A Hybrid Algorithm for Vehicle Detection and Tracking

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ABSTRACT

Vehicle detection plays an important role in making decisions for the purpose of traffic control and management due to increasing congestion on highways. Compared to still images, video frames provide more information about how vehicles and scenarios change over time. A novel and efficient algorithm based on image processing using ariel cameras for vehicle detection is proposed. The main aim is to detect vehicles in a traffic data from video frames. Although various researches have been done in this area and many methods have been implemented, still this area has room for improvements. With a view to do improvements, it is proposed to develop an unique algorithm for vehicle data recognition and tracking using Gaussian mixture model and blob detection methods. First, we differentiate the foreground from background in frames by learning the background. Here, foreground detector detects the object and a binary computation is done to define rectangular regions around every detected object. To detect the moving object correctly and to remove the noise some morphological operations have been applied. Then the final counting is done by tracking the detected objects and their regions. The results are encouraging and got detection and tracking using the Gaussian Mixture Model and Blob Detection methods.

Keywords – Image Processing, Vehicle Detection, Vehicle Tracking, Vehicle Counting.

1. INTRODUCTION

The goals of Intelligent Transport System (ITS) is to enhance public safety, reduce congestion, improved travel and transit information, generate cost savings to motor carriers and emergency operators, reduce detrimental environmental impacts, etc. The efficiency of an ITS is mainly based on the performance and comprehensiveness of vehicle detection technology. Vehicle detection and tracking are integral part of any vehicle detection technology, since it gathers all or part of information that are used in an effective ITS. It is defined as a system capable of detecting vehicles and measure of parameters such as count, speed, incidents etc. vehicle detection by video cameras is one of the most promising non-intuitive technologies for large scale data collection and implementation of advanced traffic control and management schemes and is also the basis for vehicle tracking. The correct vehicle detection results in better tracking. But it is not easy as think to detect the event or tracking the object.

An Automatic vehicle counting system makes use of video data acquired from stationary traffic cameras, performing causal mathematical operations over a set of frames obtained from the video to estimate the number of vehicles present in a scene. It is just the ability of automatically extract and recognize the traffic data e.g. total number of vehicles, vehicle number and label from a video. Counting vehicles gives us the information needed to obtain basic understanding over the flow of traffic in any region under surveillance. In each video frame, Gaussian mixture model differentiates objects in motion from the background by tracking detected objects inside a specific region of the frame, and then counting is carried out.

A Gaussian Mixture Model (GMM) is a function to measure parametric probability density represented as a weighted sum of Gaussian component densities. GMMs are extensively used in various areas of applications. Now GMM carries out the job of separating the foreground and background from image frames by learning the background of a scene. A threshold value is calculated to determine the similarity of the objective specification of the quality of acolor regardless of its luminance between the background learnt by GMM and the current observed image is a pixel in the foreground obtained by the GMM.

Blob detection is a technique by which system can trace the movements of objects within frame. A blob is a group of pixels identified as an object. These pixels are grouped, in current frame, together by utilizing a contour detection algorithm. The contour detection algorithm groups the individual pixels into disconnected classes, and then finds the contours surrounding each class. Each class is marked as a candidate blob (CB). The positions of the CB, in current frame, are compared using the k-Means clustering that finds the centers of clusters and groups the input samples CB around the clusters to identify the vehicles in each region. The
moving vehicle is counted when it passes the base line. Tracking is carried out only inside a specific region of the frame, called Count Box, to ensure unnecessary redundancy in computation and higher performance. Tracking is done by searching for centroids in a small rectangular region around centroids detected in the earlier frame, if not found then it is added to a ‘tracks’ array as a newly found object.

2. PROPOSED METHOD
In order to detect and track vehicles efficiently on roads we use Gaussian mixture model. Foreground is detected from moving vehicles in video frames and thereafter vehicles are tracked from detected results. “Figure 1” shows the flowchart of our proposed method.

2.1 Gaussian Mixture Model
A Gaussian Mixture Model (GMM) is a parametric probability density function represented as a weighted sum of Gaussian mixture densities. GMM’s are commonly used as a parametric model of probability distribution of continuous measurements. In order to give better understanding of the algorithm used for background subtraction the following steps were adopted to achieve desired results:

Figure 1: Flowchart of proposed method
1. Firstly, we compare each input pixels to the mean 'μ' of associated components. If the value of a pixel is close enough to a chosen component mean then that component is considered as matched component. In order to be a matched component the difference between the mean and pixel component must be smaller compared to component standard deviation. 

2. Secondly, update Gaussian weight, mean and standard deviation to reflect new obtained pixel value. In relation to non-matched components the weights „w” decreases whereas the mean and standard deviation remain same.

3. Thirdly, here we identify which components are parts of background. To do this a threshold value is applied to the component weights „w”.

