Moving Vehicle Detection based on Motion Segmentation Algorithm using Hypothesis Test

M. B. Patil
PG Scholars
Dept. Comp. Science Engg.
G.H.R.I.E.M, Jalgaon , India

S. P. Patil
Assistant Professor
Dept. Comp. Science Engg.
G.H.R.I.E.M, Jalgaon ,India

***Abstract*-Moving vehicle detection is an essential task in intelligent transportation system. In this proposed work motion segmentation algorithm is used for detecting accurate moving vehicle from the video sequence. Hypothesis test is the first step which is used to find out the pixel in the video frame is still or moving. In next step the median filter removes noise or isolated spots from the result which is produced by hypothesis test. At last, MB mask is formed from the binary mask M. The MB mask covers the whole object which contains in given video. Experimental results show the proposed strategy is robust with low complexity. Proposed method produces segmentation objects in video coding practice.**

Keywords- motion segmentation; hypothesis test; vehicle detection.

I. INTRODUCTION

Moving objects in the video decomposed from its background by using motion segmentation algorithm. In many proposed work this segmentation is the first step. It is an essential building block for video indexing, inspection, metrology, robotics, video surveillance, traffic monitoring and many other applications. Detecting moving objects is an important aspect of computer vision and has a wide range of surveillance applications. The accurate location of objects does not only provide a focus of attention for post processing but also can reduce the redundant computation for the incorrect motion of the moving object. The successful detection of moving object is a difficult task because of various parameters like as occlusion, shadow, weather conditions, jamming and noise [1]. So many proposed systems refers motion segmentation algorithm for detecting object from the video.

There are lots of challenges are handled those affects over moving vehicle. These challenges are

- Weather conditions: - There are various complex weather conditions for example sunny, cloudy, and rainy and nights. These all weather conditions affects over on vehicles when system try to detect it [1].
- Multiple objects: it is the ability to deal with more than one object in the scene.
-
- Occlusion:-Occlusion is also the real challenge which will be occurred because of jamming number of vehicles on the single road.
- Shadow effects:-It is occurred when the vehicle passing away from the shadow of trees or shadow of any another vehicle.
- Noisy:-Noise is occurred due to various things so this also the biggest challenge.

In view of the convenience of obtaining background image offline in a surveillance system, a motion segmentation algorithm based on hypothesis test is proposed in this paper. It is well known that motion objects and noise all can cause luminance change of pixels and the change can be detected by the difference between the current frame and a reference frame. Median filtering is further used for eliminating those isolated spots produced due to hypothesis test. At last, a macro block (MB) mask is formed according to the number of moving pixels in MBs.

This paper is organized as follows. Section II addresses the literature survey. Section III presents the algorithm with their detail. Finally, experimental results are given in Section IV, and the conclusion is presented in Section V.

II. LITERATURE SURVEY

Fellow et al. [1] proposes the method which will try to detect vehicle for complex weather conditions like sunny days, rainy days, sunrise, sunset, cloudy days, fog, or at night and also handle the problem. They combine various steps for detecting accurate vehicle in complex environments. The first step is Histogram extension (HE) which removes the effects of weather and light impact. In second step they use gray-level differential value method (GDVM) which used to segments moving objects. Finally, tracking and error compensation are applied to refine the target tracking quality. But the disadvantage of this approach does not detect vehicle which is out of region of interest (ROI) area and so many vehicle are not detected.

Kumar et al. [2] proposes an unsupervised approach. In unsupervised learning approach they have to represent scenes from video in the form of layers means this proposed method is composition of layers. By using different layers they segments the moving objects and try to detect that object accurately but it fails when the condition of undersegment and over segment is occurred in the video. Cremers et al. [3] presents a novel variation approach for segments the image plane into a set of regions of parametric motion on the basis of two consecutive frames from an image sequence. They proposes model which is based on a conditional probability for the spatio-temporal image gradient, given a particular velocity model, and on a geometric prior on the estimated motion field favouring motion boundaries of minimal length. They do not find objects if the data is missing in the frame.

Shen et al [4] proposes a method which recovers a high-resolution (HR) image from several low-resolution images. The low resolution images contain noise, blur, and down sampled. They use maximum a posterior (MAP) framework which is the combination of motion estimation, segmentation and super resolution. The MAP formulation is solved by using a cyclic coordinate descent optimization procedure. After solving MAP formulation, it founds motion fields, segmentation fields, and HR images.

