Effective Object Detection and Background Subtraction by using M.O.I

Billipilli Rajasri
PG Scholar, Department of ECE
Sri Mittapalli College of Engineering

Z Vazraiah
Assistant Professor, Department of ECE
Sri Mittapalli College of Engineering

Abstract - **This paper proposes efficient motion detection and people counting based on background subtraction using dynamic threshold approach with mathematical morphology. Here these different methods are used effectively for object detection and compare these performance based on accurate detection. Here the techniques frame differences, dynamic threshold based detection will be used. After the object foreground detection, the parameters like speed, velocity motion will be determined. For this, most of previous methods depend on the assumption that the background is static over short time periods. In dynamic threshold based object detection, morphological process and filtering also used effectively for unwanted pixel removal from the background. The background frame will be updated by comparing the current frame intensities with reference frame. Along with this dynamic threshold, mathematical morphology also used which has an ability of greatly attenuating color variations generated by background motions while still highlighting moving objects. Finally the simulated results will be shown that used approximate median with mathematical morphology approach is effective rather than prior background subtraction methods in dynamic texture scenes and performance parameters of moving object such sensitivity, speed and velocity will be evaluated by using MOI.**

Keywords: Background modeling, M.O.I, background subtraction, video segmentation, video surveillance.

I. INTRODUCTION

In the past two decades object detection and tracking in video is a challenging problem and has been extensively investigated. It has applications in various fields such as video compression, video surveillance, human-computer interaction, video indexing and retrieval etc. Object detection [1] involves locating object in the frames of a video sequence, while object tracking represents the process of monitoring the object's spatial and temporal changes in each frame. Object detection can be performed through regionbased image segmentation, background subtraction, temporal differencing, active contour models, and generalized Hough transforms. In order to allow highresolution images of the people in the scene to be acquired it is reasonable to assume that such people move about in the scene. The suggested background model initially determines the nature of each pixel as stationary or non-stationary and considers only the stationary pixels for background model formation. In the background model, for each pixel location a range of values are defined. Subsequently, in object extraction phase our scheme employs a local threshold, unlike the use of global threshold in conventional schemes.

To monitor the scene reliably it is essential that the processing time per frame be as low as possible. Hence it is important that the techniques which are employed are as simple and as efficient as possible. In surveillance system video sequences are obtained through static cameras and fixed background. A popular approach called background subtraction is used in this scenario, where moving objects in a scene can be obtained by comparing each frame of the video with a background. Firstly, video frames captured from a camera are input to the background subtractor. Pre processing stages are used for filtration and to change the raw input video to a processable format. Background modelling then uses the observed video frame to calculate and update the background model that is representative of the scene without any objects of interest. Foreground detection is where the pixels that show a significant difference to those in the background model are flagged as foreground. Data validation is used to examine the found objects of interest and to eliminate any false matches. A foreground mask can then be output in which pixels are assigned as foreground or background. For effective object detection misclassified objects and shadows are removed.

II. RELATED WORK

Here an adaptive model for backgrounds containing significant stochastic motion (e.g. water). The new model is based on a generalization of the Stauffer– Grimson background model, where each mixture component is modelled as a dynamic texture. We derive an online Kmeans algorithm for updating the parameters using a set test2 of sufficient statistics of the model. Finally, we report on experimental results, which show that the proposed background model both quantitatively and qualitatively outperforms state-of-the-art methods in scenes containing significant background motions. In ViBe, each pixel in the background can take values from its preceding frames in same location or its neighbor [7]. Then it compares this set to the current pixel value in order to determine whether that pixel belongs to the background, and adapts the model by choosing randomly which value to substitute from the background model. Kim and Kim introduced a novel background subtraction algorithm for dynamic texture scenes [8]. The scheme adopts a clustering-based feature, called fuzzy color histogram (FCH), which has an ability of greatly attenuating color variations generated by background motions while highlighting moving objects. Instead of segmenting a frame pixel-by-pixel, Reddy *et al.* used an overlapping block-by-block approach for detection of foreground objects [9]. The scheme passes the texture information of each block through three cascading classifiers to classify them as background or foreground. The results are then integrated with a probabilistic voting scheme at pixel level for the final segmentation.

The greatest challenge on monitoring characters from a monocular video scene is to track targets under occlusion conditions. In this work, we present a scheme to automatically track and count people in a surveillance system. First, a dynamic background subtraction module is employed to model light variation and then to determine pedestrian objects from a static scene. To identify foreground objects as characters, positions and sizes of foreground regions are treated as decision features. Moreover, the performance to track individuals is improved by using the modified overlap tracker, which investigates the centroid distance between neighbouring objects to help on target tracking in occlusion states of merging and splitting. On the experiments of tracking and counting people in three video sequences, the results exhibit that the proposed scheme can improve the averaged detection ratio about 10% as compared to the conventional work significant background motions.

