Vehicle Detecting Method Based on Gaussian Mixture Models and Blob Analysis

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***Abstract*—Vehicle detection process provides relevant information about traffic patterns, crash occurrences and traffic peak times in roadways. This paper presents a vehicle detection method in a video sequence using foreground detector based on a Gaussian Mixture Model and Blob Analysis. The proposed method is composed of four major steps: foreground segmentation, blob detection, blob analysis and blob tracking. An implementation of proposed technique has been performed using MATLAB R2017a. The experimental results show that the proposed method can provide useful information for intelligent transportation systems.**

***Keywords*— Foreground detection, blob analysis, Gaussian mixture models, vehicle detection.**

I. Introduction

The correct detection of vehicles is part of the cornerstone of intelligent transportation systems because it solves the most important issue when building a traffic surveillance system. Missing the detection of a vehicle denotes an unreliable system that will not even be able to perform functionalities that depend on vehicle detection such as traffic flow density, average traffic speed or the total amount of vehicle in a fixed time interval. Video cameras are one of the common traffic sensors because of its ability to collect a large amount of information.

Gaussian Mixture Model (GMM) is currently a popular method in vehicles detection [1]-[3] due to the reliability that it has shown in the background extraction and foreground segmentation process consequently the characteristics of a moving object in video surveillance are easier to detect. However, this method has not shown good results on high levels of light variance and shadow, video resolution, and vehicle density on the road [4]. Hence, this method still exposes some areas of research and improvement.

The main objective of this paper is to describe the combination of a Gaussian Mixture Models and Blob Analysis to detect vehicles in motion. This paper is organized as follows: Section II gives a suitable background on essential definitions and techniques associated with the proposed work. Section III and Section IV discusses the proposed methodology and its experimental results respectively. Finally, Section V presents a conclusion and future work.

II. Background Information

A. Video Processing

Video processing is a subcategory of Digital Signal Processing techniques in which video frames from a continuous stream are processed one (or more) at a time. This type of processing is critical in systems that have live video or where the video data is so large that loading the entire set into the workspace is inefficient [5]. To process the dataset used in this paper the Computer Vision System Toolbox from MATLAB & Simulink was used.

B. Gaussian Mixture Model

Gaussian Mixture Models (GMM) is a type of density model consisting of Gaussian function components. This algorithm is used to perform the background extraction process because it is reliable towards light variances and repetitive object detection conditions [6]. This method is one of the oldest semi-supervised learning methods and commonly used in image processing [7].

According to this model, each pixel in an image frame is modeled as a K Gaussian distribution. K stand for the number of Gaussian distribution model usage. Each Gaussian model represents a different pixel color. In this case, grayscale image use scalar value, while the RGB image use vector value. The value of K is determined on image resolution consideration, computer system performance, and background models complexity. For each image frame, each pixel is matched with a K Gaussian distribution model. As formula (1) states, a pixel match with one of Gaussian distribution model if it is included in 2.5 deviations standard range. On the contrary, if a pixel has value beyond 2.5 deviation standard then the pixel is declared as an unfit to the Gaussian distribution model.

$$\mu_k - 2.5 * \sigma_k < X_t < \mu_k + 2.5 * \sigma_k \qquad (1)$$

Chance of K Gaussian distribution function modeling is described as follows (2).

$$P(X_t) = \sum_{k=1}^{K} \omega_{k,t} * n\left(X_t, \mu_{k,t}, \Sigma_{k,t}\right) \qquad (2)$$

Where the K value indicates the number of distribution, $\omega_{k,t}$ is the weight of Gaussian function to-K at time t and $n\left(X_t, \mu_{k,t}, \Sigma_{k,t}\right)$ is Gaussian probability density function.

For computational reasons this formula assumes that the red, green, and blue pixel values are independent and have the same variances [7].

The next step consists of determining for each pixel if it will be included in the foreground or the background object. The initial step lies on sorting the existing model based on the fitness value (ω/σ^2), where the optimal distribution as background remain placed on top priority, and the distribution that do not reflect background is laid on the lowest priority. From several distribution models, several high values are selected until its weight values meet the predetermined threshold value. The selected distribution model will be selected as a background candidate.

