MOVING OBJECT DETECTION IN AIRBORNE VIDEOS

Selvakumar S[#1]
M.E – Final year
Department of Computer Science and Engineering
P.B college of Engineering
Sriperumbadur, Chennai, India-602117.
Selva.gingee@gmail.com

Rajalakshmi K[#2]
Assistant professor
Department of Computer Science and Engineering
P.B college of Engineering
Sriperumbadur, Chennai, India-602117.
kjrcse@gmail.com

Abstract – In recent years aerial surveillance important aspect in digital image processing .It provide wide range of applications such as intelligent transport, traffic monitoring, police surveillance and military applications. It has been very challenging issue whether recognize the object in flying view, motion of the camera, movement objects and static object. In this work we proposed system to recognize fast moving object in airborne videos called MOD .To deal with pixel wise classification for moving object detection it performing relations among neighboring pixels. For edge detection to apply moment to adjust thresholds of canny edge detector automatically this increases the flexibility for accuracy for the different aerial view images. Afterward the classifications we are used DBN (Dynamic Bayesian Network).Experiments were conducted on a number of different airborne videos. Then the results display elasticity and good simplification abilities of the planned method on changing data set with airborne images taken at different camera angles while under different heights of camera .

Keywords *– Moving Object Detection, Aerial surveillance, Dynamic Bayesian Networks, Airborne videos*

1. INTRODUCTION

Detection moving object is a significant aspect in aerial videos. The sense of difficulty moving object detection in aerial videos includes camera movement and diverse heights outcome in different size of objects. Compared with ground plane monitoring, airborne monitoring is more compact for surveillance of hasty moving objects and its cover wide area with low cost. The purpose has been to congregate high-resolution still images of an area under scrutiny that could afterward be examined by human or device analysts to obtain information of interest. at present, there is mounting attention in using video cameras for these responsibilities. Video interpretation can be used to identify and geo-locate moving objects in actual time and to manage the camera, for example, to follow detected vehicles or regularly supervise a site. Therefore aerial surveillance system becomes a tremendous enhancement of ground-plane surveillance systems. Vision based technique is one of the approach to analyze moving object from videos. In this paper, we are going to express an unmanned mechanism kept at higher elevation which will without human intervention detect ground moving object.

.

2. RELATED WORKS

Plenty of investigate has been done in object detection from airborne videos Hinz and Baumgarter[1] utilized a hierarchical representation that describe levels of details moving vehicle features. This method based on cascade classifier has produce lot of miss identifications of moving object. Luo-wei tsai, Jun-wei hsieh et al.[2] proposed a new detection method using color transform model. This method is not accurately suitable for moving object but it's good for static object. Hansen et al.[3] provide an affine model for the operation of motion detection.

R. Lin, X. Cao, et al.[4] proposed technique by subtracting backdrop colors of each frame and then sophisticated the object candidate regions by enforcing size constraints of object. Choi and yang [5] as given new algorithm for vehicle detection using symmetric belongings of car shapes. These produce lots miss detections because symmetrical details of building or road markings. In addition, similar to [6], the algorithm in [5] past experience on mean-shift clustering algorithm for color segmentation. The main disadvantage of these algorithms a moving object tends to alienated as several regions since object roofs and may be the windscreen of vehicles usually has dissimilar colors. Moreover, nearby objects might be clustered as one region if they have comparable colors. It may high computational difficulty of mean –shift- segmentation algorithm.

Hong, Ruan et al.[7] presented an EM(Expectation-Maximization) based on joint spatio-temporal multiframe information processing technique for the multiple target tracking . Three energy density functions are approximated by Gaussian mixtures and estimated by a joint EM estimation. But these approach lots miss detection and also not worked in the rotated objects. Daniel A. lavigne et al. [8] proposed a methodology Scale Invariant Feature Transform (SIFT). This technology effectively generates the all key points and then SVM is also classifying these key points to an extent. This methodology also having same problem which is high computational complexity in pixel classification.

Xuelong Li et al. [10] proposed an extension of the HOG features are utilized in training a linear SVM classifier. This linear classification is used for the final moving object classification. But this work high false alarm rate.

