A SURVEY ON ABANDONED OBJECT DETECTION

[1] **Ajit C Joshi,** [2] **Keerthan R,** [3]**Kuna Manoj,** [4]**Saritha A. N**
[1,2,3] Undergraduate Students
[4] Assistant Professor
Department of Computer Science & Engineering
BMSCE, Bangalore

Abstract— Automatic video surveillance is a rapidly expanding field, driven by increases in the affordability of technology and the perceived need for security. The number of cameras in cities is increasing in a large scale. Efficiency and Robustness are the two key factors for successful video surveillance systems due to the large scale data processing and complex video analysis. Manually monitoring many live feeds will decrease the efficiency. Instead of that software which will monitor for threats and alert the user will be lot helpful and it also provides an efficient way for video surveillance.

Index Terms— Abandoned object, Background Subtraction, Static object, Blob tracker, Edge detection.

I. INTRODUCTION

Any object, luggage or bag which is left unattended for a certain period of time is considered as an abandoned object. These objects have to be taken care of, since it poses major security threat to people at public places. The abandoned baggage problem has recently attracted considerable interests, and in many different ways solutions have been attempted.

In most automatic surveillance systems, firstly objects of interest are detected, usually by background subtraction which will find moving objects. Detected objects are tracked by a tracking module. Basic block diagram of abandoned object detection system shown in Fig(1) indicates different steps involved in processing a video. These type of systems provides an efficient mechanism for detecting moving objects, but practical implementations suffer from many limitations in complex surveillance video conditions such as quick lighting changes, severe weather, heavy occlusion, non-rigid objects, crowding etc. A slow moving or a stopped object can result in the object being adapted piecemeal into the background. Since the object dissolves into multiple fragments this may lead to errors in tracking and false “ghost” fragments appear where the background contains the object after it moves away. The focus of this paper is on the problems of foreground analysis and background subtraction in long term scene monitoring to handle quick light changes, foreground fragments, static objects, abandoned and removed objects, objects which are moving slowly, and objects that stop for significant periods of time. In general, false foregrounds are caused by quick lighting changes.

II. LITERATURE SURVEY

For video surveillance systems with stationary cameras background subtraction (BGS) is conventional and an effective approach to detect moving objects. To detect moving objects in a dynamic scene, many adaptive background subtraction techniques have been developed.

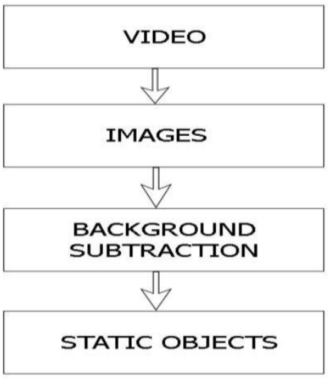

Fig1.Basic block diagram of abandoned object detection system

Grimson and stauffer modeled each pixelas a mixture of Guassian and used an on-line approximation to update the model. Their system can deal with removing or introducing objects and slow lighting changes from the scene. A prediction-based online method for the modeling of dynamic scenes was proposed by Monnet. Their approach has been tested on a coast line along with ocean waves and a scene with swaying trees. However, a lot of images without moving objects were needed to learn the background model, and the if the objects move in the same direction as the ocean waves moving objects cannot be detected.. Mittal and Paragios [7] presented motion-based background subtraction by using adaptive kernel density estimation. In their method, optical flow is utilized and computed as a feature in a higher dimensional space. They successfully handled complex backgrounds but the computational cost is relatively high. A few hybrid change detectors have been developed which combine temporal difference imaging and adaptive background estimation to detect regions of change. To deal with lighting changes Huwer [10] proposed a method of combining a temporal difference method with an adaptive background model subtraction scheme. These methods can adapt to quick image variations such as a light turning on or off. Li [5] proposed a Bayesian framework that incorporates spectral, spatial, and temporal features to characterize the background appearance at each pixel. Their method can handle both static and dynamic backgrounds and good performance was obtained on image sequences containing targets of interest in a variety of environments, e.g., public buildings, offices, campuses, subway stations, parking lots, airports, and sidewalks. Recently, some methods have been developed which integrate discriminative features with tracking for object tracking and scene segmentation and a few researchers start to work on developing background subtraction methods from moving cameras.

Because of its efficiency and robustnes mixture of Gaussians BGS method is becoming popular in recent years. However it cannot adapt to quick lighting changes. Many techniques have been developed to handle quick lighting changes or to improve the performance of the mixture of Gaussians method.

Although many researchers have examined background subtraction, not many researches have been done on foreground analysis. Cucchiara [6] analyzed the foreground as moving object, shadow, and ghost by using the optical flow based motion information. Because of the computation of optical flow the computational cost is relatively expensive for real-time video surveillance systems.

