International Journal of Engineering In Advanced Research Science and Technology ISSN: 2278-256

February 2016 VOLUME -1 ISSUE-2 Page: 7791-95

A NOVEL METHOD FOR VIDEO SURVIELLANCE APPLICATION USING BACKGROUND SUBTRACTION

[1]. RAHUL MATHAMSETTY, [2].T.ADITYA KUMAR

[1]. PG Student, Prasiddha College of Engineering and Technology, Anathavaram

2. Assist Professor, Prasiddha College of Engineering and Technology, Anathavaram

Abstract - Vehicle detection and classification plays a prominent role in traffic surveillance systems. In the past many methods had been derived and implemented still we find some problems of detection and classification. These problems mainly occur in dynamic texture such as rain fall, moving trees, mountain and camera configuration. In order to overcome these problems on the vehicles they are some essential traffic parameters, such as vehicle counting, detection and classification. In this paper, to avoid detection and classification problems frame background subtraction has been proposed. Firstly the background method is used to detect the moving objects from the vehicle video. The morphological operation 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, we calculate the vehicle count from video. Experimental results are shown better segmentation and tracking results compare to Gaussian mixture of model (GMM).

Key words: vehicle classification, vehicle detection, vehicle tracking, background subtraction and traffic surveillance system.

I. 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. ITS is an evolving scientific and engineering discipline whose 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 model is proposed in [4]. The adopted model for vehicle classification is a generic vehicle model based on the shape of a typical sedan. For the purpose of estimating vehicle parameters, we have to build

International Journal of Engineering In Advanced Research Science and Technology ISSN: 2278-256
March 2016
VOLUME -2
ISSUE-3
Page:7791-95

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].

The rest of this paper is organized as follows. In section II, we describe the overview of the GMM method. The background subtraction methods of vehicle detection, vehicle tracking, vehicle classification and counting are introduced in sections III. Section IV gives some experimental results. Finally, a conclusion will be presented in section V.

II. GMM 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 static lighting, that value would be relatively constant. If we 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 there 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

$$P(X_t) = \sum_{i=1}^{K} \omega_{i,t} * \eta(X_t, \mu_{i,t}, \Sigma_{i,t})$$

Where K is the number of distributions, $\omega_{i,t}$ is an estimate of the weight (what portion of the data is accounted for by this Gaussian) 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.

III. BACKGROUND DIFFERENCE

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 technology. 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 flowchart of proposed method as shown in figure.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 static once and foreground model is moving objects.in this system roads are background model and moving vehicles are foreground model.Algorithm used for background subtraction method:

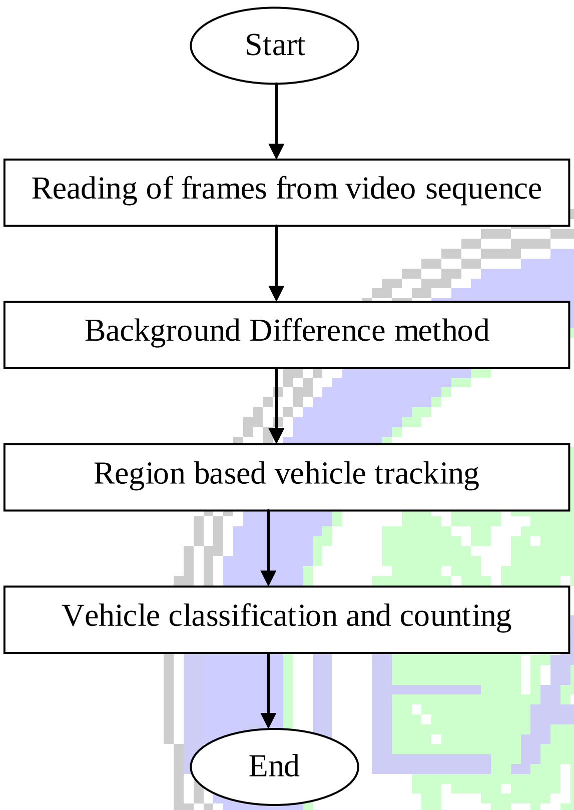

Fig.1. flowchart of proposed method

For segmentation and classification each vehicle should be first detected and tracked from video frames. We propose a robust approach to segment moving objects for video surveillance applications. We 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. The approach we choose 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

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 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. The algorithm of background frames segmentation as shown below

```
Fr=rgb2gray(fr);
    background_frame=abs(double(background)-
double(previous frame)
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;
```

