Performance Analysis of Vehicle Detection in Unstructured Environment

Abinaya V[1],Sowmiya P [2]

Assistant Professor[1], M.E Communication Systems[2]

Department of Electronics and Communication Engineering

Bharathiyar Institute of Engineering for Women

(abinayavelmurugan9@gmail.com)[1],(sugi1811@gmail.com)[2]

Abstract

Moving object detection is low-level, main task for any graphic reconnaissance system. One of the aim of this project. To describe various approaches of moving object detection such as background subtraction, temporal difference. A statistical mean technique is used to overcome the problematic in preceding techniques. We propose a modified arithmetical mean technique with noise eliminating process that is computationally fast, by allowing the parallel processing. This paper also presents an effective traffic reconnaissance system for detecting and tracking moving vehicles in nighttime traffic scenes. The proposed method classifies vehicles by detecting and finding vehicle headlights and taillights using image segmentation and pattern analysis techniques. This proposed technique, overcome the problems of traditional methodology of moving object detection.

I. INTRODUCTION

Tracking is closely related to constructing correspondences between frames. Traditional tracking approaches focus on finding *low-level* correspondences based on image evidence. Online models for low-level correspondences are generally employed to adapt to the changing appearances of the target [1]–[3]. However, one notable shortcoming of these online models is that they are constructed and updated based on the previous appearance of the target without much semantic understanding.

Therefore, they are limited in predicting unprecedented states of the target due to significant view changes and occlusion, and easily drift in the case when the appearance of the target changes too fast. Figure 1(a) shows an example where the visual appearance of the target changes dramatically in a very short time period, making low-level image correspondences unstable. Without other information, it is very likely to cause tracking failure, no matter what online model is used. However, if we can recognize this target as a car at a higher level, the tracking task becomes to find the same *car* in the subsequent images instead of finding the object with the same low-level appearance. Therefore, the discriminative information provided by the car category, i.e., the *high-level* correspondences, can be utilized to help successfully track the target.

In other words, to make tracking consistently effective in various challenging scenarios, it is necessary to combine both low-level and high-level correspondences. Some offline-trained high-level detectors with semantic meanings have already been introduced into the tracking-by detection scheme for some specific tracking tasks, especially for human tracking [4]–[5] and vehicle tracking [7], which largely improves the tracking performance. However, these models assume the semantic meanings of targets are already known before tracking, and accordingly cannot be applied to many general applications. Consider a video surveillance scenario with a complex scene, the categories of the moving objects cannot be predicted. Nevertheless, every moving object should be correctly tracked for subsequent analysis, no matter whether it is a human, a car or even an animal. Christo Ananth et al. [6] proposed a system about Efficient Sensor Network for Vehicle Security. Today vehicle theft rate is very high, greater challenges are coming from thieves thus tracking/ alarming systems are being deployed with an increasingly popularity .As per as security is concerned today most of the vehicles are running on the LPG so it is necessary to monitor any leakage or level of LPG in order to provide safety to passenger. Also in this fast running world everybody is in hurry so it is required to provide fully automated maintenance system to make the journey of the passenger safe, comfortable and economical. To make the system more intelligent and advanced it is required to introduce some important developments that can help to promote not only the luxurious but also safety drive to the owner. The system "Efficient Sensor Network for Vehicle Security", introduces a new trend in automobile industry.

II.RELATED WORKS

The surveillance system typically uses stationary sensors to monitor an environment of interest. The stationary sensor allows the use of the frame difference (FD) technique and the back ground modeling technique for detection ofmoving object, since interesting objects in a fixed scene are usually defined to be moving ones [1]-[10]. The FD is based on simply observing difference between two adjacent frames. By setting a threshold value, a pixel is identified as foreground if the statistic associated with the observation is higher than the threshold value. Otherwise the pixel is identified as background [1]-[14].

