GMM based Vehicle Traffic Analysis on Roads

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Abstract:
This paper presents a complete idea for analysing the behaviour of vehicles in the real-time traffic monitoring applications. Detecting and counting cars can be used to analyse traffic patterns. Detection is the first step prior to performing more sophisticated tasks such as tracking of vehicles by their type. Receiving the images through video surveillance camera in the first phase, we get use of Gaussian mixture model for each frame to achieve a precise background image. This phase is called training phase where the geometrical structure of the road is analysed. In the second phase, the received images will be compared with the trained images. Thus, the vehicles can be tracked. In third phase, a green block will surround each vehicle to enable the researches count them. With a view to do improvements, it is proposed to develop a unique algorithm for vehicle data recognition and tracking using Gaussian mixture model.

Keywords: *Detection, surveillance, Gaussian mixture model, tracking*.

1. Introduction:

Traffic monitoring is an important tool in the development of Intelligent Transport System (ITS). The application of image processing and computer vision techniques helps in improving the present methods of traffic data collection and road traffic monitoring.

Other methods such as the inductive loop, the sonar and microwave detectors have many drawbacks like high installation and maintenance cost and they are not able to identify slow or stationary vehicles. Image processing also has wide range of applications in the field of autonomous vehicle guidance, mainly for recognizing the vehicle's relative location and for obstacle detection. The problem of autonomous vehicle guidance solves several problems at different abstraction levels. The vision system can assist in the locating the vehicle with regard to its environment, which is made up of the appropriate lane and obstacles or other moving vehicles. The estimation is often done by matching the observations (images) to a presumed road. Systems for traffic monitoring normally involve two important tasks of perception: (a) estimation of road geometry and (b) vehicle and obstacle detection[1].

Traffic monitoring is used for analysing traffic figures, speed distribution data, turning traffic flows at intersections, queue-lengths, space and time occupancy rates, etc. Therefore, for monitoring systems it is important to identify the road structure. Then only we can sense the motion parameters of a vehicle. Detection of road obstacles becomes an essential and serious task for avoiding other vehicles present on the roads[2].

2. GMM:

The standard approach to object detection is background subtraction (BS) that attempts to build a representation of the background and detect moving objects by comparing each new frame with this representation. A number of different BS techniques have been proposed in the literature and some of the popular methods include mixture of Gaussians model. Basic background subtraction (BS) techniques detect foreground objects as the difference between two consecutive video frames, operate at pixel level, and are applicable to still backgrounds. Although the generic BS method is easy to understand and implement, the drawbacks of the frame difference BS are that it does not provide a mechanism for selecting the parameters, such as the detection threshold, and it is unable to deal with multimodal distributions. One of the significant techniques able to cope with multimodal background distributions and to update the detection threshold employs Gaussian mixture models (GMMs)[3].

A Gaussian Mixture Model (GMM) is a parametric probability density function represented as a weighted sum of Gaussian component densities. GMMs are commonly used as a parametric model of the probability distribution of continuous measurements or as features in a biometric system, such as colour based tracking of an object in video. In many computer related vision technology [4], it is vital to determine moving objects from a sequence of videos frames. In order to obtain this, background subtraction is applied which mainly recognizes moving objects from each portion of video frames. In video surveillance, target recognitions and banks background subtraction or segmentation technique is widely used. By using the Gaussian Mixture Model background model, frame pixels are removed from the required video to obtain the desired results. The application of background subtraction involves different factors which contain developing an algorithm which is able to detect the required object robustly, it should also be able to react to various changes like illumination, starting and stopping of moving objects.

3. PRE-PROCESSING: Temporal or spatial smoothing is employed in the early pre-processing stage to remove device noise which can be a factor under different light intensity. Smoothing technique also includes omitting various elements like environment such as rain and snow. In real-time systems, frame size and frame rate are commonly adopted to decrease the data processing rate. Another important factor in pre-processing technique is the data format used by the background subtraction model. Most algorithms can handle luminance intensity which is one scalar value per each pixel. This step makes use of the new video frame in order to compute and update the background model. The main purpose of developing a background model is that it should be robust against environmental changes in the background, but sensitive enough to determine all moving objects of interest.