Koller et al. [5] proposes method which analyse traffic scenes. The information related to scene is used to optimize traffic flow during busy period, identify stalled vehicles and accidents and making the decision of an autonomous vehicle controller. They use kalman filter which used to extract vehicle trajectories from sequence of images. Symbolic reasoned based on dynamic belief network. The symbolic language on the road gives the information about traffic events such as vehicle lane changes and stalls.

Coifman et al. [6] focuses on two stages first is vehicle segmentation and tracking and in second stages finding out accurate traffic parameters from the tracking data. For that purpose they apply different vehicle tracking strategies and then emphasis on feature based tracking for increasing detecting performance in occlusion condition and different lighting conditions. Vehicle tracking strategies can be classified into model based tracking, region based tracking active contour based tracking and feature based tracking. Feature based tracking includes camera calibration, feature detection, feature tracking and feature grouping methods.

Tamersoy et al. [7] implement novel approach for detecting vehicles from surveillance videos. This unsupervised system combines well studied computer vision and machine learning techniques. By using these unsupervised system vehicles are automatically learned from videos. For accurate result enhanced background mixture model and classifier are used. Classifier is depend on the first step of this method which is background mixture model because the classifier trained on the examples those are identify by enhanced adaptive background mixture model.

Gupte et al [8] developed algorithm for detecting and classifying vehicles in monocular image sequences those are recorded by stationary camera. This whole system process is done at three levels: raw images, region level, and vehicle level. Vehicles are modelled as rectangular patches with certain dynamic behaviour. Bartin et al. [9] studied for finding out the information of subset of highway routes and provides that information to the traveller. On the given highway routes these information is beneficial to the traveller.

As the cost of cameras and processors continues to decrease, vision-based sensing is becoming an increasingly popular alternative to traditional sensors for collecting traffic data. In order for a vision-based system to measure the speeds of vehicles, there must be a mapping from pixels in the image to coordinates in the world. They propose first techniques which are shown the relationship between 2D and 3D image co-ordinates systems using their main parameters. The second proposed technique introduced taxonomy for different calibration methods and divides the methods into two categories, depending on whether only a single vanishing point or two vanishing points. At last they uses over constrained (OC) approach that takes into account all the available measurements to refine the result of any of the individual methods, as well as to overcome the ambiguity when additional measurements are available [10].

III. MOTION SEGMENTATION ALGORITHM

Hypothesis test is used to determine motion pixel from the video captured by statistical camera model. First step determines the luminance effect of pixel means pixel luminance is changed or not changed. At second median filter removes isolated spots and finally a mask is made up by MBs that containing moving pixels.

A. *Hypothesis test for pixels*

Hypothesis test is scientific method which gives us the particular value of parameters. The basic hypothesis steps are:-

a. Develop a hypothesis concerning the values of one or more population parameters.
b. Sample the population.
c. Evaluate the hypothesis using the observed data.

In classical hypothesis testing, partition the hypothesis into two elements; the null hypothesis (H_0) and the alternative hypothesis (H_a).The null hypothesis is simply complement (not the opposite) of alternative hypothesis Ha. Here we refer that hypothesis test for finding out the luminance effect of pixels. The test statistics is the function of observed sample data upon which the statistical decision will be made. Test statistics is the absolute difference |d| of same pixel at the same location between current frame and the reference frame. This assumption of statistic is depending on Laplace distribution or Gauss distribution [11]. If noise is assumed to obey Gauss distribution then d^2 should be taken as the statistic. At last, whether the current pixel is moving or not is decided. Let H_0 denotes the pixel is still and H_a denotes the pixel is moving. As per above H_0 is complement of H_a. Due to noise in the video, acceptance or rejection of H_0 does not mean H_0 is right or wrong that will be decided by test. Therefore two kinds of errors can be occurred that is acceptance of the false and rejection of true. For controlling error of rejecting true not to be too big we set a significance level S. S is defined as per Gauss distribution in Equ.1.

$$S = \text{Prob}\ [\ (d/\sigma)^2 > t_S \mid H_0] \quad (1)$$

S is defined as per Laplace distribution in Equ.2.

$$S = \text{Prob}\ (2\gamma|d| > t_S \mid H_0) \quad (2)$$

Where $(d/\sigma)^2$ and $2\gamma|d|$ are two test statistics corresponding to Gauss and Laplace distribution noise respectively. S is the standard deviation of noise distribution and γ satisfies $\gamma^2 = 2/\ \sigma^2$. It is known from statistic theory that given hypothesis H_0. $(d/\sigma)^2$ and $2\gamma|d|$ obey χ^2 distribution with single and two degree of freedom respectively. Therefore given the significant level S, determines the quantile t_S by using χ^2 distribution.