IV. EXPERIMENTAL RESULTS

In this Paper, a real-time background difference technique which can detect moving object on a dynamic texture videos was implemented using MATLAB R2009

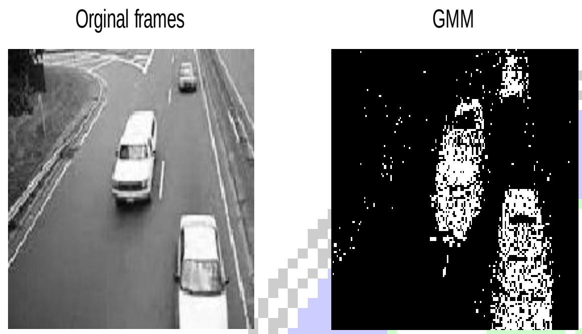

Fig.2. Detection of moving objects using GMM method

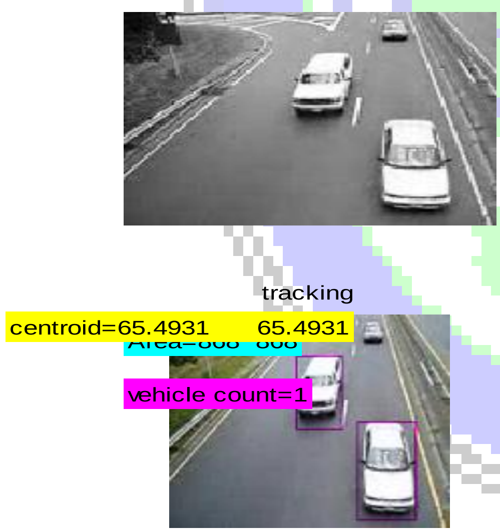

Fig.3. Detection of moving objects using background frame difference

In Figure 3, shows the detection object using background frame differencing method. The comparison between mixture of Gaussian method and background frame Differencing method, background Frame Differencing method give better detection. The mixture of Gaussian more noise and if we do the extraction of image, it makes the extraction more lousy.

V. CONCLUSION

In this paper, to detect the objects and tracking using background difference method. 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.

REFERENCES

[1]. J..w. Hsieh, S.·H. yu, y'·S. Chen, and w..F. Hu, Automatic Traffic Surveillance System for Vehicle Tracking and Classification IEEE Transactions on Intelligent Transportation Systems, vol. 7, no. 2, pp. 175"187, June 2006.

[2]. S. Gupte, O. Masoud, R. F. K. Martin, and N. P. Papanikolopoulos,Detection and Classification of Vehicles IEEE Transactions on Intelligent Transportation Systems, vol. 3, no. I, pp. 37"47, March 2002.

[3].D. Beymer, P. Mclauchlan, B. Coifman, and J. Malik, A RealTime Computer Vision System for Measuring Traffic Parameters IEEE International Conference on Computer Vision and Pattern Recognition, pp. 495-501, 1997.

[4].D. Koller, Moving Object Recognition and Classification based on Recursive Shape Parameter Estimation Israel Con! on Artificial Intelligence and Computer Vision, pp. 27"28, 1993.

[5].L. Xie, G. Zhu, M. Tang, H. Xu, and Z. Zhang, Vehicles Tracking Based on Comer Feature in Video-

Based ITSJ IEEE Inti. Conf on ITS Telecommunications, pp. 163-166, June 2006.

[6].J. Zhu, Y. Lao, and Y. F. Zheng, Object Tracking in Structured Environments for Video Surveillance Applications IEEE Transactions on Circuits and Systems for Video Technology, vol. 20, no. 2, pp. 223-234, February 2010.

[7].O.Masoud and N.P.Papanikolopoulos, Robust Pedestrian Tracking Using a Model-Based ApproachJ IEEE International Conference on Intelligent Transportation Systems, pp. 338"343, 1997.

[8].JAIN, R. AND NAGEL, H. 1979. On the analysis of accumulative difference pictures from image sequences of real world scenes. IEEE Trans. Patt. Analy. Mach. Intell. 1, 2, 206–214.

[9]. RAFAEL C. GONZALEZ, RICHARD E. WOODS. (2002): Digital Image processing, Second Edition. Prentice Hall International

[10].R.Adams and L.Bischof, Seeded Region Growing IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 16, no. 6, pp. 641"647, June 1994.