If a pixel is categorized to one of the background model candidates, the pixel will be considered as background (pixel will change its value to zero or black). Otherwise, the pixel will be considered as foreground (changing its value to one or white). This selection criterion will output a black and white image.

C. Blob Analysis

Blob Analysis is a technique used in an image processing to perform foreground segmentation by declaring an area of pixels inside an image to become the object or region to be labeled [8]. To determine the blob value, some factors have to be considered to produce an optimal blob. In computer vision, some factors are the area of the label region, the centroid, bounding box, label matrix, and blob count [8].

Laplacian of Gaussian is one method used as a formulation for searching the blob value. This process starts by marking an area that is considered a foreground object, then collecting the data of the blob such as the initial pixel position, length of the x-axis and y-axis, and the pixel area. A blob area figured as in Fig. 1.

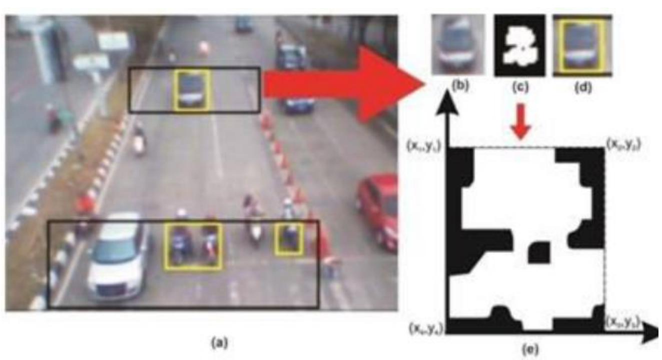


Fig. 1 Blob analysis process in vehicle detection. (a) A big frame of the original image. (b) Cropping object. (c) Foreground segmentation. (d) Object detection using bounding box. (e) Blob area in x and y-direction.

In Fig. 1, (a), (b) and (d) are the visible object obtained through a foreground detection process. However, (c) comes from a binarization process. The area of the blob can be determined by analyzing the pixel vector values of (e).

III. Proposed Methodology

There are several processes carried out in this study. Starting from implementing GMM process to perform foreground segmentation and perform vehicle's detection through blob analysis. Fig 2 represents the workflow of this methodology.

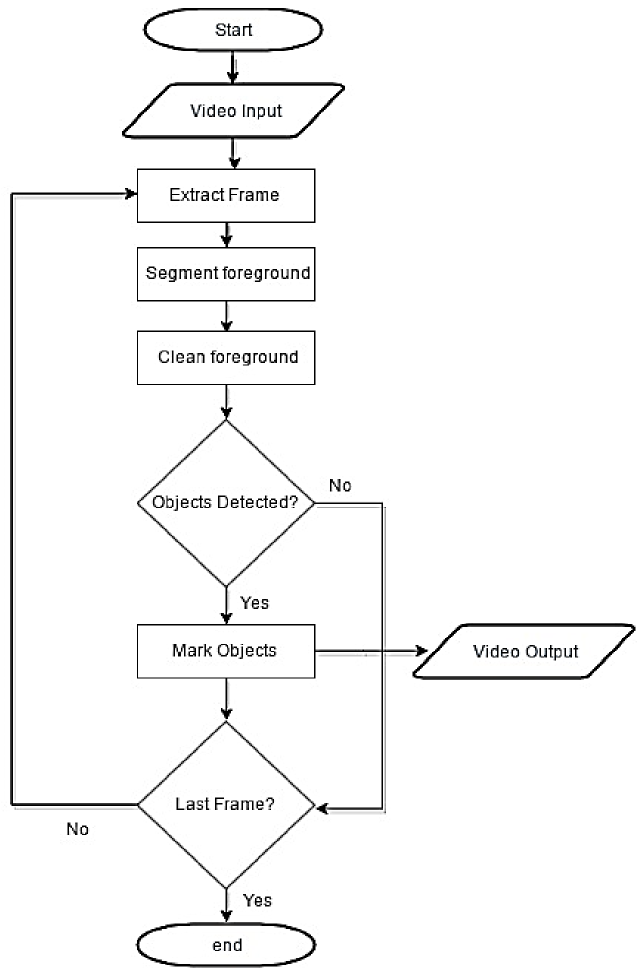
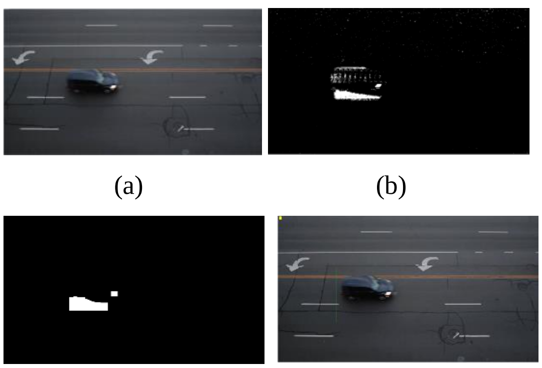