To achieve real-time detection with specified video format, several hardware-oriented foreground detection algorithms are presented. Morimoto *et al*. proposed boundary-scan-only foreground detection architecture and its FPGA-based prototype system for 80×60 sized video sequences [15]. Since a huge amount of frames is available and no scene change is occurred between frames, the detection of foreground cannot be restricted to observe difference between two adjacent frames. Instead, the large amount of frames is used as the observation period for making foreground/background decision. Such approach is called background modeling approach [16]-[18]. The mixture of Gaussian (MoG) [19]-[20] and the non-parametric model [16]-[18] are two typically used models. To achieve real-time processing, some simplifications are presented for the most computationally intensive part, the background model constructing. Tsai *et al*. presented a VLSI architecture using multiple background maintenance technique .

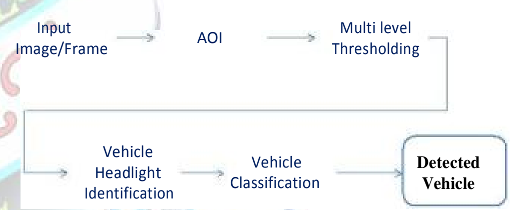
The constructing background model in the architecture is based on look-up-table manner. Jiang presented a simplified mixture of Gaussian (SMoG) algorithm and its architecture design. To overcome such dynamic background problem, the issue of tolerating background motions while detecting foreground motions is explored, and various sophisticated background modeling approaches are presented . However, such approaches substantially increase the hardware cost and are not easily realized for real-time application.

III.PROPOSED SYSTEM

Moving object detection is the basic step for further analysis of video. Every tracking method requires an object detection mechanism either in every frame or when the object first appears in the video. It handles segmentation of moving objects from stationary background objects .We use the temporal information computed from a sequence of frames to reduce the number of false detections .This temporal information is usually in the form of frame differencing, which highlights regions that changes dynamically in consecutive frames. Object detection can be achieved by building a representation of the scene called the background model and then finding deviations from the model for each incoming frame.

Any significant change in an image region from the background model signifies a moving object. The pixels constituting the regions undergoing change are marked for further processing. Temporal differencing method uses the pixel-wise difference between two or three consecutive frames in video imagery to extract moving regions. It is a highly adaptive approach to dynamic scene changes .Let In(x) represent the gray-level intensity value at pixel position x and at time instance n of video image sequence I, which is in the range [0, 255]. T is the threshold initially set to a pre-determined value. Two-frame temporal differencing scheme suggests that a pixel is moving if it satisfies the following:

Proposed system model for vehicle detection and Classification:



Fast bright-object segmentation process based on automatic multilevel histogram thresholding. Locating headlights and tail lights using the connected components analysis. Spatial clustering process for grouping these bright components to obtain groups of vehicle lights. Feature based vehicle tracking. Feature based vehicle identification and Classification. Lines of roads and divider are detected using Hough transform. Draw the line which passes through the middle of the image in horizontal direction.AOI is the region between the middle line and detected road boundaries.

PROCEDURE FOR DETECTION OF ROAD LINE SEGMENTS:

➤ **STEP1:**

- Convert the Road Image in to two binary Images using Threshold method.
- By doing repeated experiments, we set threshold as 50.
- At this stage ,the road region is not exactly separated.
- To exactly separate or locate the boundary of the Road region, we use Edge detection followed by Hough Transform.

STEP2:

- Find the Edge Image from the foreground Image(Road Image) using 'canny' Edge Detection method.

STEP3:

- Apply Hough Transform.
- It detects the line in the binary Image for the particular Orientation Image.
- The hough function implements the Standard Hough Transform (SHT). The SHT uses the parametric representation of a line:
- rho = x*cos(theta) + y*sin(theta)
- Where theta=particular Orientation(1,2,3,……..180).
- At this stage, we get 180 Hough Transformed Images.
- From these 180 Images, find the image which have most possible line segments.
- To find the maximum length line segment, apply morphological operation.
- Morphologically open binary image(bwareaopen) is used to remove small objects.
- It removes the smallest line segments by keeping the boundry lines of the Road Image.
- Choose each pixel in the morphological opened Road Image.
- If the pixel(I)==0,no change will be made in the Original Color Road Image.
- If the pixel(I)==1,Change the Corresponding 'R' Component pixel value to 255 and G=0 and B=0 of that Particular Pixel.
- To preliminarily screen out non vehicle illuminating objects, such as street lamps and traffic lights located at the top side of traffic scenes, and to effectively and rapidly locate the sufficiently reliable and clear features of moving vehicles, and efficiently save the redundant computational costs for the embedded system implementation, we apply a detection area for each traffic scene.
- This detection area is the midline of the traffic-scene image and bounded by the most left and right lanes.

