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(x-\mu)^2}{2\sigma^2}} \right] \\ &= \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(x-\mu)^2}{2\sigma^2}} \cdot \frac{2(x-\mu)}{2\sigma^2} \\ &= \mathcal{N}(y_i; \mu, \sigma^2) \cdot \frac{(x-\mu)}{\sigma^2}. \end{aligned} \tag{Eq. 6}$$

Differentiating Eq. 5 with respect to μ_B , we obtain:

$$\sum_{i=1}^n \frac{1}{(\pi_B \mathcal{N}(y_i; \mu_B, \sigma^2) + \pi_F \mathcal{N}(y_i; \mu_F, \sigma^2))} \pi_B \mathcal{N}(y_i; \mu_B, \sigma^2) \frac{y_i - \mu_B}{\sigma^2} = 0. \tag{Eq. 7}$$

There are 3 steps in EM algorithm. First, fixing the parameters and solving for the hidden variables' posterior distribution. Second, fixing the posterior distribution for the hidden variables and optimizing the parameters. Lastly, repeat these two steps until convergence [6]. Before deriving the algorithm, there's a key fact: Jensen's Inequality:

$$\log(E[X]) \geq E([\log X]) \tag{Eq. 8}$$

The Inputs of the EM Algorithm as shown as below:

Variables: Observation y , joint distribution $p_{Y,C}(y, c; \theta)$, conditional distribution $p_{C|Y}(c|y; \theta)$, initial values $\theta^{(0)}$

- 1: **function** EM ($p_{Y,C}(y, c; \theta), p_{Y,C}(y, c; \theta), \theta^{(0)}$)
- 2: **for** iteration $t \in 1, 2, \dots$ **do**

3: $q_c^{(t)} \leftarrow p_{c|Y}(c|y; \theta^{(t-1)})$
 4: $\theta^{(t)} \leftarrow \operatorname{argmax}_{\theta} E_{q_c^{(t)}} p_{Y,C}(y, c; \theta)$
 5: **if** $\theta^{(t)} \approx \theta^{(t-1)}$ **then**
 6: return $\theta^{(t)}$ Algo. (1)

2.3 Algorithms in MATLAB

There are GMM packages that had installed in MATLAB for the vehicle detection model. Each algorithm has specific function while interpreting the video. The MATLAB command is shown as below:

First command is used to interpret the images into background image and current image.

```
vision.ForegroundDetector('NumGaussians',5,  
'NumTrainingFrames', 20, 'InitialVariance', 500);
```

Second command is used to remove the small spots or can be called noise on the frame.

```
Structure = strel('square',3);  
Noise_Free_Object = imopen(the_Object, Structure);
```

Third command is used to detect the images and bounding the image detected.

```
Bounding_Box = vision.BlobAnalysis('BoundingBoxOutputPort', true, ...  
'AreaOutputPort', false, 'CentroidOutputPort', false, ...  
'MinimumBlobArea', 300);
```

2.4 Flowchart of Research

In this study, the vehicle detection model is proposed by using GMM and EM algorithms in MATLAB. The vehicle detection is executed based on GMM package in MATLAB. If the model does not run properly in this step, the first step will be repeated until the algorithm runs properly. Otherwise, the vehicle detection algorithm in MATLAB is examined with different types of video road conditions. The flow chart of research methodology is summarized in Figure 1.

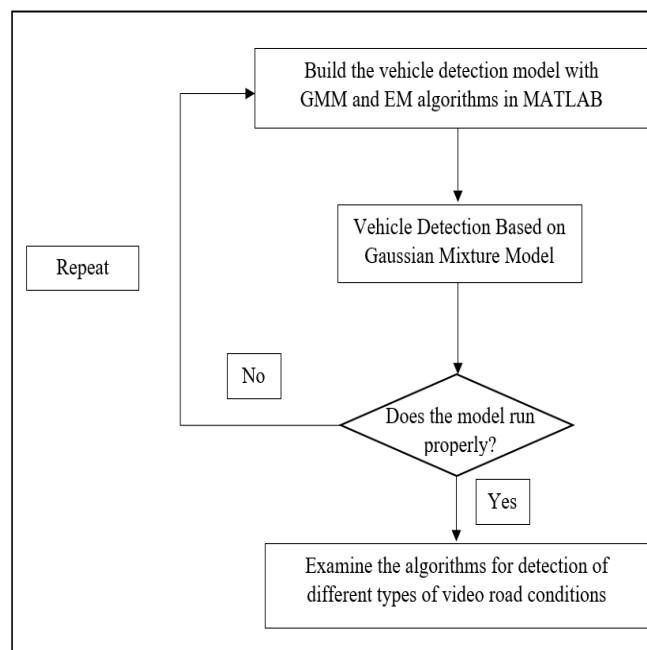


Figure 1: Flow Chart of Research Methodology

3. Results and Discussion

The result is obtained using MATLAB software based on GMM after running with 4 video samples taken from SENA Traffic Systems Sdn. Bhd. The location in the video is located at Lebuhyaya Bukit Jalil, Puchong. Four different types of road condition are considered which are Normal Day, Normal Night, Raining Day and Raining Night in AVI format. Each sample for testing is about 1 minute. The results of vehicle detection for each condition are determined.

