Abandoned Object Detection in Complicated Environments

Kahlil Muchtar[1], Chih-Yang Lin*[2], Li-Wei Kang[3], and Chia-Hung Yeh[1]
[1]Department of Electrical Engineering, National Sun Yat-sen University, Kaohsiung, Taiwan, R.O.C.
E-mail: mr.k.stt@gmail.com Tel: +886-7-5252000
E-mail: yeh@mail.ee.nsysu.edu.tw Tel: +886-7-5252000
[2]Dept. of Computer Science & Information Engineering, Asia University, Taichung, Taiwan, R.O.C.
E-mail: andrewlin@asia.edu.tw Tel: +886-4-23323456
[3]Dept. of Computer Science & Information Engineering, National Yunlin University of Science and Technology, Yunlin, Taiwan
E-mail: lwkang@yuntech.edu.tw Tel:+886-5-5342601

Abstract — **In video surveillance, tracking-based approaches are very popular especially for detecting abandoned objects in public areas. Once the object has been tracked, the object status can be further classified as removed or abandoned. However, some shortcomings were found on tracking-based approaches, e.g. illumination changes and occlusion. Therefore, in this paper, an alternative approach to detect abandoned objects is proposed by incorporating background modeling and Markov model. In addition the shadow removal is employed to rectify detected objects and obtain more accurate results. The experimental results show that the proposed scheme is better than other methods in terms of accuracy and correctness.**

I. Introduction

Recently several bombing attacks in public areas happened, such as the Boston marathon bombing and an attempted crime of bombing at Taiwan HSR (High Speed Railway). The preventive action is imperative and wide scale deployment of surveillance systems are in demand. In many cases, terrorists typically put a bomb in personal materials (bag, small box, etc.) and then leave it in a public area. From this fact, one of the most important surveillance systems is how to detect the left/abandoned object and activate the alarms to let the security officer sweep and clean the area immediately. In literatures, many abandoned object detection methods have been proposed for different purposes and environments such as public safety, traffic monitoring, retail and so forth [1-4], [5, 7, 8], [9, 11, 16, 17, 19, 20, 22-24, 28, 30, 31, 33]. An object is regarded as abandoned/left if it is static and unattended at the scene, and it was not there before; in other words, an object that was carried by a person is set to be labeled "abandoned/left" if the owner left it and it becomes unattended for a period of time. In contrast, the removed object means the left object is taken away. Since the surveillance system is a long-term working system, illumination changes should be taken into account. In addition, the crowds walking near the object may increase the difficulty of detection and influence the correctness of detection results.

Conventional abandoned object detection methods can be separated into two approaches: one is based on tracking methodology [1, 3, 7, 10, 14], and the other is based on the detection approach [15, 27, 32]. In the tracking-based methods, Beynon et al. [3] applied the Kalman filter to track foreground objects and used a Bayesian classifier to search for candidate static objects. The candidate static objects are then verified by a finite state machine. Guler and Farrow [7] focused on drop-off events detection to obtain the candidate static objects. The abandoned objects are extracted according to a stationary object confidence image, in which each pixel value indicates the confidence representing whether the pixel belongs to a static object. In the detection-based approach, Tian et al. [29] used background subtraction and foreground analysis to detect the left-object. They subsequently combined it with a tracking method to alleviate the false positive.

In this paper, we propose an automatic system for abandoned object detection. The main contribution of the method is to provide a comprehensive solution, which can identify the status of an object, abandoned, removed, or partially occluded. We employ the combination of background modeling based on mixture of Gaussians (GMM) [25, 26] and Markov Random Field (MRF) [6]. Furthermore, we employ a cast-shadow approach to enhance the shape of the abandoned object. By combining these two approaches the abandoned object detection can perform well and obtain accurate results.

The remainder of this paper is organized as follows: First, we briefly review the Gaussian mixture model in Section 2. Then, in Section 3, we elaborate on the proposed background construction and MRF. The issues related to the design of the management system for abandoned objects are also explored. Our experimental results are presented and discussed in Section 4. Finally, the paper ends with conclusions in Section 5.

II. The Gaussian Mixture Model

The Gaussian Mixture Model (GMM) was proposed by Grimson and Stauffer [26]. The authors presented pixel-based method to model each pixel (regarded as background) into a mixture of Gaussians. The number of Gaussians K is typically set from 3 to 5. In addition, each Gaussian has its own weight to represent the portion of the data accounted for from corresponding distribution. The probability that a pixel regards a value x at a certain time X_t is given as follows [26]

$$P(X_t) = \sum_{j=1}^{K} \omega_{j,t} * \eta(X_t, m_{j,t}, \sum_{j,t}), \quad (1)$$

where K is the number of Gaussian distributions, $\omega_{j,t}$ is the weight estimation of the j_{th} Gaussian in the mixture at time t, $m_{j,t}$ and $\Sigma_{j,t}$ are the mean value and covariance matrix respectively, of the j_{th} Gaussian in the mixture at time t, and η is a Gaussian *pdf* (probability density function) defined in (2)

$$\eta(X_t, m, \sum) = \frac{1}{(2\pi)^{\frac{n}{2}} |\Sigma|^{\frac{1}{2}}} e^{-\frac{1}{2}(X_t - m_t)^T \Sigma^{-1} (X_t - m_t)} \quad (2)$$

For computation efficiency, $\sum_{k,t}$ is defined as $\sigma_k^2 I$ to represent the covariance of the k^{th} model component.

