International Journal of Research in Engineering and Science (IJRES)
ISSN (Online): 2320-9364, ISSN (Print): 2320-9356
www.ijres.org Volume 1 Issue 2 ǁ June 2013 ǁ PP.41-44

A New Approach for Vehicle Detection in Aerial Surveillances

Divya Michael[1], Paul P Mathai[2]

[1](Dept. of Computer Science & Engineering, FISAT Angamaly, M. G. University, India)
[2](Dept. of Computer Science & Engineering, FISAT Angamaly, M. G. University, India)

Abstract— *Target object detection in aerial surveillance using image processing techniques is growing more and more important. Aerial surveillance is more suitable for monitoring fast-moving targets and covers a much larger spatial area. Aerial view has the advantage of providing a better perspective of the area being covered. These techniques make use of the aerial videos taken from aerial vehicles. Vehicle detection technique has a variety of applications, such as traffic management, police and military. The purpose of this technical report is to provide a survey of research related to the application of vehicle detection techniques for traffic management and other applications and also to present the proposed system.*
Index Terms—*Aerial surveillance, Background subtraction, Feature extraction, Gaussian mixture, SVM, Vehicle classification, Vehicle detection*.

I. INTRODUCTION

In recent years, the analysis of aerial videos taken from aerial vehicle has become an important issue. The increase in the number of vehicles on roadway networks has led transport management agencies to allow use of technology advances resulting in better decisions. According to this perspective aerial surveillance has better place nowadays. Aerial surveillance is more suitable for providing increased monitoring results in case of fast-moving targets and covers a much larger spatial area. So these aerial surveillance systems become excellent supplements of ground-plane surveillance systems. One of the main topics in intelligent aerial surveillance is vehicle detection and tracking. The difficulties involved in the aerial Surveillance include the camera motions such as rotation, panning and tilting. Also the different camera heights largely affect the detection results. Vision based techniques is one of the most common approach to analyze vehicles from images or videos.

In this system, design a pixelwise classification method for vehicle detection and novelty lies in the fact that, instead of performing pixelwise classification, relationship among the neighboring pixels in a particular region are preserved in the feature extraction process. The vehicle detection technique consist of three parts i.e., a background subtraction model, vehicle detection and tracking.

In this system, design a pixelwise classification method for vehicle detection and novelty lies in the fact that, instead of performing pixelwise classification, relationship among the neighboring pixels in a particular region are preserved in the feature extraction process. The vehicle detection technique consist of three parts i.e., a background subtraction model, vehicle detection and tracking.

The Gaussian mixture algorithm used for background subtraction developed by Stauffer and Grimson [1] aims to segment moving foreground objects from relatively stationary objects. Recently pixel-based probabilistic model methods gained lots of interests and have shown good detection results. The values of a particular pixel are modeled as a mixture of adaptive Gaussians. At each iteration Gaussians are evaluated using a simple heuristic to determine which ones are mostly likely to correspond to the background pixels. Those pixels that do not match with the background Gaussians are classified as foreground.

In the detection phase, first perform background color removal. Afterward, the feature extraction procedure is performed as in the training phase. The extracted features from feature extraction phase serve as the input to support vector machine, which indicates whether a pixel belongs to a vehicle or not. There is no need to generate multiscale sliding windows either. The detection task is based on pixel wise classification and the features are extracted in a neighborhood region of each pixel. Finally, the extracted features comprise of pixel-level information and also the relationship among neighboring pixels in a region. This design is more effective and efficient than region-based or multiscale sliding window detection methods.

This system considers features including local feature points, vehicle colors and edges. For vehicle color extraction, system utilizes color transform to separate vehicle colors and non-vehicle colors effectively. For edge detection, system applies moment-preserving method to adjust the thresholds for canny edge detector automatically, which in turn increases the adaptability and accuracy of the system. A support vector machine is constructed for classification purpose and features are extracted. The extracted features comprise not only pixel-level information but also relationship among neighboring pixels in a region is considered.

This paper mentions various methodologies for target object detection in aerial surveillance Section 2 summarizes important works related to vehicle detection and also presented the proposed system and section 3 concludes the discussion.