3.1 Result of Normal Day Video

Figure 2 shows the frame that captured from the Normal Day video sample while Figure 3 shows the result of background subtraction by GMM in MATLAB.



Figure 2: “Normal Day” Video Sample



Figure 3: Result of frame after using GMM (Normal Day)

Figure 4 shows the noise removing phase of Figure 3 to obtain the clearer image that will affect the performance of the vehicle detection model to the video sample. The green boxes show the detected vehicles. Figure 5 shows the vehicle detection in Normal Day video sample in MATLAB. The green boxes show the detected vehicles.

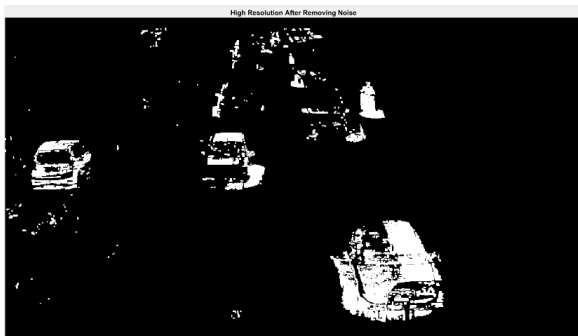


Figure 4: Frame after removing the noise (Normal Day)

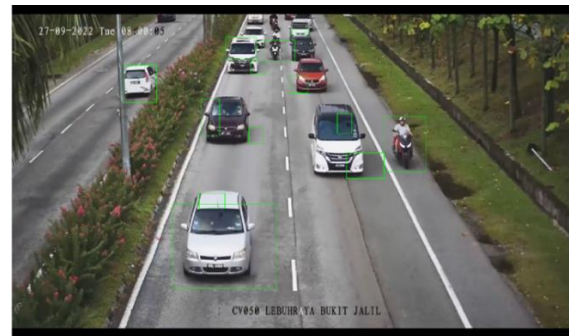


Figure 5: Result of Detected Vehicle (Normal Day)

The results shown in Figure 5 were barely satisfied due to some detection error in the video. This is because the model does not detect the vehicle completely due to the reflection of the light. Therefore, the algorithm still needs to improve to capture the vehicle more accurately.

3.2 Result of Normal Night Video

Figure 6 shows the frame that captured from the Normal Night video sample. The video also requires separating into different frame to conduct the phase of background subtraction. Figure 7 shows the result of background subtraction by GMM in MATLAB.



Figure 6: "Normal Night" Video Sample



Figure 7: Result of frame after using GMM (Normal Night)

Figure 8 shows the noise removing phase of Figure 7. The light of the vehicle will be considered as foreground and the algorithm will turn it into white image. Figure 9 shows the vehicle detection in Normal Night video sample in MATLAB, providing by the green boxes.

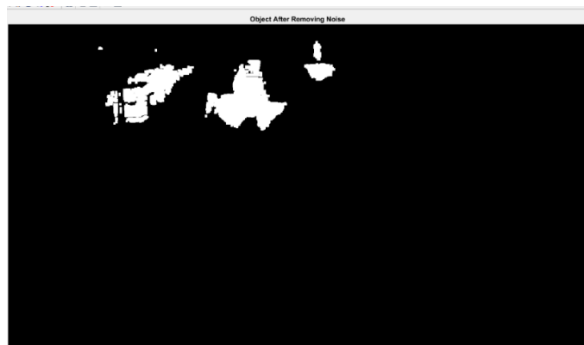


Figure 8: Frame after removing the noise (Normal Night)

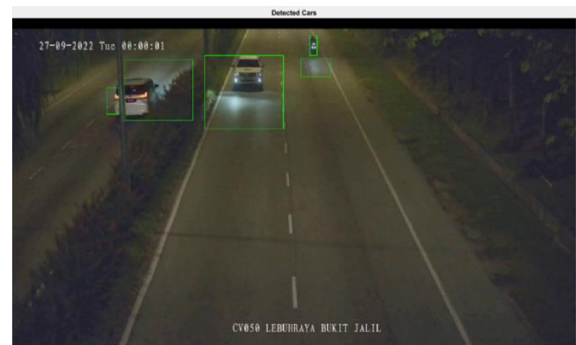


Figure 9: Result of Detected Vehicle (Normal Night)

The result has a poor performance compared to the result of day video sample. The result had shown that the weakness of the algorithm that cannot differentiate the background and foreground accurately due to the contrast of the frame. As result, the algorithm will consider the light as a vehicle.