The statistic $(d/\sigma)^2$ or $2\gamma|d|$ is computed at every location of the difference image. If the statistic is beyond t_S, the current pixel is marked as "moving"; or marked as "still". The parameter S can be regarded as a probability of making error I that rejects H_0 while it is true. The S at which error I take place depends on the threshold t_S, which is specified by a surveillance operator. In practice, the size of S is not very crucial; there is little influence over the segmentation result when it varies between 10^{-6} and 10^{-2}.

B. Median filtering

After completing hypothesis test, motion pixel is marked as "0" and still pixel marked as "1". Therefore, the result of segmentation of the current frame is a binary image. Error II, that is, still pixels are decided as moving ones due to the noise can happen however and due to that spots will present in the binary mask but the probability is small. Median filter is applied for removing occurred spots due to error II. The 2-D median filter repeats the following steps for each pixel in the binary image.

- Store the neighbouring pixels with odd size in a window.
- Sort the values of pixels in the window in numeric order.
- Pick the median from the window as the central pixel value.

C. Formation of MB mask :-

The MB mask is generated after executing first two steps sequentially that is hypothesis test and median filtering but these steps does not produce appropriate results. The typical problem is the mask cannot cover motion objects completely. For improving segmentation result we use MB mask. Median filtering process generates a binary mask M. Formation of MB mask requires to divide binary mask M into several MBs.

For each MB, as long as it contains motion pixels in it, it is marked as a motion MB, as shown in Fig. 1. There are two types of sizes of MBs; small MBs and larger MBs. The small MBs is apply for objects with coarse texture while larger MBs for objects with plain texture. For improve robustness of this algorithm the larger MBs are selected. Although MB mask is often larger than the actual object and the segmented regions will comprise of part of background, a few of background information will help we understand the gesture and behaviour of motion objects in view of the surveillance aim. In addition, a MB is a rectangular region that can lower greatly coding complexity for the object-based coding strategy.

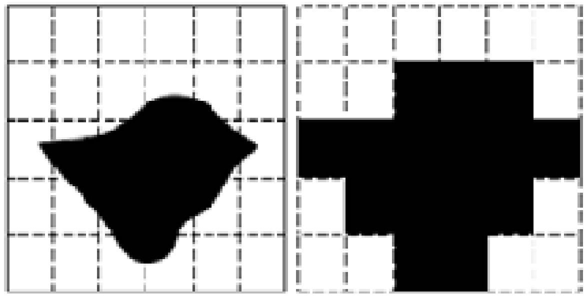

Fig.1. Segmentation mask of an object (The left part of figure shows binary mask M and right part of figure shows MB mask generated from binary mask M).

IV. EXPERIMETAL RESULTS

In the video surveillance, from the given video the background is easily extracted. Therefore, we gain the statistical characteristic of camera noise by the difference between background image and frames without motion objects. Here by applying test statistics the test frames of video sequences are shown in fig. 2.

Experiments on the sequences above use $2\gamma|d|$ and $(d/\sigma)^2$ as test statistics at different S value to implement motion segmentation. Taking the hypothesis test for pixels, the binary mask which

Fig.2. Test frame from video

represents "1" as still and "0" as moving and the ultimate segmentation region covered by a MB mask and the ultimate segmentation regions covered by MB masks for a given video is shown in Fig. 3. Fig. 3-(a) shows the result of hypothesis. Fig 3-(b) shows result of median filter and Fig. 3(c) Segmentation result in which vehicles are detected from the given video.