II. RELATED WORK

S. Srinivasan, H. Latchman, J. Shea, T. Wong, and J. McNair [2] have introduced a method for the airborne video registration and traffic-flow parameter estimation which focus on airborne helicopter video for estimating traffic parameters. The airborne video is taken from a digital video camera attached to the skid of the helicopter. Roll, pitch, and yaw of the helicopter make the video difficult to view, unstable and the derived parameters less accurate. To avoid this, a frame-by-frame video-registration technique using a feature tracker to automatically determine control-point correspondences is present in the system. This feature tracker is used to track fixed features through the sequence of images in the video. These feature-location correspondences are used as control points to compute a polynomial transformation function to warp every frame in the sequence successively to the reference. The reference frame can be any one of the frames in the video segment. By changing the tracking-window orientation, the same feature tracker can be used to track moving vehicles within the registered video segment. The advantages of the system include excessive reliance on sensor data, inadequate stabilization and availability of elevation maps.

S. Hinz and A. Baumgartner [3] utilized a hierarchical model that describes different levels of details of vehicle features. In this system, vehicles are represented in different levels and details of vehicle are increasing from left to right. Hierarchical model describes the appearance of vehicle at different levels. At lowest level vehicle substructures are described like type of vehicle and last level represents 3D information and local context of vehicle. The advantage of this system is that it neither relies on external information like digital map or site models, nor it is limited to any specific vehicle models. As disadvantage, the system would miss vehicles when the contrast is weak or when the influences of neighboring objects are present.

H. Cheng and J.Wus [4] have introduced an adaptive ROI estimation algorithm by analyzing the way the camera is operated. The system proposes an ego-motion of the camera computed from adjacent video frames, and deriving the ROI defined by the operator while capturing the video using an adaptive operator attention model. When monitoring a building beside a highway, only those moving objects associated with the building, such as objects entering or leaving the building, are of interest. Therefore, accurate ROI estimation for aerial surveillance applications must be adaptive and cannot always use the same type of objects, such as moving objects as ROI.

Lin et al [5] proposed a method by subtracting background colors of each frame and then refined vehicle candidate regions by enforcing size constraints of vehicles. The disadvantage of the system is that, it assumed too many parameters such as the smallest and largest sizes of vehicles, height and the focus of the airborne camera etc. Assuming these parameters as known priors might not be realistic in real applications. Also the vehicle detection method is based on cascade classifiers.

Cheng and Butler [6] considered multiple clues and used a mixture of experts to merge the clues for vehicle detection in aerial images. The system consists of color segmentation via mean-shift algorithm and motion analysis via change detection. Also they presented a trainable sequential maximum a posterior method for multiscale analysis and enforcement of contextual information. The system contains a method by subtracting background colors of each frame and then refined vehicle candidate regions by enforcing size constraints of vehicles. A large number of positive and negative training samples need to be collected for the training purpose. Also considers multiscale sliding windows which are generated at the detection stage. The main demerit of this method is that there are a lot of miss detections on rotated vehicles. The faces with poses are easily missed if only frontal faces are trained. Also if faces with poses are added as positive samples, then the number of false alarms would surge.

J. Y. Choi and Y. K. Yang [7] have proposed a vehicle detection algorithm using the symmetric property of car shapes. But this is prone to false detections such as symmetrical details of buildings or road markings. In order to avoid this, a log-polar histogram shape descriptor is used to verify the shape of the candidates. The shape descriptor is obtained from a fixed vehicle model, making the algorithm inflexible. Also the algorithm relied on mean-shift clustering algorithm for image color segmentation. Moreover, nearby vehicles might be clustered as one region if they have similar colors. The advantage is that, using symmetric property of car shapes, object can easily detect. Disadvantages include a vehicle tends to be separated as many regions since car roofs and windshields usually have different colors. Also the high computational complexity of mean-shift segmentation algorithm is another concern.

Luo-weitsai, Jun-weihsieh, Kuo-chin fan [8] proposed a novel vehicle detection method using color transform model. The detection procedure consists of different stages. In the first stage a color transformation model is used to separate vehicle colors from nonvehicle colors effectively. This color model transforms (R,G,B) color components into the color domain (u,v). The technique which is adopted for this is dimensionality reduction. Beginning of the technique follows the collection of several thousands of training images and these training images are collected by projecting all colors of input pixels on the color space. The classification is carried out by means of a Bayesian classifier. By using this method the authors insist that vehicles can be very robustly and accurately verified and detected from static images.