4. FOREGROUND DETECTION: In this step, it recognizes the pixels in the frame. Foreground detection compares the video frame with the Background model, and identify candidate foreground pixels from the frame. To check whether the pixel is significantly different from the corresponding background estimate is a widely-used approach for foreground detection.

5. DATA VALIDATION: Finally, this step removed any pixels which are not relevant to the image. It involves the process of improving the foreground mask based on the information obtained from the outside background model. Most background models lack three main points: 1. ignoring any correlation between neighbouring pixels 2. The rate of adaption may not match the moving speed[6] of the foreground object. 3. Non-stationary pixels, from moving leavers or shadow cast by objects in motion are at times mistaken for true foreground object.

6. PROPOSED METHOD:

Receiving the images through video surveillance camera in first phase, we get use of GMM[5] for each frame to achieve a precise background image. This process will be repeated as long as we seize an accurate background images. This phase is called training phase. In the second phase, the received images will be analyzed a long with the trained images to extract the vehicles (moving objects) based on this analysis. As the mention above, we may extract vehicles more accurately as long as, we have a more precise trained background images.

In third phase, a green block will surround each vehicles to enable the researches count them. Either inaccurate training of the background images or the shadow of moving vehicles might cause problems in detecting vehicles in motion in the second phase. To solve these problems, we used of merging the blocks which overlap the other blocks to compute the volume and density of traffic accuracy. Finally, the report of traffic can be presented by post processing.

Flow chart of GMM:

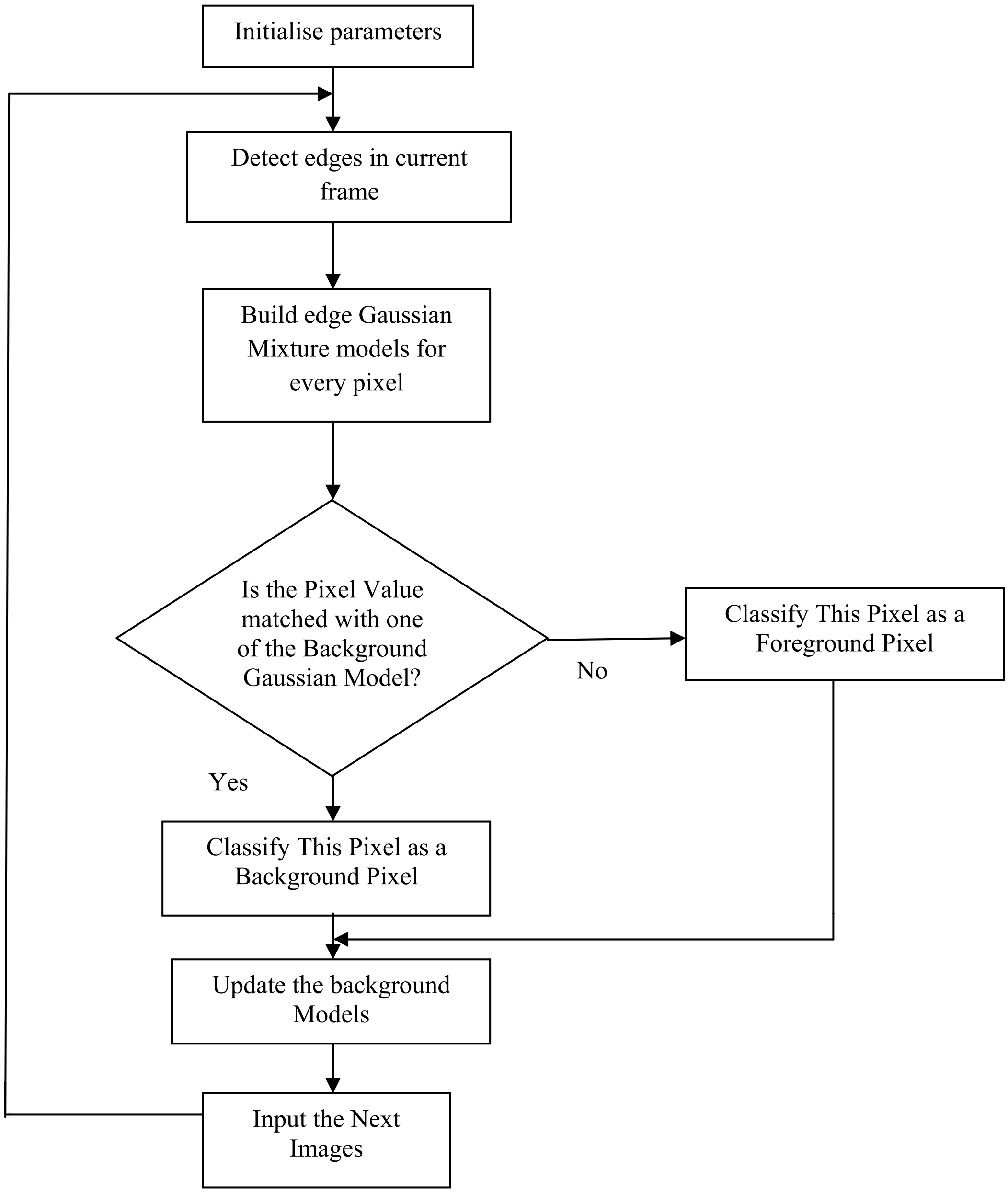

Figure (b) FLOW CHART OF GMM

- Firstly, each input pixel is compared to the mean of associated components. If the value is close enough then we consider it as a matched component. Else, it is considered as foreground pixel.
- The matched pixel is named as background pixel. The background models are then updated and next images are taken as input.
- Thirdly, we identify which components are parts of background models. To do this, a threshold value is added to the component weights.
- Finally, we determine the foreground pixels. These foreground pixels should not match with the background pixels[7].

Results:

In figure (c), the video frame is shown which calculates and updates the background model. In figure (d), the foreground components of the video frame are detected.

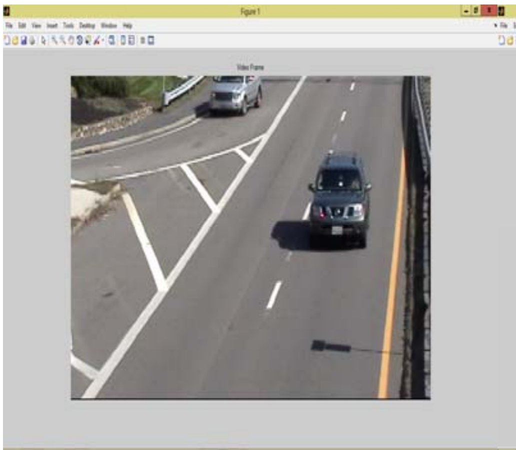

Figure (c) Video frame

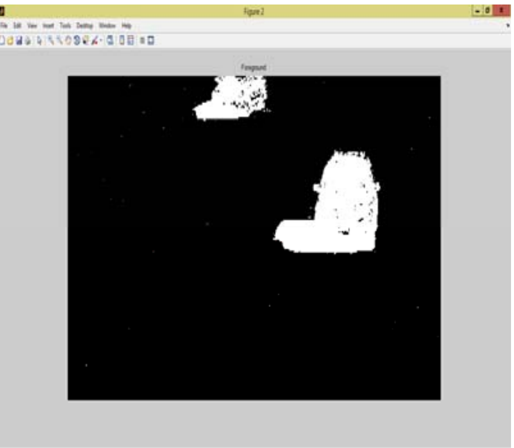

Figure (d) Foreground

In figure (e), clean foreground is shown and finally the background and foreground pixels are compared and the vehicles are identified which is shown in figure (f).

