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A NOVEL DETECTION AND TRACKING ALGORITHM FOR TRAFFIC SURVEILLANCE SYSTEM

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ABSTRACT
Vehicle detection and tracking place a vital role in traffic surveillance system (TSS). In the past, many methods had been introduced and implemented still a challenging issue because of dynamic textures such as rain fall, snow and absence of light. Therefore to overcome these problems introduce a novel tracking algorithm based on background subtraction and morphological operations. Firstly the background method is used to detect the moving objects from the video and then morphological operations are applied to remove the noise regions and obtaining more accurate segmentation results. After vehicle detection, a object-based vehicle tracking method is used for building the correspondence between vehicles detected at different time instants. After vehicle tracking, calculate the vehicle count from video.

KEYWORDS: vehicle detection, vehicle tracking, background subtraction, TSS and GMM.

INTRODUCTION
An Intelligent Transportation System (ITS) is the application that incorporates electronic, computer and communication technologies into vehicles and roadways for monitoring traffic conditions, reducing congestion, enhancing mobility, and so on. The primary goal is to minimize the travel time of all travelers and merchandise while ensuring safety, through fair distribution of available resources, especially under the scenario of increasing travel speeds, a significantly large number of travelers, and a high demand for precise and timely information by travelers. To achieve its goal, ITS must bring about a seamless and natural integration of the different modes of transportation, including vehicular traffic, trains, cargo air transport, passenger air transport, marine ferries, and others through asynchronous distributed control and coordination algorithms.

As a result of the integration, the traveler will [1] gain access to accurate status information of any transportation mode from any point in the system, [2] compute the most efficient route or reroute across all different transportation modes by processing the available information through personalized decision aids, and [3] be permitted to effect reservations, dynamically, even while en route, on any transportation system. An approach that uses parameterized 3D is proposed in [4]. For the purpose of estimating vehicle parameters, It can build the correspondence among the vehicles detected at the different frames by tracking schemes. The corners are detected as features for vehicle tracking in [5]. In [3], it uses a feature-based approach with occlusion reasoning for vehicle tracking in congested traffic scenes. Additionally, the vehicles are tracked through sub-features instead of entire vehicle to handle occlusion effect. More recently, a stochastic approach called particle filtering are widely used for tracking vehicles by relaxing the Gaussian assumption of vehicle motion [6]. This paper was formed as follows. In section II, describe the overview of the GMM method. In section III The background subtraction method of vehicle detection, vehicle tracking and counting are introduced. In Section IV gives some experimental results. In Section V Finally conclusion was presented.

GAUSSIAN MIXTURE OF MODEL METHOD
It is basically performed by using Gaussian distribution which has the most supportive function and the least variance. This model is often used for clustering of data. Clusters are assigned by selecting the component that maximizes the posterior probability.

Each pixel is modeled separately by a mixture of K Gaussians. This algorithm converts each pixel into a Gaussian model and calculates the probably of the image based on the sum of the models. The value of each pixel represents a measurement of the radiance in the direction of the sensor of the first object intersected by the pixel's optical ray. With a static background and lighting, that value would be relatively constant. It can assume that independent Gaussian noise is incurred in the sampling process, its density could be described by a single Gaussian distribution centered at the mean pixel value. Unfortunately, the most interesting video sequences involve lighting changes, scene changes, and moving objects. If lighting changes occurred in a static scene, it would be necessary for the Gaussian to track those changes. If a static object was added to the scene and was not incorporated into the background until it had been longer than the previous object, the corresponding pixels could be considered foreground for arbitrarily long periods. This would lead to accumulated errors in the foreground estimation, resulting in poor tracking behavior. These factors suggest that more recent observations may be more important in determining the Gaussian parameter estimates. These are the guiding factors in our choice of model and update procedure. The recent history of each pixel, $\{X1…..Xt\}$ is modeled by a mixture of K Gaussian distributions. The probability of observing the current pixel value is

$$P\,(X_t) = \sum_{i=1}^{K} \omega_i, t * \eta\,(X_{t,}\mu_{i,}t, \textstyle\sum_{i,t})$$

Where K is the number of distributions, $\omega i, t$ is an estimate of the weight of the ith Gaussian in the mixture at time t, $\mu i, t$ is the mean value of the ith Gaussian in the mixture at time t.