B. Morris and M. Trivedi [9] proposed a tracking system with ability to classify vehicles into three classes such as sedan, semi, truck+SUV+van. This system was developed after comparing classification schemes using vehicle images and measurements. The most accurate among this learned classifier was integrated into tracking software which greatly improved the accuracy on low resolution traffic video.

J. W. Hsieh, S. H. Yu, Y. S. Chen, and W. F. Hu [10] proposed a vehicle tracking and classification technique to estimate important traffic parameters from video sequences using one camera. The system has the ability to categorize vehicles into more specific classes by introducing a new linearity feature in vehicle representation. Also this system can easily tackle the problem of vehicle occlusion caused by shadows. This problem is solved by shadow algorithm that uses a set of lines to eliminate all unwanted shadows.

Background subtraction is a process which aims to segment moving foreground objects from a relatively stationary background. Recently pixel-based probabilistic model methods gained lots of interests and have shown good detection results. Background modeling by Gaussian mixtures is a pixel based process. Let $\mathbf{x}$ be a random process representing the value of a given pixel in time. A convenient framework to model the probability density function of $\mathbf{x}$ is the parametric Gaussian mixture model where the density is composed of a sum of Gaussians. Let $p(\mathbf{x})$ denotes the probability density function of a Gaussian mixture comprising K component densities. The mixture of Gaussians algorithm, proposed by Stauffer and Grimson [1], estimates these parameters over time to obtain a robust representation of the background.Here every pixel is checked against K Gaussian distributions until a match is found and if no match is found for a pixel, the least probable distribution is replaced with a distribution with current value as its mean value. The advantage includes its good accuracy and disadvantages include high computational cost and high execution time.

Zivkovic [11] proposed an approach which reduces the computation time and memory bandwidth. Here, a Bayesian approach is formulated to select the required number of Gaussian modes for each pixel in the scene. In scenes with static background, this approach assigns a single mode Gaussian to model most of the pixels which helps to reduce average processing time by 32%.However in the outdoor video (trees sequence), results show only a 2% improvement since a significantly large portion of the scene requires a multimodal model. In the GMM algorithm the weights of the Gaussian mixture represent the fraction of the data samples 'x(t)' that belongs to the particular mode in the model. This system used a Dirichlet prior with negative coefficients. This is done with an intention of accepting a class only if there is enough evidence from the data samples for the existence of the class. Advantages include fast compared to GMM, efficient and accurate. Disadvantage includes reduced computation time.

D.S. Lee [12] proposed an effective gaussian mixture learning for video background subtraction, each pixel in a frame is modeled as a stochastic process and the modes of the GMM are arranged in decreasing order of their weights. A predefined fraction of the weights proposed to use modes with low weights to model the foreground and higher weight to be selected as the background. A match of an incoming pixel to any of the modes defines the pixel as background or foreground. Advantages are fast compared to GMM and makes fast learning. Disadvantages include high memory requirement

P. Gorur and B. Amrutur [13] proposed a speeded up gaussian mixture model algorithm for background subtraction combines fast learning of effective GMM with automatic selection of number of modes in improved GMM to obtain a high efficient and accurate scheme. This concept is a modification to his adaptive GMM algorithm that further reduces execution time by replacing expensive floating point computations with low cost integer operations. In order to maintain accuracy, derive a heuristic that computes periodic floating point updates for the GMM weight parameter using the value of an integer counter. Limitations of GMM includes good accuracy of GMM comes at high computational cost, slow learning rate and GMM with more modes is slower compared to single gaussian scheme. Advantages of speeded up GMM include computation time reduction, fast learning and highly efficient and accurate.

A. Proposed Method

The proposed system presents a new vehicle detection framework that preserves the advantages of the existing works and avoids their drawbacks. The vehicle detection frame work can be classified into training phase and the detection phase [17]. In the training phase, it is possible to extract multiple features including local edge and corner features. In the detection phase, perform background color removal using speeded up GMM. This speeded up gaussian mixture model algorithm for background subtraction combines fast learning of effective GMM with automatic selection of number of modes in improved GMM to obtain a high efficient and accurate scheme. Then features are extracted in the training phase. The proposed system consist of a new color model to separate vehicle colors from non-vehicle colors effectively and this color model transforms (R,G,B) color components into the color domain (u,v). In this (u,v) color model vehicle colors and nonvehicle colors have less overlapping regions .The support vector machine (SVM) is used to classify vehicle colors and non-vehicle colors effectively. A support vector machine is again used for classification of vehicle and non-vehicle pixel.