Video Type	Number of frames	Video width	Video Height	Processing Time in Sec per frame	False Negative Rate
Traffic.avi	120	160	120	0.2519	0.2083
Input2.avi	79	352	288	0.2401	0.0001

Illustration of detection area of traffic scenes

Headlight Identification:

$$D_h(C_i, C_j) = \max(l_{C_i}, l_{C_j}) - \min(r_{C_i}, r_{C_j})$$

$$D_v(C_i, C_j) = \max(t_{C_i}, t_{C_j}) - \min(b_{C_i}, b_{C_j})$$

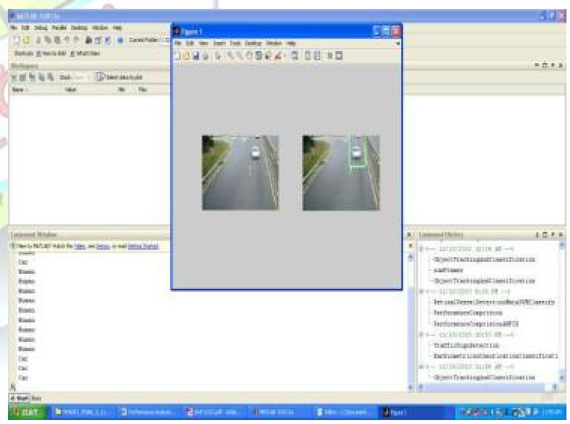
[illegible] or $D_v(C_i, C_j)$ will be negative.

The RGB Image is converted in to Ycb Cr image.Y is the luminance or gray scale image.The thresholding is applied on the Y components only to extract the bright objects.In our proposed work, multilevel thresholding is use to separate the light source of the vehicles from other bright objects.

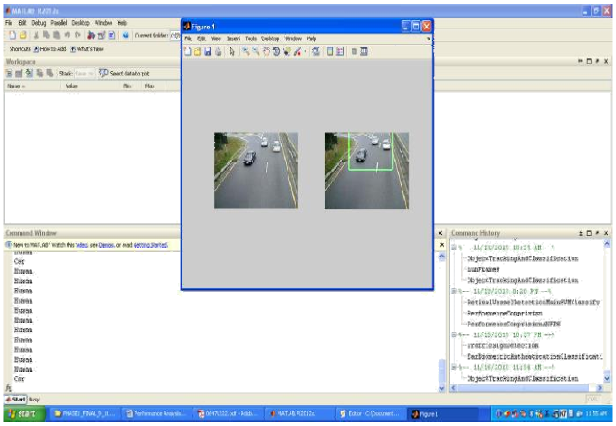
Computation of width and Height using connected component Analysis:

1) C_i denotes the ith lighting component to be processed.
2) CS_k denotes the kth set of bright components $CS_k = \{C_i, i = 0, 1, \ldots, p\}$, while the amount of its contained lighting components is denoted as $|CS_k|$.
3) The locations of a certain component C_i employed in the spatial classification process are their top, bottom, left, and right coordinates, denoted as t_{C_i}, b_{C_i}, l_{C_i}, and r_{C_i}, respectively.
4) The width and height of a bright component C_i are denoted as $W(C_i)$ and $H(C_i)$, respectively.
5) The horizontal distance D_h and the vertical distance D_v between a pair of ith and jth lighting components are defined as

<u>Simulation Screenshot for traffic.avi video:</u>



Simulation Screenshot for trafficinput2.avi video



Performance Analysis:

Video Type	Existing	Proposed
Number of frames	120	120
Video width	160	160
Video Height	120	120
Processing Time in Sec per frame	0.3519	0.2519
False Negative Rate	0.3761	0.2083
Accuracy	62.39	79.17

REFERENCES

[1] S. Avidan, "Ensemble tracking," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 29, no. 2, pp. 261–271, Feb. 2007.

