Moving Vehicle Detection and Tracking using GMM and Kalman Filter on Highway Traffic

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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 proposed algorithm consisting of four stages i.e., extraction of foreground from background using Gaussian Mixture Model, noise removal using morphological operations, vehicle detection and tracking using Kalman filter and finally vehicle counting. Experiments are carried out over a wide range of vehicles, road segments and camera heights and an efficiency of 97% is achieved.

KEYWORDS

GMM, morphological operations, Kalman filter

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. There are many techniques and papers introduced by many scientists for backend process in video surveillance.

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 [1,2], a difference between consecutive frames is computed and the pixels greater than threshold are considered as foreground. In the approximate median [3], 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[4,5,6]. 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[7], 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 generally 3 to 5 Gaussians. In [8], 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.

The Kalman filter is a set of mathematical equations that provides an efficient computational (recursive) means to estimate the state of process in a way that minimizes the mean of squared error. In 1960, R.E.Kalman[9] published a paper describing a recursive solution to the discrete data linear filtering problem[9]. The filter is very powerful in various aspects: it supports estimations of past, present and even future states and it can do even when the precise nature of the modeled system is unknown[10]. It is used to estimate the state of linear system where state is assumed to be distributed as a Gaussian. Object tracking is performed by predicting objects position from previous position and verifying existence of object at the predicted position. Secondly the observed likelihood function and motion model must be learnt by some sample of image sequence before tracking is performed[11,12]. The Kalman filter estimates the process by using a form of feedback control. The filter estimates the process state at some time and then obtains feedback in the form of noisy measurements. The equations of Kalman filter falls in two groups: time update equations and measurement update equations. The time update equations are responsible for projecting forward the current state and error covariance estimates to obtain priori estimate for next step. The measurement update equations are responsible for feedback. That is used for incorporating new measurement into the priori estimate to obtain an improved posterior estimate. The time update equations can also be thought of as predictor equations, while the measurement update equations can be thought of as
corrector equations. The time update projects the current state estimate ahead in time. The measurement update adjusts the projected estimate by an actual measurement at that time.

2. PROPOSED METHOD
In order to detect and track vehicles efficiently on roads we use Gaussian mixture model and Kalman filter. Foreground is detected from moving vehicles in video frames and thereafter vehicles are tracked from detected results. “Figure1” 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:

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 components 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.

The probability given in a mixture of K Gaussians is shown in (1)

\[ p(x) = \sum_{j=1}^{k} w_j \cdot N(x/\mu_j, \sum_j)...(1) \]

Where \( w_j \) is the prior probability of j th Gaussian

\[ \sum_{j=1}^{k} w_j = 1 \text{ and } 0 \leq w_j \leq 1 \]

For d dimensions, the Gaussian distribution of a vector \( x = (x^1, x^2,...,x^d)^T \) is shown in (2)

\[ N(x/\mu, \Sigma) = \frac{1}{(2\pi)^{d/2} \sqrt{|\Sigma|}} \exp\left(-\frac{1}{2}(x-\mu)^T \sum^{-1} (x-\mu)\right) ...(2) \]

Where \( \mu \) is the mean and \( \Sigma \) is the covariance matrix.

Figure 1: Flowchart of proposed method
2.2 Morphological Operations
Morphological operations are used to remove noise. Commonly used morphological operations are dilation, erosion, closing, opening, thinning, thickening, skeletization etc. Out of these the two basic morphological operations are dilation and erosion.

Dilation: Dilation is typically applied to binary images, but there are versions that work on grey scale. The basic effect of operator on binary image is to gradually enlarge the boundaries of regions of foreground pixels (i.e., white pixels typically). Thus areas of foreground pixels grow in size while holes within those regions become smaller.

Erosion: Erosion is typically applied to binary images, but there are versions that work on grey scale. The basic effect of operator on binary image is to erode away the boundaries of regions of foreground pixels (i.e., white pixels typically). Thus areas of foreground pixels shrink in size while holes within those regions become larger.