3. PROPOSED MOVING OBJECT DETECTION FRAME WORK

In this system, we design a new object detection frame work that conserve the advantages of the existing works avoid their drawbacks. In this frame work divided into detection phase and sample training phase. In sample training phase remove several features including local edge and corner features, as well as object color to instruct a dynamic Baysien network (DBN). In the detection phase, we first achieve backdrop color removal similar to the procedure proposed in [9]. Subsequently, the identical feature extraction process is performed as in the training phase. The extracted features serve as the facts to suppose the unknown state of the trained DBN, which indicates whether a pixel belongs to a vehicle or not. In this work, we do not perform region-based categorization, which would very much depend on results of color segmentation algorithms such as mean shift. There is no need to create multiscale sliding windows either. The distinctive feature of the proposed framework is that the detection task is based on pixel wise classification. However, the features are extracted in a neighborhood region of each pixel. Therefore, the extracted features contain not only pixel-level information but also association among adjacent pixels in a region. Such design is more efficient and well-organized than region-based or multiscale sliding window detection methods. In the detection phase first convert aerial video into multiple number of frames after conversion process the frames to account into the feature extraction that include dependable colors to train with DBN (Dynamic Baysian Network). That this phase initially each fames need to background color exclusion as the same in the [5].After that the same feature extraction continue with those all frames with local feature extraction like Edge exclusion and corner exclusion then feature extraction in DBN which is indicate that pixels are belongs the moving object or not. This approach is not based on the region based classification .Here used the new approach that is a environs region of pixel as same in the each pixel of frame. This extracted feature not only gives pixel level information and also produces an association among the nearest pixels in a region. Then final step in the Detection phase the elimination and morphological process that eliminating to extract object from their natural environment this all process to produce the result of object detection.

I. Background Color Removal

Since non moving object covering most part of the entire scene in aerial images, here the color histogram of every frame and remove the colors that appear most often in the view. These removal pixels do not need to be considered in subsequence detection process. Performing background color elimination cannot only false alarms but also speed up the recognition process.

II. Feature Extraction

The feature extraction is performed both two phases in the system. In Training phase having local feature extraction in that process corner and edges are typically located in pixels with more information. Here we are used Harries corner detector [10] to detect corner. For edge detection, we have used standard Canny Edge Detector [11]. Canny Edge Detector has couple of important thresholds i.e. Upper threshold TH_{high} and Lower threshold TH_{low} . Tsai's moment preserving method is used. The method is as follows. Let *l* be an image of k pixels and gray value of each pixel (a,b) is given by *l*(a,b). The i^{th} moment M_i of *l i*s definite a

$M_i = (1/k) \sum_j k_j (y_j)^i = \sum_j x_j (y_j)^i$ $i = 0, 1, 2$

Where P_j is the total number of pixels in image f with gray value y_j and $x_j = p_j/p$.

III. Dynamic Bayesian Network (DBN)

For detection of vehicle we have used the pixel wise classification using the DBN. The structure of DBN model is shown in figure 2. Node O_t and O_{t-1}denotes the pixel belonging to the vehicle at the time slice t and t-1 correspondingly. The state O_t dependents on the state O_{t-1}. For each and every time interval t, state O_t has effect on P_t, Q_t, R_t,S_t, V_t. These annotations are self-governing of each other. The symbols used for supervision in our system are discrete symbols. In training stage, by utilizing the expectation-maximization algorithm we get the conditional probability tables of the DBN model obtained features from various videos. In detection phase Bayesian rule is used to attain the possibility that a pixel belongs to the moving object color i.e.

$$\mathbf{P\ (Vt|Pt,Qt,Rt,St,Vt,Ot\text{-}1) = P(Ot|Pt)\ P\ (Ot|St) * P(Ot|Vt)\ P\ (Ot|Pt) *P\ (Ot|Ot\text{-}1)\ P\ (Ot\text{-}1)}$$