In many video surveillance systems, object detection is followed by object tracking to associate the detections across time and describe the behavior of objects. Most of these systems operate in a feed-forward manner to pass detections from background subtraction to the tracker and then tracks are processed or stored further, for instance by behavior analysis modules. Many object tracking techniques focus on handling occlusions but how to track slow moving or stopped objects for long term scene monitoring are neglected. Boult [9] describe a system that performs well at detecting slow moving objects. Few systems have investigated the possibility of feedback from tracking to background subtraction. Some systems used feedback from the frame level and employed feedback from tracking. By using track state estimates to constrain and direct image segmentation via background subtraction and connected components analysis Abbott [1] proposed a method to reduce computational cost in visual tracking systems. Harville [8] used application-specific high level feedback (frame level, non-person detector, and person detector and tracker).

Stauffer and Grimson [11] first introduced a mixture Gaussians for BGS by modeling the background model as *K* Gaussian mixtures. For each pixel, the mixture weights at time *t* are updated based the weights at time *t-1* as:

$$\omega_{i,t} = (1-\alpha)\omega_{i,t-1} + \alpha(M_{k,t}). \quad [11] \qquad (1)$$

Where α is the learning rate. For each new pixel value, X*t*, is checked against the existing *K* Gaussian distributions, until a match is found. Here, a match is defined as a pixel value within 2.5 standard deviations of a distribution.Mk s, is 1 for the model which matched and 0 for the remaining models. Assuming the red, green, and blue pixel values are independent and have the same variances, we write:
Σk s = σk2 I. After the Gaussians are ranked in descending order of ω/α, the first *B* distributions are chosen as the background model, where

$$B = \arg\min_b \left(\sum_{k=1}^{b} \omega_k > T \right), \quad [11] \qquad (2)$$

and *T* is the minimum fraction of the data that should be accounted for by the background. The value of σ remains same for unmatched distributions. In implementation, two significant parameters, and *T*, need to be set. In this paper, we set *K = 3* (three Gaussians), a =0.005, and *T* = 0.4. We implement the method for both grayscale and RGB video inputs. All the test results in our system are from the same set of parameters. The original mixture of Gaussians method is robust to camera noise, periodic motions from a cluttered background, and slow lighting changes. However it cannot handle: 1) quick lighting changes; 2) detect static regions; 3) fragments; 4) classify abandoned or removed objects; 5) camera view changes; 6) objects that stop for a significant period of time; and 7) slow-moving objects. We describe some solutions for these problems in the following sections.

The abandoned baggage problem has recently attracted considerable interests, and in many different ways solutions have been attempted , each inevitably with its own limitations. Several tracking models have been proposed based on a variety of techniques.
Lv [2] combines a Kalman filter-based blob tracker with a shape-based human tracker to detect objects and people in motion. Event detection is set up in a Bayesian inference framework. Stauffer and Grimson present an event detection module that classifies objects, including the abandoned objects, using neural network, but is limited to detecting only one abandoned object at a time. The probabilistic tracking model proposed by Smith is built of a mixed state dynamic Bayesian network and a trans-dimensional Markov chainMonteCarlo (MCMC) method. Bhargava [3] characterize the event of object abandonment by its constituent sub-events. Their algorithm verifies a sequence of foreground observations by pre-defined event representation and temporal constraints.

Adaptive background subtraction (ABS) has been a popular choice to detect unknown, removed or changed articles in the foreground.ABS methods, build and maintain a statistical model of the background, usually implemented in conjunction with an object tracker.

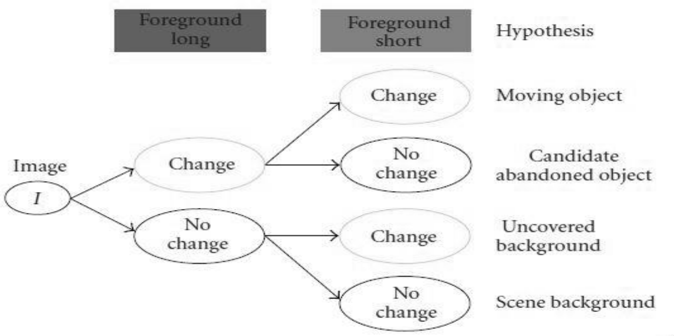

Fig2. Hypotheses on long- and short-term foregrounds.

Porikli [1] demonstrated static object detection using short-term and long-term backgrounds constructed using different adaptation rates.However, in general, ABS-based systems may end up the integrating stationary foreground objects into the background before they are actually deserted. Their performance also suffers considerably from foreground clutter.