BACKGROUND SUBTRACTION METHOD

In this section, we describe how to segment the moving vehicles from video. Firstly, the moving regions are segmented from the background by using background difference method. Then, the geometric properties of the segmented regions are used to remove the false regions.

In order to improve the accuracy of segmentation and tracking results, the pixels of shadow are also removed. The flow chart of proposed method as shown in fig.1. In this, two models are used first is foreground and second is background. The subtraction of foreground from background is nothing but background subtraction. Background model is a static and foreground model is moving objects. In this system roads are background model and moving vehicles are foreground model. Algorithm used for vehicle detection and tracking is background subtraction method.
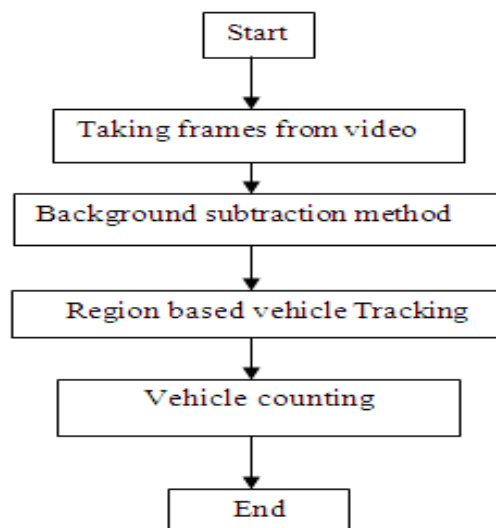

Fig.1. Flow chat of proposed algorithm

For segmentation of the image from video frames to detect and track the vehicle. For this to propose a robust approach to segment moving objects for video surveillance application and demonstrate that a jointly use of frame by background difference with a background subtraction algorithm allows us to have a better and fast pixel foreground classification without the need of random pixel background learning. When the camera is static,

different moving objects can be detected through background difference method. This approach was to perform background difference [8] on background and current frames in the image acquisition loop, which identifies moving objects from vehicle video frame that differs significantly from the previous frame. The proposed method basically employs the frame subtraction operator.

The frame subtraction operator [9] takes two images as input and produces as output a third image whose pixel values are ones or zeros. The subtraction of two images is performed straightforwardly in a single pass. The output pixel values are given by:

$$Q(i, j) = P1(i, j) - P2(i, j)$$

Where P1=background frame and P2=current frame from given video. There are many challenges in developing a good background differencing algorithm for vehicle detection. First, it must be robust against changes in illumination. Second, it should avoid detecting non-stationary background frame such as moving leaves, rain, snow, and shadows cast by moving objects. In our efforts to develop a high performance algorithm for vehicle tracking. In our work we have tried to overcome the difficulties in our vehicle detection module. Using background differencing on background-by-frame basis a moving object, if any, is detected with high accuracy and efficiency. Once the object has been detected it is tracked by employing an region based vehicle tracking method.

Fr=rgb2gray(fr);

background_frame=abs (double (background)-
double(previousframe)

for j=1:width

for k=1:height

If background_frame(k,j)>threshold
Fg(k,j)=fr(k,j);

Else

Fd(k,j)=0

SIMULATION RESULTS

Original frame   subtraction frame
Fig.2. Detection of moving objects using Background subtraction method

Fig.3. Tracking of moving objects and its count using background subtraction method

In Fig.2 shows the detection of moving objects using background subtraction and morphological operations such as opening and closing operations. Fig.3 shows tracking of objects using proposed method.

CONCLUSION

To conclude this proposed algorithm to detect the objects and tracking using background subtraction and morphological operations. This technique is detecting objects and tracking accurately. This algorithm is efficient and robust for the dynamic environment with new objects in it. This system has been successfully used to identify moving vehicles and tracking in outdoor environments; this system achieves our goals of real-time performance over boundless experience of time lacking human intrusion.

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