III. CONCLUSION

This paper has focused on important methods to detect vehicles from different video sequences. This vehicle detection system escapes from the existing frameworks of vehicle detection in aerial surveillance, which is either region based or sliding window based. Instead a pixel wise classification method for vehicle detection is proposed. This method checks the relations among neighboring pixels in a region which are preserved in the feature extraction process. Features extracted comprise not only pixel-level information but also region-level information. Finally classify vehicle colors and non-vehicle colors effectively using support vector machine.

REFERENCES

[1] C. Stauffer and W. Grimson. "Adaptive background mixture models for real-time tracking." IEEE Conf. on Computer Vision and Patteren Recognition, vol. 2,pp. 246-252, June 1999.

[2] S. Srinivasan, H. Latchman, J. Shea, T. Wong, and J.Mc Nair, "Airborne traffic surveillance systems: Video surveillance of highway traffic," in Pro.ACm 2nd Int. Workshop Video Surveillance Sens.Netw., 2004,pp. 131-135

[3] S. S. Hinz and A. Baumgartner, "Vehicle detection in aerial images using generic features, grouping, and context," in Proc. DAGM-Symp., Sep.2001, vol. 2191, Lecture Notes in Computer Science, pp. 45–52.

[4] H. Cheng and J.Wus, "Adaptive region of interest estimation for aerial surveillance video," in Proc. IEEE Int. Conf. Image Process., 2005, vol. 3, pp. 860–863.

[5] R. Lin, X. Cao, Y. Xu, C.Wu, and H. Qiao, "Airborne moving vehicle detection for urban traffic surveillance," in Proc. 11th Int. IEEE Conf. Intell. Transp. Syst., Oct. 2008, pp. 163–167

[6] H. Cheng and D. Butler, ―Segmentation of aerial surveillance video using a mixture of experts,‖ in Proc. IEEE Digit. Imaging Comput.—Tech. Appl., 2005, p. 66.

[7] J. Y. Choi and Y. K. Yang, "Vehicle detection from aerial images using local shape information," Adv. Image Video Technol., vol. 5414, Lecture Notes in Computer Science, pp. 227–236, Jan. 2009.

[8] L. W. Tsai, J. W. Hsieh, and K. C. Fan, "Vehicle detection using normalized color and edge map," IEEE Trans. Image Process., vol. 16, no.3, pp. 850–864, Mar. 2007.

[9] B. Morris and M. Trivedi, "Robust classification and tracking of vehicles in traffic video streams," in Proc. IEEE ITSC, 2006, pp. 1078–1083.

[10] J. W. Hsieh, S. H. Yu, Y. S. Chen, and W. F. Hu, "Automatic traffic surveillance system for vehicle tracking and classification," IEEE Trans.Intell. Transp. Syst., vol. 7, no. 2, pp. 175–187, Jun. 2006.

[11] Z. Zivkovic." Improved adaptive gaussian mixture model for background subtraction."Int'l Conf. on Pattern Recognition, 2:28–31, 2004.

[12] D.-S. Lee. "Effective gaussian mixture learning for video background subtraction." IEEE Trans. on Pattern Analysis and Ma-chine Intelligence, 27:827–832, 2005.

[13] P. Gorur and B. Amrutur. Speeded up gaussian mixture model algorithm for background subtraction. In IEEE International Conference on Advanced Video and Signal-Based Surveillance (AVSS), pages 386–391, Sept. 2011.

[14] C. G. Harris and M. J. Stephens, "A combined corner and edge detector,"inProc. 4th Alvey Vis. Conf., 1988, pp. 147–151.

[15] J. F. Canny, "A computational approach to edge detection," IEEE Trans. Pattern Anal. Mach. Intell., vol. PAMI-8, no. 6, pp. 679–698,Nov. 1986.

[16] W. H. Tsai, "Moment-preserving thresholding: A new approach,"Comput. Vis.Graph., Image Process., vol. 29, no. 3, pp. 377–393, 1985.

[17] Hsu-Yung Cheng, Chih-Chia Weng, and Yi-Ying Chen "Vehicle Detection in Aerial urveillance Using Dynamic Bayesian Networks" IEEE Trans. On Image Processing, Vol. 21, No. 4, April 2012.