International Journal of Advanced Research in Electronics and Communication Engineering (IJARECE)
Volume 3, Issue 11, November 2014

Segmentation of Moving Vehicles under Complex Outdoor Condition Using Block Matching Algorithm

Agalya A[*1], Nirmalakumari k [#2], Rajkumar P [#3],Rajalakshmi A [#4],Janani B [#5]

[*]PG scholar, Bannari Amman Institute of Technology,
Sathyamangalam,Tamilnadu,India.
[#]Assistant Professor(Sr.G), Dept.of ECE, Bannari Amman Institute of Technology,
Sathyamangalam,Tamilnadu,India.
#Robert Bosch Engineering And Business Solutions Limited,
Coimbatore, Tamilnadu,India.
[#]PG scholar, Bannari Amman Institute of Technology,
Sathyamangalam,Tamilnadu, India.
#PG scholar, Bannari Amman Institute of Technology,
Sathyamangalam,Tamilnadu,India.

***Abstract*-In the presence of unfavorable luminance conditions or in the presence of camera noise, the segmentation and motion detection of traffic vehicles in an outdoor environment, particularly under non ideal weather condition such as snowfall, heavy rain, fog is still an area of active research. In computer vision system, to detect moving objects Gaussian-based background modeling is used. But it has some limitation. So we propose an approach using the block matching algorithm, which robustly detects the motion of interest and can suppress the false motion in a challenging outdoor environment. To measure in BMA, The sum of absolute difference (SAD) is commonly used and this determines the motion/change in video sequences. BMA was adopted by many video-coding standards such as MPEG-1/2/4, H.261, H.263, and H.264/AVC. FS or exhaustive search algorithms consider every pixel in the block and provide optimum results This algorithm segment multiple vehicles and even able to detect the human intervention in an unrestricted area.**

***Keywords*: Block matching algorithm, vehicle tracking, Human detection.**

I. INTRODUCTION

The surveillance for humans and vehicles in dynamic scenes is one of the sectors in computer vision [1]-[3]. Weather conditions, noisy low-quality videos, and dynamic background are the factors that affect the segmentation of moving vehicles in outdoor traffic sequences. To develop more accurate and robust algorithms for moving object detection and segmentation, many researchers have been involved in work that is related to video surveillance [9].
The challenging outdoor surroundings:

- The serious limitation to the visibility of moving objects causes complex weather condition such as snowfall, heavy rain and fog.
- Wind or the passing of a heavy vehicle may cause the vibration of camera.

Our segmentation algorithm suppresses the noise that is introduced due to small camera movements to obtain efficient result. Due to snowy or foggy weather, it reduces the false motion. The segmentation using BMA is challenging, because it is essential to suppress the motion vectors that result from changing background. It varies from frame to frame, due to the dynamic nature of background. FS is computationally expensive but it is very efficient in determining the motion and reduces the computation time. A computationally efficient approach makes use of temporal difference that was obtained using three consecutive frames to identify moving regions in a traffic sequence[13]. This approach assumes that the background is stationary and any object that has significant motion is considered part of the foreground. For clustering of vehicle trajectories it makes use MOG for segmenting moving vehicles. A sudden change in global illumination can change the entire frame into foreground. The temporal difference can result from numerous other factors such as adverse weather conditions, camera noise and small camera movements.

II. RELATED PROJECTS

The segmentation can be classified as frame/temporal differencing and background modeling. Mixture of Gaussians is a widely used approach for background modeling to detect moving objects from static cameras. Gaussian distribution model is used for building the background model.
Frame differencing compares categorizing areas and successive frames that have pixels difference greater than the certain threshold as foreground

 All Rights Reserved © 2014 IJARECE

regions. Temporal differencing makes use of the pixel-wise differences between two or three consecutive frames in an image sequence to extract moving regions. It is very adaptive to dynamic environment, but generally does a poor job of extracting all the relevant pixels. An improved version uses three-frame instead of two-frame differencing.

Background subtraction is a popular method for motion segmentation, especially under those situations with a relatively static background. It detects moving regions in an image by taking the difference between the current image and the reference background image in a pixel-by-pixel fashion. It is simple, but extremely sensitive to changes in dynamic scenes derived from lighting and extraneous events.

III. SEGMENTATION PROCESS

Background/foreground detection is an essential component of most video surveillance systems involving object detection and tracking. Such systems require both robustness to lighting variation and computer feasibility. Most of the existing solutions either make strict assumptions about the scene or simply fail when handling abrupt lighting variations resulting from moving clouds or camera automated gain control. The proposed segmentation system will be described below. This methodology is based on five main parts: 1) Background modeling; 2) Foreground pixels validation criteria; 3)Shadows/Highlight removal; 4)Blob validation.