[2] B. Babenko, M.-H. Yang, and S. Belongie, "Visual tracking with online multiple instance learning," in *Proc. Conf. Comput. Vis. Pattern Recognit.*, 2009, pp. 983–990.

[3] H. Grabner, M. Grabner, and H. Bischof, "Real-time tracking via on-line boosting," in *Proc. British Mach. Vis. Conf.*, 2006, pp. 1–10.

[4] Y. Li, H. Ai, T. Yamashita, S. Lao, and M. Kawade, "Tracking in low frame rate video: A cascade particle filter with discriminative observers of different life spans," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 30, no. 10, pp. 1728–1740, Oct. 2008.

[5] B. Wu and R. Nevatia, "Detection and tracking of multiple, partially occluded humans by Bayesian combination of edgelet based part detectors," *Int. J. Comput. Vis.*, vol. 75, no. 2, pp. 247–266, Nov. 2007.

[6] Christo Ananth, I.Uma Sankari, A.Vidhya, M.Vickneshwari, P.Karthiga, "Efficient Sensor Network for Vehicle Security", International Journal of Advanced Scientific and Technical Research (IJASR), Volume 2, Issue 4, March-April 2014,pp – 871-877

[7] B. Leibe, K. Schindler, N. Cornelis, and L. V. Gool, "Coupled object detection and tracking from static cameras and moving vehicles," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 30, no. 10, pp. 1683–1698, Oct. 2008.

[8] A. Yilmaz, O. Javed, and M. Shah, "Object tracking: A survey," *ACM Comput. Surv.*, vol. 38, no. 4, pp. pp. 1–13, 2006.

[9] M. Isard and A. Blake, "Contour tracking by stochastic propagation of conditional density," in *Proc. Eur. Conf. Comput. Vis.*, 1996, pp. 343–356.

[10] Z. Kalal, J. Matas, and K. Mikolajczyk, "P-N learning: Bootstrapping binary classifiers by structural constraints," in *Proc. Conf. Comput. Vis. Pattern Recognit.*, 2010, pp. 49–56.

[11] A. Srivastava and E. Klassen, "Bayesian and geometric subspace tracking," *Adv. Appl. Probab.*, vol. 36, pp. 43–56, Dec. 2004.

[12] F. Porikli, O. Tuzel, and P. Meer, "Covariance tracking using model update

Recognit., 2006, pp. 728–735.

[13] A. Tyagi and J. W. Davis, "A recursive filter for linear systems on Riemannian manifolds," in *Proc. Conf. Comput. Vis. Pattern Recognit.*, 2008, pp. 1–8.

[14] J. Kwon, K. M. Lee, and F. C. Park, "Visual tracking via geometric particle filtering on the affine group with optimal importance functions," in *Proc. Conf. Comput. Vis. Pattern Recognit.*, 2009, pp. 991–998.

[15] X. Mei and H. Ling, "Robust visual tracking using _1 minimization," in *Proc. Int. Conf. Comput. Vis.*, 2009, pp. 1436–1443.

[16] R. Li and R. Chellappa, "Aligning spatio-temporal signals on a special manifold," in *Proc. Eur. Conf. Comput. Vis.*, 2010, pp. 547–560.

[17] C. Bibby and I. Reid, "Real-time tracking of multiple occluding objects using level sets," in *Proc. Conf. Comput. Vis. Pattern Recognit.*, 2010, pp. 1307–1314.

[18] N. Alt, S. Hinterstoisser, and N. Navab, "Rapid selection of reliable templates for visual tracking," in *Proc. Conf. Comput. Vis. Pattern Recognit.*, 2010, pp. 1355–1362.

[19] J. Fan, "Toward robust visual tracking: Creating reliable observations from videos," Ph.D. thesis, Dept. Comput. Eng., Northwestern Univ., Evanston, IL, 2011.

[20] X. Mei, H. Ling, and Y. Wu, "Minimum error bounded efficient _1 tracker with occlusion detection," in *Proc. Conf. Comput. Vis. Pattern Recognit.*, 2011, pp. 1257–1264.