3.3 Result of Raining Day Video

Figure 10 shows the frame that captured from the Raining Day video sample. Due to the effect of the bad weather, the frame of the video had come out the blur image. The blur image had affected the performance of the background subtraction process. Figure 11 shows the result of background subtraction by GMM in MATLAB.



Figure 10: "Raining Day" Video Sample



Figure 11: Result of frame after using GMM (Raining Day)

Figure 12 shows the noise removing phase of Figure 11. The noise removing process does not have significant affect in the result because mostly the noise inside the frame had been considered in the big group of the white foreground. Figure 13 shows the vehicle detection in Raining Day video sample in MATLAB, providing by the green boxes.

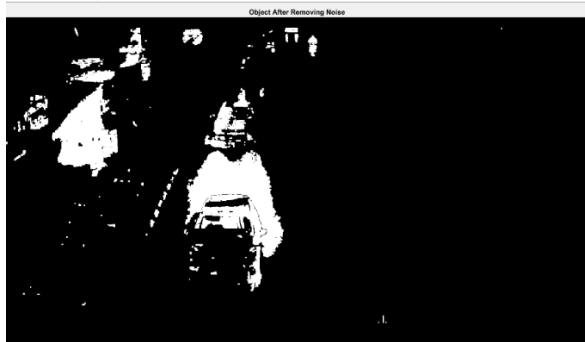


Figure 12: Frame after removing the noise (Raining Day)



Figure 13: Results of Detected Vehicle (Raining Day)

The vehicle detection model had functioned normally when applied in the video sample, but the effect of the weather still cannot be ignored during the experiment. The result of vehicle detection model still unsatisfied because the algorithm had detected light as a vehicle and the detection is barely accurate.

3.4 Result of Raining Night Video

Figure 14 shows the frame that captured from the Raining Night video sample. The “Raining Night” video sample had the most confusing issues while conducting the background subtraction process due to the pixel in the video had been interrupted by the bad weather and brightness of the road. Figure 15 shows the result of background subtraction by GMM in MATLAB.



Figure 14: “Raining Night” Video Sample



Figure 15: Result of frame after using GMM (Raining Night)

Figure 16 shows the noise removing phase of Figure 15. The noise in the frame had shown insignificant effect to the image processed. This is because the insufficient light and reflection of light of the vehicles. The vehicle detection model faced some challenges while testing with the “Raining Night” video sample. Figure 17 shows the vehicle detection in Raining Night video sample in MATLAB, providing by the green boxes.

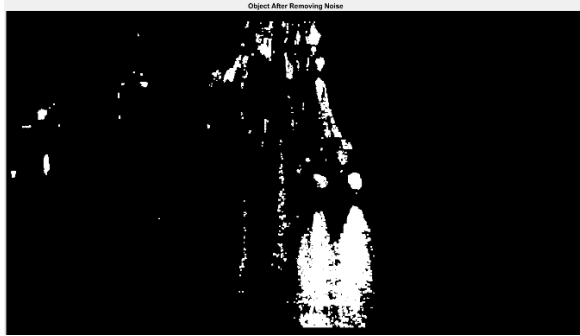


Figure 16: Frame after removing the noise (Raining Night)



Figure 17: Results of Detected Vehicle (Raining Night)

The scene inside the video didn't show clear images for the detection algorithm to detect the background and foreground properly. Therefore, the vehicle detection model had considered the light in the frame as an object. The result of the vehicle detection model needs to improve by enhancing the algorithm and required clearer video sample.

4. Conclusion

There are some challenges faced while developing the vehicle detection algorithm. The development of vehicle detection algorithm will require the application of GMM and EM algorithm using MATLAB programming. The vehicle detection algorithm in MATLAB software had functioned well on each video samples but the results show barely satisfactory due to the weakness of current vehicle detection algorithm that could not adapt with the different road condition and compatible of MATLAB version. The result of day video is better compared to the night video because of the contrast between the background and foreground of the frames. The resolution of the datasets is playing an important role in the experiment. The vehicle detection algorithm developed had interpreted different results based on different type of condition of datasets in this research. In the future study, it is recommended to use other video format to obtain better result. Besides, the result will be better if the video sample have higher resolution.

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