A. Background Modeling

In order to achieve a good segmentation in an outdoor environment it is necessary to have a background model that considers all scenes' variations not classified as foreground. Three different background images are used to model the background, namely the primary background (BP), the secondary background (BS) and the median background (BM). The BP background has to have, at all times, the background model that is closest to the current frame. The BS background is used to model objects classified as static but that can undergo small variations in position and/or in shape

B. Foreground Pixels Validation Criteria

Most systems compute the difference between the current frame and the background image and consider as targets the pixels above a certain threshold. Then, neighborhood pixels are clustered to form possible foreground regions. This process usually leaves gaps that might lead to erroneous foreground detection. Morphology can be used to fill in these gaps.

C. Shadow/Highlight Removal

In order to detect shadow/highlight on the segmented regions it is computed the color normalized cross-correlation (CNCC). This solution measures the similarity between BtP and It. The color of the pixel is represented in the bi-conic HSL space in order to split the color information from the brightness values [4]

IV . PROPOSED SYSTEM

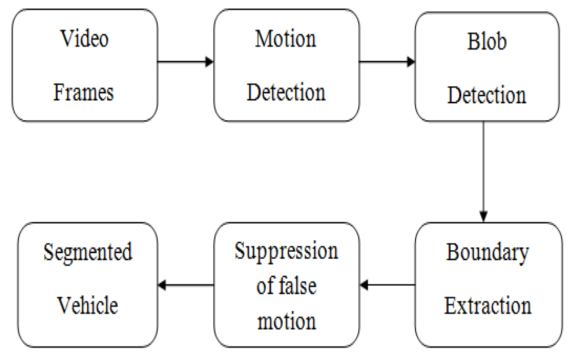


Fig 1. Block diagram of Moving vehicle segmentation

V. MOVING VEHICLE SEGMENTATION

A. Motion detection

It is the process of detecting a change in position of an object relative to its surroundings or the change in the surroundings relative to an object. It can be achieved by both mechanical and electronic methods. When motion detection is accomplished by natural organisms, it is called motion perception. Motion can be detected by, infrared, optics, sound, and magnetism.

B. Blob detection

In the field of computer vision, it refers to mathematical methods that are aimed at detecting regions in a digital image that differ in properties, such as brightness or color, compared to areas surrounding those regions.

Blob detection was used to obtain regions for further processing. Normally , a blob is a region of a digital image in which some properties are constant.

C. Boundary extraction

The goal of boundary extraction is to find the pixels that are on the boundary of objects in the image. On the edges of the vehicle, we regroup blocks because edges reflect higher temporal change than the body and finally we can get the boundary of the vehicles.

 All Rights Reserved © 2014 IJARECE

D. Suppression of false motion

It is the movement of' an extremity where there should be no motion, such as at the point of a fracture. Due to dynamic background, most of the false motion is eliminated.

VI . BLOCK MATCHING ALGORITHM

The MPEG and H.26X standards use block matching algorithm for motion detection and estimation. In the block-matching algorithm ,each current frame is divide into equal-size blocks, called source blocks. Each source block is associated with a search region in the reference frame.

The objective of block-matching is to find a candidate block in the search region best matched to the source block. The relative distances between a source block and its candidate blocks are called motion vectors. The motion of each block is assumed to be uniform .In full search block matching algorithm, all candidates within search window are examined. In order to avoid this complexity, we should reduce search positions to fast block matching algorithm. The difference between sum of intensity values can be used as a lower bound for SAD value. This bound is used to exclude search points.

VII . SIMULATION AND ANALYSIS

Fig.. 2 Video Frame

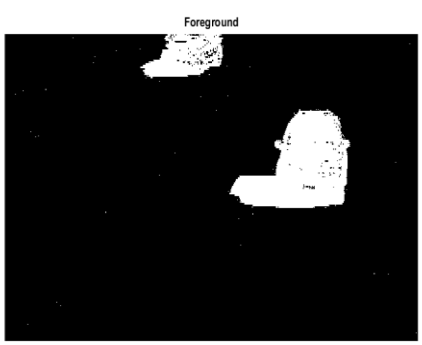
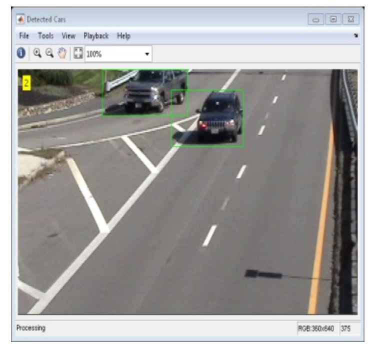


Fig. 3 Foreground

Fig. 4 Clean foreground



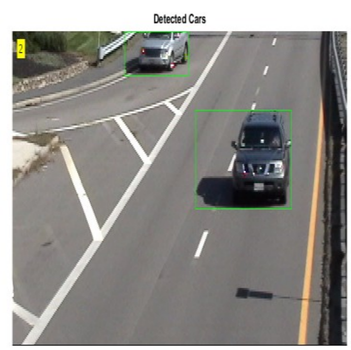


Fig. 4 Detected cars

VIII. CONCLUSIONS

Our proposed techniques shows the robustness of our algorithm in retaining all the moving vehicles and reducing the false motion with the similar texture as that of the dominating background even under poor visibility. Our algorithm considerably reduces false motion that was caused due to different weather conditions such as snowfall, fog and heavy rain. This algorithm detects multiple vehicles simultaneously and to segregate the moving vehicles from the background. We can further reduce their effect and obtain a much clearer background by preprocessing these frames.