The process of localizing pixel intensity transitions is called edge detection. It is been used for object recognition, segmentation etc. Sobel[12,13] edge detection method uses derivative based approach for edge detection. Derivative based technique calculates gradient in different directions and combines all of them, so that it will give the outline of object. Disadvantage of this method is, it will consider high intensity shadows also as an object.

Much work has also been done on multi-view surveillance systems. These systems offer the significant merits of inferring the 3D spatial position of all objects, their size,depth and motion. Although such systems have been largely successful, the deployment of multiple cameras per location is usually not practical in wide spread public areas such as the railways. The goal is to be able to utilize existing camera facilities for monitoring in public space, demanding little or no changes or additional expense. Thus, this paper limits the work to monocular image sequences.

III. CONCLUSION

Most of the proposed methods aiming to detect static objects based on the detection of motion and pixel level analysis, achieved by means of background subtraction, followed by some kind of tracking. Background subtraction is a commonly used technique for the segmentation of foreground regions in video sequences taken from a static camera, which basically based on detecting the moving objects from the difference between the current frame and a background model. In order to achieve good segmentation results, the background model must be regularly kept updated so as to adapt to the varying lighting conditions and to stationary changes in the scene. Therefore, background subtraction techniques often do not suffice for the detection of stationary objects and thus supplemented by an additional approach.

Usually Abandoned Object Detection(AOD) algorithms have to work in crowded areas and heavy traffic areas. So it is important that the algorithm will be able to adapt to quick light changes, shadows and able to distinguish humans and vehicles from objects and should work efficiently even the input video is of lower quality. By using adaptive background subtraction method, which can detect moving and static objects effectively. By enhancing the input image quality and pre-processing the efficiency of algorithm can be increased.

IV. ACKNOWLEDGMENT

The work reported in this paper is supported by the college through the TECHNICAL EDUCATION QUALITY IMPROVEMENT PROGRAMME [TEQIP-II] of the MHRD, Government of India.

REFERENCES

- **[1]** F Porikli, Y. Ivanov, T. Haga,, "Robust abandoned object detection using dual foregrounds",EURASIP Journal on Advances in Signal Processing, 2008.
- **[2]** PETS2006Benchmark athttp://www.cvg.rdg.ac.uk/PETS2006/data/html
- **[3]** L. Brown, A.W. Senior, Y. Tian, J. Connell, A. Hampapur, Chiao-fe Shu, Hans Merkl, and Max Lu, "Performance Evaluation of Surveillance Systems Under Varying Conditions," IEEE Workshop on Performance Evaluation of Tracking and Surveillance, 2005.
- **[4]** ..R. Abbott and L. Williams, "Multiple target tracking with lazy background subtraction and connected components analysis", Tech. Rep., University of New Mexico, June 2005.
- **[5]** Liyuan Li, "Statistical Modeling of Complex Backgrounds for Foreground Object Detection",IEEE TRANSACTIONS ON IMAGE PROCESSING, VOL. 13, NO. 11, NOVEMBER 2004.
- **[6]** R. Cucchiara, C. Grana, M. Piccardi, and A. Prati, "Detecting Moving Objects, Ghosts, and Shadows in Video Streams," IEEE Trans. on PAMI, 25: (10), October 2003.
- **[7]** A. Monnet, A. Mittal, N. Paragios, and V. Ramesh. Background modeling and subtraction of dynamic scenes. In *ICCV*, pages 1305–1312, Nice, France, October 2003.
- **[8]** M. Harville, "A Framework for High-level Feedback to adaptive, per-pixel, Mixture-of Gaussian Background Models", Proceedings on ECCV, 2002.
- **[9]** T. Boult, R. Micheals, X. Gao, and M. Eckmann, "Into the woods: Visual surveillance of non-cooperative and camouflaged targets in complex outdoor settings", Proceedings of the IEEE, vol. 89, no. 10, October 2001.
- **[10]** Huwer "Adaptive Change Detection for Real-Time Surveillance Applications",Visual Surveillance, 2000. Proceedings. Third IEEE International Workshop.
- **[11]** Chris Stauffer and W.E.L Grimson "Adaptive background mixture models for real-time tracking",Computer Vision and Pattern Recognition, 1999. IEEE Computer Society Conference.
- **[12]** SOBEL, I., An Isotropic 3×3 Gradient Operator, Machine Vision for three – Dimensional Scenes, Freeman, H., Academic Pres, NY, 376-379, 1998.
- **[13]** SOBEL, I., Camera Models and Perception, Ph.D. thesis, Stanford University, Stanford, CA, 1995.