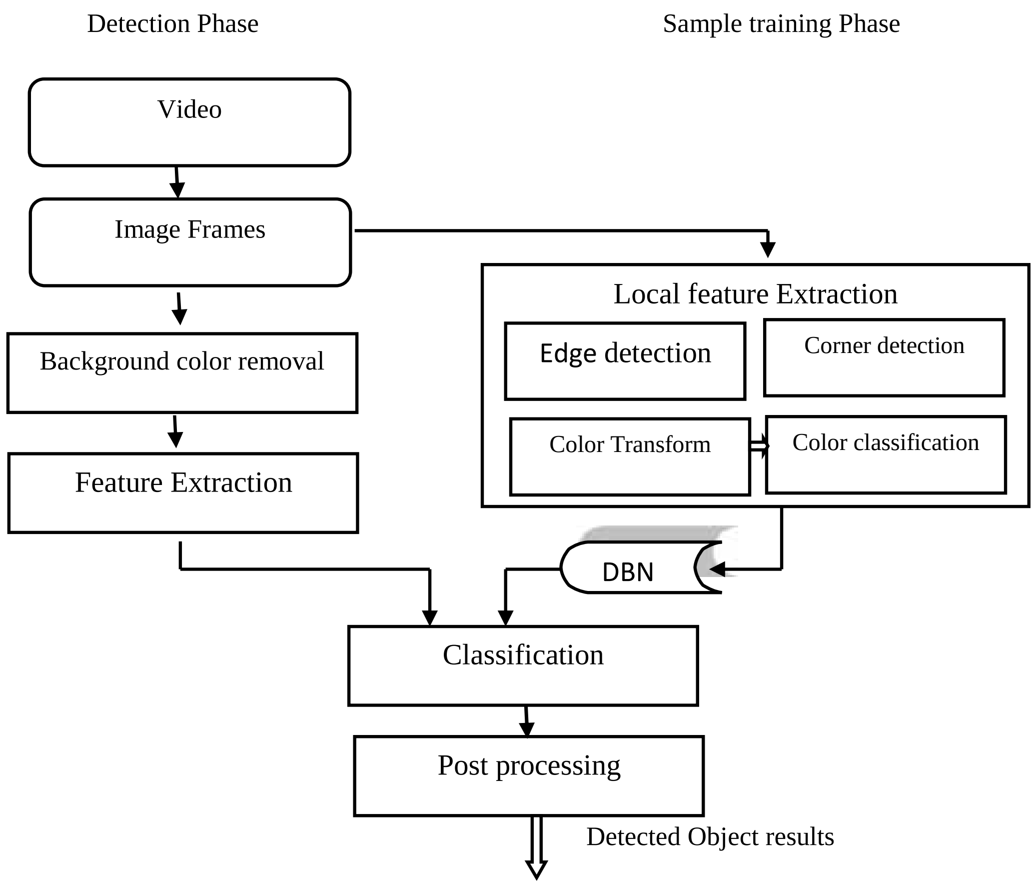

Fig1. Proposed Frame Work

The joint probability i.e. represents the probability that a given pixel is a pixel of object color at a time slice t considering all the state and the observations of the previous time slice. Since all observations are independent then by definition of the inhabitant Bayesian rule of conditional probability, the required joint probability can be factorized. This model can also use along with Bayesian network to elucidate whether the given color is the object color or not.

IV.POST PROCESSING

In this post processing module some morphological operations to enhance the detection facade and carry out associated component tagging to get the vehicle objects. The size and the portion ratio constraints are applied again after morphological operations in the post processing stage to eradicate objects that are impossible to be vehicles. Conversely, the restrictions used here are very loose.

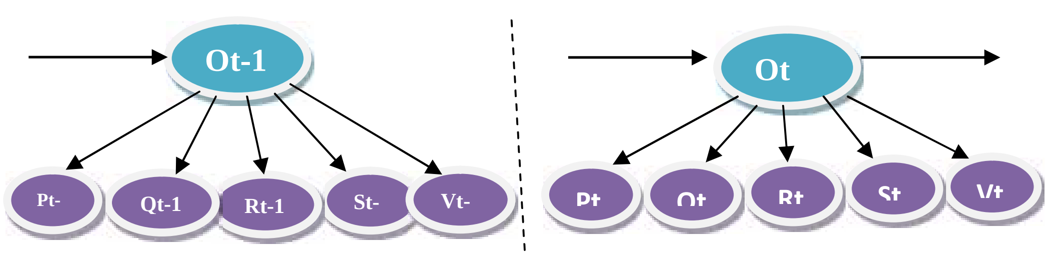

Fig 2. Pixelwise classification using DBN.

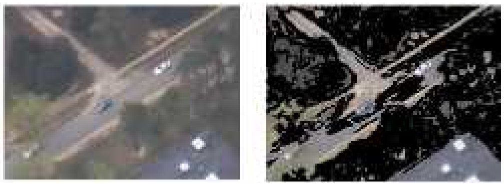

Fig 3. Backdrop color deletion results.