 All Rights Reserved © 2014 IJARECE

REFERENCES

[1] T. Bodsky, R. Cohen, E. Cohen-Solal, S. Gutta, D. Lyons, V. Philomin, and M. Trajkovic, "Visual surveillance in retail stores and in the home," in *Advanced Video-Based Surveillance Systems*. Boston, MA: Kluwer, Apr. 2001, ch. 4, pp. 50–61.

[2] W. Hu, T. Tan, L. Wang, and S. Maybank, "A survey on visual surveillance of object motion and behaviors*," IEEE Trans. Syst.,Man, Cybern. C: Appl. Rev., vol. 34, no. 3, pp. 334–350, Aug. 2004.*

[3] I. Haritaoglu, D. Harwood, and L. Davis, "W4: Who, When, Where,What: A real-time system for detecting and tracking people," in *Proc. Int. Conf. Face Gesture Recog., Nara, Japan, Apr. 14–16, 1998, pp. 222–227.*

[4] L. Wang and N. H. C. Yung, "Extraction of moving objects from their background based on multiple adaptive thresholds and boundary evaluation*," IEEE Trans. Intell. Transp. Syst., vol. 11, no. 1, pp. 40–51, Mar. 2010.*

[5] N. Buch, S. A. Velastin, and J. Orwell, "A review of computer vision techniques for the analysis of urban traffic," *IEEE Trans. Intell. Transp. Syst., vol. 12, no. 3, pp. 920–929, Sep. 2011*

[6] Y. K. Ki and D. Y. Lee, "A traffic accident recording and reporting model at intersections*," IEEE Trans. Intell. Transp. Syst., vol. 8, no. 2, pp. 188– 194, Jun. 2007.*

[7] Z. Yu and Y. Chen, "A real-time motion detection algorithm for traffic monitoring systems based on consecutive temporal difference," in *Proc. 7th Asian Control Conf.*, Hong Kong, China, Aug. 27–29, 2009, pp. 1594–1599.

[8] N. J. B. McFarlane and C. P. Schofield, "Segmentation and tracking of piglets in images," *Mach. Vis. Appl.*, vol. 8, no. 3, pp. 187–193, May 1995.

[9] K. Onoguchi, "Moving object detection using a cross correlation between a short accumulated histogram and a long accumulated histogram," in *Proc. 18th Int. Conf. Pattern Recog.*, Hong Kong, China, Aug. 20–24, 2006, vol. 4, pp. 896–899.

[10] 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.

[11] A. Monnet, A. Mittal, N. Paragios, and V. Ramesh, "Background mod- eling and subtraction of dynamic scenes," in *Proc. 9th IEEE Int. Conf. Comput. Vis.*, Nice, France, Oct. 13–16, 2003, vol. 2, pp. 1305–1312.

[12] C. Wren, A. Azabayejani, T. Darrel, and A. Pentland, "Pfnder: Real-time tracking of the human body," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 19, no. 7, pp. 780–785, Jul. 1997.

[13] W. E. L. Grimson and C. Stauffer, "Adaptive background mixture models for real-time tracking," in *Proc. IEEE Conf. Comput Vis. Pattern Recog.*, Fort Collins, CO, Jun. 23–25, 1999, vol. 1, pp. 22–29.

[14] S. Atev, G. Miller, and N. P. Papanikolopoulos, "Clustering of vehicle trajectories," *IEEE Trans. Intell. Transp. Syst.*, vol. 11, no. 3, pp. 647– 657, Sep. 2010.

[15] S. C. S. Cheung and C. Kamath, "Robust techniques for background subtraction in urban traffic video," in *Proc. SPIE Video Commun. Image Process.*, Jan. 2004, vol. 5388, pp. 881–892.

[16] P. Kaewtrakulpong and R. Bowden, "An improved adaptive background mixture model for real-time tracking with shadow detection," in *Proc. 2nd Eur. Workshop Adv. Video Based Surv. Syst.*, Kingston, U.K., Sep. 2001.

[17] W. Zhang, X. Z. Fang, and X. Yang, "Moving vehicles segmentation based on Bayesian framework for Gaussian motion model," *Pattern Recognit. Lett.*, vol. 27, no. 9, pp. 956–967, Jul. 2006.