III. Extraction of Four Grounds

In most background subtraction algorithms, it is assumed uniform thus preventing any decision bias by moving objects. An exception is the work of El Gammal et al. [3], who proposed foreground modeling for human body and of Sheikh and Shah, who proposed a general foreground model using past frames. While the first model is object-specific, the second one necessitates slow object motion as otherwise background samples contaminate PF. Although this could be mitigated by object tracking such an approach would be illogical (track an object in order to detect it). Instead, we propose a foreground model based on small spatial neighborhood, i.e. in the same frame. Recently, we have demonstrated that periodicity in time also holds spatially; local-in-time and local-in-space models produce equivalent background characteristics.

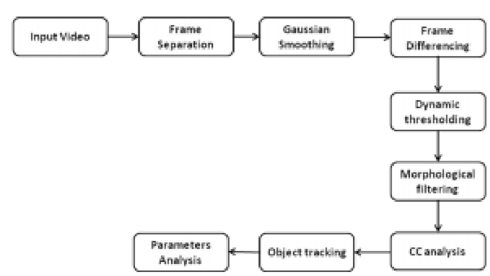
$$P_{fi}\,\bar{I}(n) = \frac{1}{Nf_i(n)} \sum_{m \in N f_{i(n)}} K(I(n) - \bar{I}(m))$$

After successfully developing the background model a local thresholding based background subtraction is used to find the foreground objects. This can be accomplished by modeling labels as a Markov random field of which is a particular realization. MRF models have been successfully used in motion detection reducing scattered false detections and smoothing region boundaries. We propose a Markov model within the binary hypothesis test while maintaining non parametric. Our approach extends early methods using single-Gaussian and uniform and shares Markovianity with more recent formulations. Also, despite the use of accelerated simulated annealing in, the computational complexity is high. Although one can seek local minima by means of one-at-a-time search such as the iterated conditional modes algorithm in this case a binary solution is identical to our binary hypothesis test. Also, our approach uses spatial periodicity whereas the one is based on temporal periodicity which necessitates slow motion or tracking of foreground objects.

$$\frac{P_B\,\bar{I}(n)}{P_F I(n)} = \prod \frac{P(\bar{E}=e^F)}{P(E=e^B)}$$

IV. MOI System Design

An Input Video (.avi files) is converted into still images for processing it and to detect the moving objects by using M.O.I [motion of interest]. These sequences of images gathered from video files by finding the information about it through 'aviinfo' command. These frames are converted into images with help of the command 'frame2im'. Create the name to each images and this process will be continued for all the video frames.



Conventionally, the first frame or a combination of first few frames is considered as the background model. However, this model is susceptible to illumination variation, dynamic objects in the background, and also to small changes in the background like waving of leaves etc. A number of solutions to such problems are reported, where the background model is frequently updated at higher computational cost and thereby making them unsuitable for real time deployment. Further, these solutions do not distinguish between object and shadow. To alleviate these limitations we propose an intensity range based background

A Gaussian smoothing is the result of blurring an image by a Gaussian function. It is a widely used effect in graphics software, typically to reduce image noise and reduce detail.

Gaussian smoothing is also used as a pre-processing stage in computer vision algorithms in order to enhance image structures at different scales—see scale space representation and scale space implementation. Mathematically, applying a Gaussian blur to an image is the same as convolving the image with a Gaussian function.

Gauss Coeff = (1/sqrt (2*pi*sig^2)) (exp (x^2+y^2/2*sig^2))

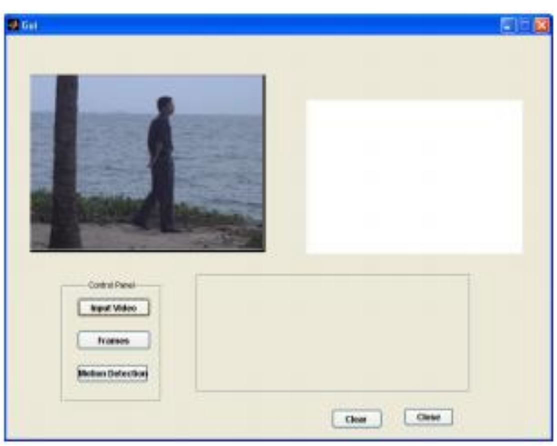
Where, x, y, sig - input coordinates corresponds to the target and standard Deviation.