4. EXPERIMENTAL RESULTS

Here the experimental results are making obvious. To analyze the recital of the proposed system, a variety of video sequences with different scenes and special filming altitudes are used. The sample video is infeasible to suppose prior information of camera heights and target object sizes for this difficult data set. When performing backdrop color removal, Quantize the color histogram bins as 16* 16* 16. Colors equivalent to the first eight highest bins are regarded as backdrop colors and detached from the scene.

Fig .4. Results of moving object color classification

To get hold of the conditional probability tables of the DBN, The detection correctness is calculated by the number of false positives per frame and hit rate. When applying SVM, we need to choose the block size $x\,\acute{}\,y$ to form a trial. We obtain each 3 × 4 block to form a feature vector for improved recognition results. For the experimental feature of dynamic Bayesian networks, to choose the size of the locality area for feature extraction, we plot the detection accuracy using different neighborhood sizes in Fig.5.We can study that the locality area for p L with size of 7×7 yields the best detection correctness. Bn or DBN are used to classify the colored pixels. The ellipses are the finishing object detection results after execute post processing. DBN perform better than BN because it includes information along time. When observing detection results of successive frames, we also notice that the detection results via DBN are more constant.

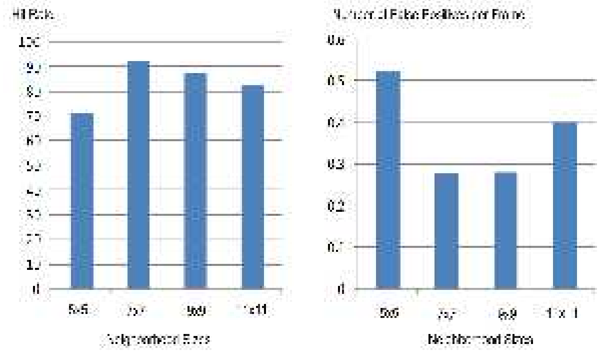

Fig.5 False positive per frame and Hit rates for different neighbor sizes.

In Fig.6.we illustrate some detection results from different surveillance videos with different camera angle and height. The sizes vehicles and the orientation differ a lot in different scenes. We can observe that the experimental results show suppleness and good simplification abilities of the proposed method.

Fig .6. Detection results of different environment with a variety of camera heights and angles.

5. CONCLUSION AND FUTURE WORK

The proposed moving object detection system for airborne videos does not presume any former information of camera heights, object sizes, and aspect ratios. This system doesn't perform region-based classification, this system highly depend on computational concentrated color segmentation algorithms such as mean shift. It doesn't produce multiscale sliding windows that are not proper for detecting rotated vehicles either. Instead, DBN for pixel wise classification method for the vehicle detection. In spite of performing pixelwise classification, relations among adjacent pixels in a region are potted in the feature extraction process. Consequently, the extracted features not only contain pixel-level information and also region-level information. Since the colors of the vehicles would not dramatically vary due to the sway of the camera heights and angles, use only a less number of negative and positive samples to train the SVM for vehicle color categorization.

Moreover, the very less number of frames only required to train the DBN. Overall, the complete framework does not require a large amount of training samples. Moment preserves to improve the Canny edge detector, which increases the flexibility and the correctness for detection in various aerial images. The experimental results illustrate suppleness and good simplification abilities of the proposed method on a demanding data set with aerial surveillance images taken at different environment and under different camera angles and heights. The upcoming work extend to perform moving object tracking on the detected vehicles can further steady the detection results. Automatic moving object detection and tracking could serve as the base for event analysis in smart aerial surveillance systems.

REFERENCES

[1] 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.

[2] Luo-wei tsai, Jun-wei hsieh, member, IEEE, and Kuo-chin fan, member, IEEE, "Vehicle detection using normalized color and edge map", IEEE Transactions On Image Processing, vol. 16, no. 3, March 2007.

[3] M. Hansen, P. Anadan, K. Dana, G. van de Wal, P. Burt, "Real-timescene stabilization and Mosaic Construction", Proc of IEEE CVPR,1994, 54-62) .

[4] 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.

[5] 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.

[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] L.Hong ,Y.Ruan, W.Li, D.Wicker, J.Layne, "Energy based video tracking using joint target density processing with an application to unnamed aerial surveillance," in IET computer Vision iet-cvi:20070017, Oct 2007.

[8] Samir Sahli, Yueh Ouyang , Yunlong Sheng , Daniel A. lavigne "Robust vehicle detection in low-resolution aerial imagery" aImage Science group.

[9] 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.

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

[11] 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.