4. Fourthly, in the final step we determine the foreground pixels. Pixels that are identified as foreground doesn’t match which any other components that are determined as background

2.2 Blob detection:

In the area of image processing, Blob detection is a technique by which system can trace the movements of objects within frame. A blob is a group of pixels identifies as an object. This detection mechanism finds the blob’s position in successive image frames. The blob area must be defined before any detection of blob where Pixels with similar light values or color values are grouped together to find the blob. Every surface has subtle variations in real world scenario, so if only one light or color value is selected, a blob might be only few pixels. When trying to group images into useful components it might be useless as a complete unit. The system must detect the blobs in the new image and make meaningful connections between the seemingly different blobs present in each frame. It needs to define the relative importance of factors including location, size and color to decide if the blob in the new frame is similar enough to the previous blob to receive the same label. It can be explained like the following steps: search through each pixel in the array: check if the pixel is a blob color, label it '1' otherwise label it 0 go and search the next pixel if it is also a blob color and if it is adjacent to blob 1 label it '1' else label it '2' (or more) repeat the loop until all pixels are done In this research blob detection uses contrast in a binary image to compute a detected region, it’s centroid, and the area of the blob. The GMM supplies the pixels detected as foreground. These pixels are grouped, in current frame, together by utilizing a contour detection algorithm. The contour detection algorithm groups the individual pixels into disconnected classes, and then ends the contours surrounding each class. Each class is marked as a candidate blob (CB). These CB are then checked by their size and small blobs are removed from the algorithm to reduce false detections. The positions of the CB, in current frame, are compared using the k-Means clustering that ends the centers of clusters and groups the input samples CB around the clusters to identify the vehicles in each region. The moving vehicle is counted when it passes the base line. When the vehicle passes through that area, the frame is recorded. In each region the blob with the same label are analyzed and the vehicle count is incremented.

2.3GMMs and Image Noise Filtering

Initially foreground extraction is an important task. Generally a natural background includes large objects such as trees, road, floor, buildings etc., each of which contains pixels with similar intensity values but intensities differ considerably with each other. Foreground is extracted from background using Gaussian Mixture model(GMM) . A Gaussian Mixture Model (GMM) is a parametric probability density function represented as a weighted sum of Gaussian densities. GMM’s are used in various fields. Some of the fields are machine learning, astronomy, biochemistry and many more. In this application, GMM carries out the job of separating foreground from a background by learning the background of the scene. The application of backgrounds subtraction involves developing an algorithm which is able to detect required object robustly and also be able to react to various changes like illumination, starting and stopping of vehicles etc., various techniques exist for foreground extraction. In the methods based on frame differencing, a difference between consecutive frames is computed and the pixels greater than threshold are considered as foreground. In the approximate median, the running estimate of median is incremented by one if the input pixel is larger than the estimate and decreased by one if smaller. A popular framework of background modeling which is relatively close to our work uses GMM modeling of pixels. In these methods background modeling are performed for each pixel in the frame. The input frame pixels which are not following the model are termed as foreground pixels. Extension to GMM also exist which is adaptive GMM, where the number of Gaussians are assigned to
each pixel and are updated over time. In all the methods based on GMM for background modeling, each pixel of the frame is modeled by Gaussians. Based on color change at each pixel reference image model is created. Then depending on the threshold calculated from the model, foreground pixels are classified. Next is removal of noise. There are several types of noises like median noise, mean noise, impulse noise, Gaussian noise, bilateral noise etc., but have some drawbacks (i) The median filter is a non-linear filtering technique often used to remove noise. It is widely used in digital image processing because under certain conditions it preserves edges while removing noise. The main problem of the median filter is its high computational cost. (ii) A bilateral filter is a non-linear filter, edge preserving and noise removing smoothing filter. The intensity value at each pixel in the image is replaced by a weighted average of intensity values from nearby pixels. But the drawback is it gives false detections. (iii) The Average (mean) filter smooth data thus eliminating noise. This filter performs spatial filtering on each individual pixel in an image using the grey level values in a square or rectangular window surrounding each pixel. But the drawback is it does not work for more number of connected components. To overcome all these drawbacks we use morphological operations to reduce noise. Morphological image processing pursues the goals of removing these imperfections by accounting for the form and structure of video. Finally here comes vehicle detection and tracking of vehicles in a video. Tracking algorithms have been greatly researched due to increasing interest in tracking applications together with the development of novel techniques aiming to answer the challenges of real time tracking. However despite of potential advancements it is still challenging to develop a set of standard approaches that are approximate for all the applications. The general aim behind tracking is to estimate the target objects in video sequences over an interval.

2.4 Blob Analysis
Blob analysis identifies potential objects and puts a box around them. It finds the area of the blob and from the rectangular fit around each blob, the centroid of the object can be extracted for tracking the object. An additional rule that the ratio of area of blob to the area of rectangle around a blob should be greater than 0.4 ensures that unnecessary objects are not detected.

2.5 Tracking and Counting
Tracking is carried out only inside a specific region of the frame, called Count Box, to ensure unnecessary redundancy in computation and higher performance. The violet box is the count box region. Tracking is done by searching for centroids in a small rectangular region around centroids detected in the earlier frame, if not found then it is added to a ‘tracks’ array as a newly found object.

3. SIMULATION RESULTS:
Here, the input video consists of 24 cars. In figure 2, left side of the image is the input video and the other side is the filtered image after applying Gaussian mixture model.

Figure 2: Input image and filtered binary image using GMM.

Figure 3 shows the tracked vehicle in a violet colour box. And shows the area and centroid of particular vehicle in a road. In a particular image 3 cars were detected. The violet box is the count box region. Tracking is done by searching for centroids in a small rectangular region around centroids detected in the earlier frame, if not found then it is added to a ‘tracks’ array as a newly found object. Figure 4 is the vehicle counting.
Figure 3: Is the tracking of cars and calculates the centroids and areas of each vehicle

Figure 4: Vehicle counting
4. CONCLUSION:
A simple and effective system which solves the problem under study has been developed. 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. The limitation of the developed method is that for every camera data feed a considerable amount of tuning of the parameters is required to achieve the best performance. Also, it requires somewhat more processing time in highly denced traffic conditions.

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