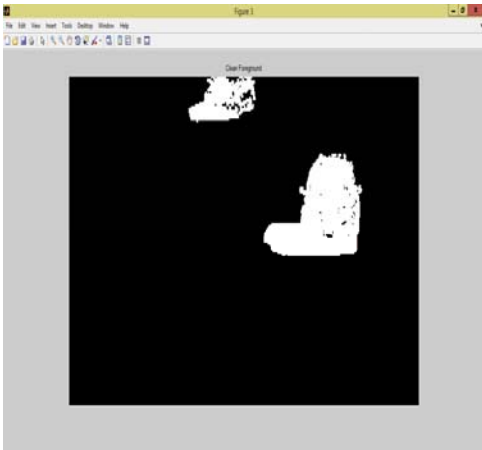

Figure (e) Clean Foreground

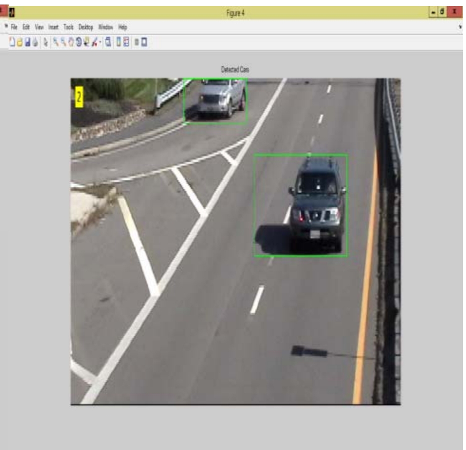

Figure (f) Detection of cars

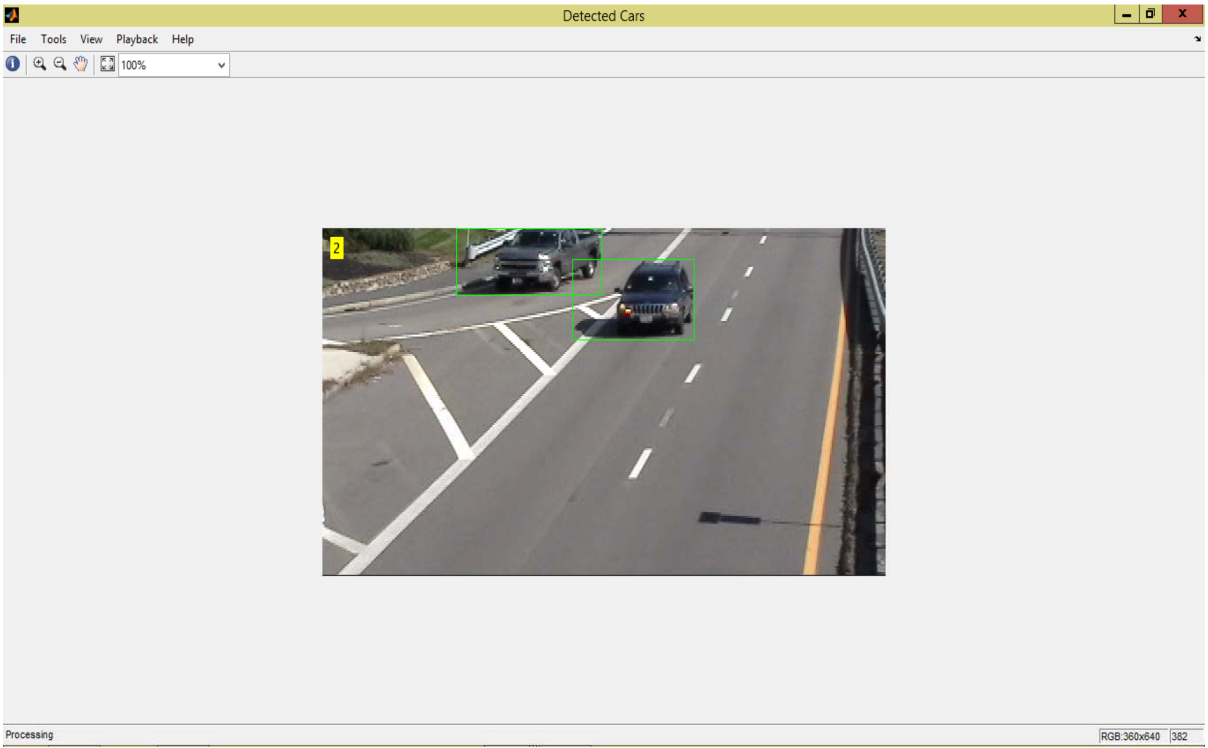

Figure (g) Detected vehicles

7. Conclusion:

In this paper, we proposed a method to pave a way for intelligent transportation systems. Our approach is of low cost and high accuracy, so the integration of this algorithm in vision systems can enhance the performance of traffic parameters estimation and vehicle detection. The detection of vehicles in a mix traffic situation of low, medium and high traffic is precisely as expected and the counting algorithm is accurate.

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