2.3 Kalman Filter
Kalman filter is also known as Linear Quadratic Estimation (LQE), is an algorithm that uses series of measurements observed over time, containing noise and other inaccuracies and produces estimates of unknown variables that tend to be more precise than those based on a single measurement alone. More formally, the Kalman filter operates recursively on streams on noisy input data to produce a statistically optimal estimate of the underlying system state. Kalman filter have numerous applications. Common applications are guidance, navigation and control of vehicles, particularly aircraft and spacecraft. The algorithm works in two step processes. One is predict and other is update and is shown in “Figure 2”.

![Figure 2: Kalman filter](image)

The predict state uses the estimate from the previous time step to produce an estimate of the state at the current time step. This predicted state estimate is also known as priori estimate because, although it is an estimate of the state at the current time step, it does not include observation information from the current time step. In the update phase, the current a priori prediction is combined with current measurements information to refine state estimate. This improved estimate is termed as a posteriori state estimate.

Equations for prediction is given in (3),(4)

Predict state estimate
\[
\hat{x}_k = A\hat{x}_{k-1} + Bu_{k-1} \tag{3}
\]

Predicted estimated covariance
\[
P_k^- = AP_k^-A^T + Q \tag{4}
\]

Equations for updation is given in (5),(6),(7)

Kalman gain
\[
k_k = P_k^-H^T(HP_k^-H^T + R)^{-1} \tag{5}
\]

Update state estimate
\[
\hat{x}_k = \hat{x}_k^- + k_k(z_k - H\hat{x}_k^-) \tag{6}
\]

Update estimated covariance
\[
P_k = (I - k_kH)P_k^- \tag{7}
\]
Where
\(A\) is the state transition model which is applied to the previous state \(x_{k-1}\)

\(B_k\) is the control input model which is applied to the control vector \(u_k\)

\(Q\), the covariance of process noise

\(H_k\), the observation model

\(R_k\), the covariance of the observation noise

Observation or measurement, \(z_k\) of the true state \(x_k\) is given in (8)

\[ z_k = H_k x_k + v_k \quad \text{(8)} \]

\(v_k\) is observation noise

3. SIMULATION RESULTS

The simulation results are shown which gives good detection and tracking of moving objects under different conditions. The performance is good and results are shown below. “Figure 3” is input frame, “Figure 4” is the output obtained after GMM is applied, “Figure 5” is the output obtained after applying morphological operations and finally “Figure 6” gives the output after Kalman filter is applied.

![Figure 3: Input Frame](image1)

![Fig.4: Output after GMM](image2)

![Fig.5: Output after Morphological Operations](image3)
The below Table 1 provides the accuracy of various vehicle detection methods based on the previous experiments.

<table>
<thead>
<tr>
<th>Method</th>
<th>Efficiency</th>
</tr>
</thead>
<tbody>
<tr>
<td>N. Friedman, S. Russell et al.,</td>
<td>66%</td>
</tr>
<tr>
<td>D. S. Lee et al.,</td>
<td>70%</td>
</tr>
<tr>
<td>Francesca Manerba et al.,</td>
<td>80%</td>
</tr>
<tr>
<td>N. McFarlane, C. Schofield et al.,</td>
<td>60%</td>
</tr>
<tr>
<td>Gagan Bansal et al.</td>
<td>87%</td>
</tr>
<tr>
<td>Proposed method</td>
<td>97%</td>
</tr>
</tbody>
</table>

4. CONCLUSION

Moving object tracking is evaluated for various surveillance and vision analysis. The first phase is segmenting the object using Gaussian mixture model which gives better understanding of grouping objects. Then the second phase is to improve the quality of video by applying morphological operations on the output obtained after GMM for better result. In the next phase vehicle detection and tracking is done using Kalman filter algorithm which gives good results. These algorithms can also be extended for night time traffic in future with good efficiency.

REFERENCES