The moving object will be detected by frame subtraction and segmentation algorithms. The frame subtraction is done by subtracting current frame and previous frame for detecting object from background. The moving object extraction from subtracted frames is done by dynamic thresholding method for foreground detection. Then background will be updated by comparing the process frame and background frame.

Morphological operations are applied on segmented binary image for smoothening the foreground region. It processes the image based on shapes and it performs on image using structuring element. The structuring elements will be created with specified shapes (disk, line, square) which contains 1's and 0's value where ones are represents the neighbourhood pixels. Dilation and erosion process will be used to enhance (smoothening) the object region by removing the unwanted pixels from outside region of foreground object. After this process, the pixels are applied for connected component analysis and then analysis the object region for counting the objects.

V. Results

Input video can be selected is as shown in figure



The objects in the input video are detected as shown in figure

Conclusion

The paper presented an efficient motion detection based on background subtraction using frame difference with thresholding and mathematical morphology. It will be enhanced with futures of connected component analysis and morphological filtering for tracking and counting moving objects. After the foreground detection, the parameters like Count, velocity of the motion was estimated and performance of object detection will be measured with sensitivity and correlation using ground truth. Finally the proposed method will be proved that effective for background subtraction in static and dynamic texture scenes compared to prior methods.

References

[1] A. Yilmaz, O. Javed, and M. Shah, "Object tracking: A survey," ACM Comput. Surv., vol. 38, Dec. 2006.

[2] C.Wren, A. Azarbayejani, T. Darrell, and A. Pentland, "Pfinder: Realtime tracking of the human body," IEEE Trans. Patt. Anal. Mach. Intell., vol. 19, no. 7, pp. 780–785, Jul. 1997.

[3] C. Stauffer and W. Grimson, "Adaptive background mixture models for real-time tracking," in IEEE Comput. Soc. Conf. CVPR, 1999, pp. 246–252.

[4] I. Haritaoglu, D. Harwood, and L. Davis, "W4: Real-time surveillance of people and their activities," IEEE Trans. Patt. Anal. Mach. Intell., vol. 22, no. 8, pp. 809–830, Aug. 2000.

[5] J. Jacques, C. Jung, and S. Musse, Back ground subtraction and shadow detection in grayscale video sequences," in Eighteenth Brazilian Symp. Computer Graphics and Image Processing, Oct. 2005, pp. 189–196.

[6] J.McHugh, J. Konrad,V. Saligrama, and P. Jodoin, "Foreground-adaptive background subtraction," IEEE Signal Process.Letters, vol. 16, no. 5, pp. 390–393, May 2009.

[7] O. Barnich and M. Van Droogenbroeck, "ViBe: A universal background subtraction algorithm for video sequences," IEEE Trans. Image Process., vol. 20, no. 6, pp. 1709–1724, Jun. 2011.

[8] W. Kim and C. Kim, "Background subtraction for dynamic texture scenes using fuzzy color histograms," IEEE Signal Process. Lett., vol. 19, no. 3, pp. 127–130, Mar. 2012.

[9] V. Reddy, C. Sanderson, and B. Lovell, "Improved foreground detection via block-based classifier cascade with probabilistic decision integration," IEEE Trans. Circuits Syst. Video Technol., vol. 23, no. 1, pp. 83–93, Jan. 2013.

[10] E. Salvador, A. Cavallaro, and T. Ebrahimi, "Cast shadow segmentation using invariant color features," Comput. Vis. Image Understand., vol. 95, no. 2, pp. 238–259, 2004.

[11] J. Choi, Y. Yoo, and J. Choi, "Adaptive shadow estimator for removing shadow of moving object," Comput. Vis. Image Understand., vol. 114, no. 9, pp. 1017–1029, 2010.
[12] Z. Liu, K. Huang, and T. Tan, "Cast shadow removal in a hierarchical manner using MRF," IEEE Trans. Circuits Syst. Video Technol., vol. 22, no. 1, pp. 56–66, Jan. 2012.
[13] L. Li,W.Huang, I.Y.H.Gu, andQ. Tian, "Foreground object detection from videos containing complex background," in Proc. Eleventh ACM Int. Conf. Multimedia, Nov. 2003, pp. 2–10.
[14] Z. Zivkovic, "Improved adaptive Gausian mixture model for background subtraction," in Proc. IEEE Int. Conf Pattern Recognition,Aug. 2004, pp. 28–31.