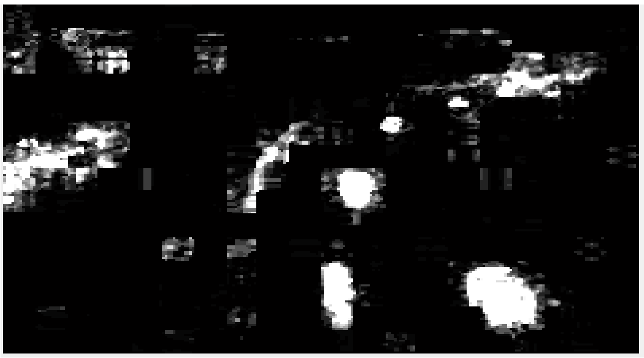

Fig.3 -(a). Result of hypothesis test

Fig.3 -(b). Result of median filter

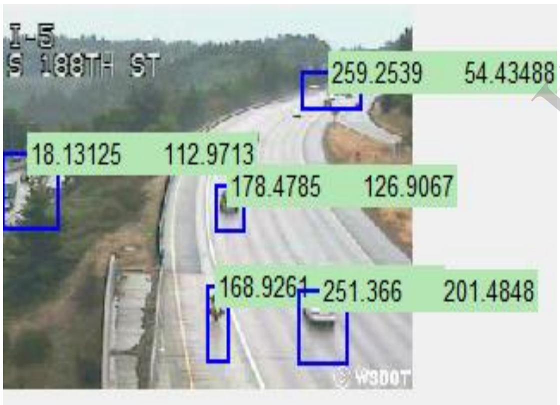

Fig.3 -(c). Segmentation result in which vehicles are detected from the given video.

V. CONCLUSION

In this paper, motion segmentation algorithm is used for surveillance video coding. There are three steps carried for motion segmentation. In first step we find out the pixel is moving or still in the video by using hypothesis test. In next step the median filter removes noise or isolated spots from the result which is produced by hypothesis test. At last, MB mask is formed from the binary mask M. The MB mask covers the whole object which contain in given video. Experimental results show the proposed “test for pixels - median filtering - MB mask” strategy is robust with low complexity.

REFERENCES

1. Bing-Fei Wu, Fellow, IEEE, and Jhy-Hong Juang,”Adaptive vehicle detector approach for complex environments,” Trans. Intell. Transp.Syst., vol. 13, no. 2, pp. 817–827, Jun. 2012.
2. M. P. Kumar, P. H. Torr, and A. Zisserman, “Learning layered motion segmentations of video,” International Journal of Computer Vision, vol. 76, no. 3, pp. 301–319, 2008.
3. D. Cremers and S. Soatto, “Motion competition: A variational approach to piecewise parametric motion segmentation,” International Journal of Computer Vision, vol. 62, no. 3, pp. 249–265, May 2005.
4. H. Shen, L. Zhang, B. Huang, and P. Li, “A map approach for joint motion estimation, segmentation, and super resolution,” IEEE Transactions on Image Processing, vol. 16, no. 2, pp. 479–490, 2007.
5. D. Koller, J. Weber, T. Huang, J. Malik, J. Ogasawara, G. Rao, and S. Russell, “Towards robust automatic traffic scene analysis in real-time,” in Proc. 12th Int. Conf. Comput. Vis. Image Process., 1994, vol. 1, pp. 126–131.
6. B. Coifman, D. Beyber, P. McLauchlan, and J. Malik, “A real-time computer vision system for vehicle tracking and traffic surveillance,” Transp.Res. Part C, vol. 6, no. 4, pp. 271–288, 1998..
7. Birgi Tamersoy and J.K. Aggarwal, “Robust Vehicle Detection for Tracking in Highway Surveillance Videos using Unsupervised Learning”,IEEE Computer Society pp. 529-534,2009.
8. S. Gupte, O. Masoud, R. F. K. Martin, and N. P. Papanikolopoulos, “Detection and classification of vehicles,” IEEE Trans. Intell. Transp. Syst., vol. 3, no. 1, pp. 37–47, Mar. 2002.
9. B. Bartin and K. Ozbay, “Determining the optimal configuration of highway routes for real-time traffic information: A case study,” IEEE Trans. Intell. Transp. Syst., vol. 11, no. 1, pp. 225–231, Mar. 2010.
10. N. K. Kanhere and S. T. Birchfield, “A taxonomy and analysis of camera calibration methods for traffic monitoring applications,” IEEE Trans. Intell. Transp. Syst., vol. 11, no. 2, pp. 441–452, Jun. 2010.
11. Til Aach, André Kaup, Rudolf Mester, “Statistical model- based change detection in moving video,” Signal Processing, vol. 31, pp.165-180, 1993.