Fig. 2 Proposed Methodology flowchart.

In this study, the video input to process was of length 9 minutes, resolution 1920x1080 pixels and 25 frames per second. The first step of this methodology is to load the video to initialize some global variables to optimize the second step, the foreground segmentation process. At this point, rather than immediately processing the entire video, this study starts by obtaining an initial video frame (a) in which the moving objects are segmented from the background (b). This helps to gradually introduce the steps used to process the video.

Furthermore, foreground segmentation process serves to separate foreground and background as described in formula (1) and (2). The foreground detector requires a certain number of video frames in order to initialize the Gaussian mixture model. This study uses the first 25% frames to initialize 3 Gaussian modes in the mixture model. GMM is initialized by specifying the number of Gaussians, minimum background ratio, learning rate, and the number of training frames. After the training, the detector begins to output more reliable segmentation results. The foreground segmentation process is not perfect and often includes undesirable noise. This method uses morphological opening with a structural element with a size of 1% of video's width, to remove the noise and to fill gaps in the detected objects (c).

Next, this methodology finds bounding boxes of each connected component corresponding to a moving vehicle by using a Blob object. The object further filters the detected foreground by rejecting blobs which contain fewer than 8% of video area. To highlight the detected cars, green boxes around them are drawn (d). The number of bounding boxes corresponds to the number of vehicles found in the video frame. The number of found cars is displayed in the upper left corner of the processed video frame. Finally, the remaining video frames are processed in the same way.



(a) (b) (c) (d)

Fig. 3 Car detected after Initialize Foreground Detector. Initial video frame (a). Initial frame foreground (b). Clean foreground (c). Detected Car (d)

IV. Experimental Results

The above method has been implemented using MATLAB R2017a. The evaluation consists of comparing the automatic detection of vehicles in videos against the manual detection. Table I. denotes the results of such evaluation.

TABLE I. RATE OF ACCURACY FOR VIDEO INPUT

Car	***Automatic Detection***	***Accuracy***
1	No	0
2	Yes	100%
3	Yes	100%
4	Partially	50%
5	Partially	50%
6	Yes	100%
7	Partially	50%
Average		64.28%

Based on data analysis result it appears that the overall accuracy of this method is 64.28%.

Misdiagnosis results can be reduced by implementing the following approaches:

- Including a step previous, the foreground segmentation to select and adjust a region of interest (ROI) based on isolated detection area for each roadway vehicle line to focus the background segmentation process on a specific area.
- Choosing an appropriate detection zone, which can embed even long vehicles.
- Segmenting the Blob minimum and maximum area values to categorize vehicles from a non-vehicle object such as a pedestrian.
- Using pattern recognition methods to teach the technique all different vehicle types by their structural shape [9].

V. Conclusions and Future Work

In this paper, I present a method based on GMM and Blob Analysis to detect vehicles on highways. Data results show that the GMM performance optimization can improve its accuracy.

Further research can be made by analyzing ROI influence with Blob Analysis on data with various ratio and resolution and influence of this technique for false positive rates. Another improvement could be implementing vehicle classification by creating different detectors.

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