Intuitively, the candidate of background colors will stay longer and more invariant than others. In addition, the corresponding Gaussians have the most supporting evidence and the least variance. This model was widely used in a real-time model integrated by an update process. When a new pixel comes in, it is checked against existing model components. The new pixel is said to match one of the weighted Gaussian distributions if its pixel value is within 99.5% of the inliers to a matched distribution. If any of the models is matched, the matched distribution will be updated. Otherwise the distribution that has the minimum weight is discarded and replaced with a distribution using the current value as its mean value, an initially high variance, and a low prior weight.

In the maintenance of the background model, the K distributions are sorted based upon the value ω/σ. The first B distributions are selected as the background model of a pixel for the scene and denoted as

$$B = \arg\min_b \left(\sum_{k=1}^{b} \omega_k > T_B\right), \quad (3)$$

where T is a predefined threshold that represents the minimum quantity of the data that must be accounted for the background model. T is usually set to about 90% in many applications.

After the incoming pixel has been determined whether it will match to the existing Gaussian distributions, the prior weights of K Gaussian distributions are changed as follows:

$$\omega_{k,t} = (1-\alpha)\omega_{k,t-1} + \alpha(M_{k,t}), \quad (4)$$

where α is the learning rate and $M_{k,t}$ is 1 for the matched distribution and 0 for the unmatched distribution. Subsequently, weights of distributions are renormalized. If the new pixel matches to a Gaussian distribution, the values of *mean* and *variance* of this distribution are updated as follows:

$$m_t = (1-\rho)m_{t-1} + \rho X_t, \quad (5)$$

$$\sigma_t^2 = (1-\rho)\sigma_{t-1}^2 + \rho(X_t - m_t)^T (X_t - m_t), \quad (6)$$

Where

$$\rho = \alpha\eta(X_t \mid m_k, \sigma_k). \quad (7)$$

III. THE PROPOSED METHOD

In this section, we firstly explain the generic AOD (Abandoned Object Detection) system. Secondly, we will delve more deeply into shadow removal integration to enhance the correctness of *AO* (abandoned object). Finally, we provide the description of MRF approach that leads to enhance object segmentation on the proposed method.

Originally our prior AOD approach consists of two modes [12]; Mode I and Mode II. For achieving a more robust system, we prefer the latter mode to build the enhanced-approach.

Robust AOD Algorithm
Input: A pixel of the incoming frame.
Output: Determine whether the input pixel belongs to an *AO* or not.

Step 1: Extract the first j ($j \leq k$) Gaussian distributions from the GMM model A with the large learning rate for the input pixel and sort them according to their weights in non-increasing order to obtain (μ_{Al}', w_{Al}', σ_{Al}'), where l = 1 to j. Similarly, extract the first j Gaussian distributions from the GMM model B with the small learning rate to obtain (μ_{Bl}', w_{Bl}', σ_{Bl}').

Step 2: Normalize w_{Al}' and w_{Bl}'.

Step 3: If $\sum_{l=1}^{j}\left[\max(w_{Al}, w_{Bl}) \times (\mu_{Al} - \mu_{Bl})\right] > TH_1$, and $\sigma_{Al}' < TH_2$, and $\sigma_{Bl}' < TH_2$, the pixel is classified as a candidate pixel of an *AO*.

Step 4: Get the corresponding bitmap *BM* of the input pixel. If *BM* is recognized as an unmatched block, and the weight of *BM* is regularly increased to the largest one in texture model *TM* after several runs, the pixel is regarded as a candidate pixel of an *AO*.

Step 5: If the frequency of the appearance of the candidate pixel is above *P* times, the pixel is considered to be a pixel of an *AO*.

In the proposed scheme, Step 4 can be optional. Texture model *TM* is obtained by applying background modeling using texture-based [13].

In some circumstances, the *AO* can be carried away and leads to false alarm. To solve such a case, we construct another primitive background using another GMM model, called PBGMM. Initially, PBGMM is unstable, but the update process is the same as that of the original GMM. However, when PBGMM becomes stable, if the new incoming pixel does not match the PBGMM, the least significant distribution of PBGMM would not be replaced, neither is the update procedure required. This is unlike the previous GMM model. Therefore, when the primitive background is stable, it only allows slight lighting changes to fit long-term monitoring, and new incoming objects would not be incorporated.

When AOD system detects a suspicious *AO*, the color histogram of the object is extracted to compare with that of the corresponding region in the primitive background. The status of the static object would be regarded as “REMOVED” if the two histograms are similar; otherwise, it is considered that an *AO* shows up.

Having PBGMM added to monitor the latest status of the observed object (remains abandoned or has been removed), our existing approach can handle complicated environment properly. Nevertheless, in most of public area cases, the probability that *AO* might be interfered by shadow is high. It leads to less-accurate *AO* detection. Therefore, in order to alleviate shadow interference and obtain more accurate segmentation in *AO*, we enhance our existing model by incorporating shadow removal scheme and Markov Random Field (MRF). We use Prati, et al. [18] method to remove the shadow. Furthermore, since using MRF we then transform the segmentation to a binary labeling problem.

In the computer vision field, MRF is a probabilistic way of representing spatial prior information (smoothness), whih was introduced by Geman and Geman [6]. In our proposed method, a MRF comprises a set of sites $\{x_1 \ldots x_n\}$ to represent pixels, and a neighborhood system $\{N_1 \ldots N_n\}$, where N_i is the set of neighbors of x_i. Each x_i and N_i contains a random variable u_i with a value in a label set $L=\{0,1\}$. The field is a MRF if and only if each u_i depends specifically on x_i and its neighbors (adjacent pixels) $x_j \in N_i$. Another common term in MRF is called clique C_{ij} as a combination of neighbors in a neighborhood system. The prior probability of clique realization is $e^{-V_{ij}}$, where V_{ij} is called the clique potential.

Now, we get into the detail on how to practically implement MRF on abandoned object detection (AOD). In this work, we focus on how deciding a label of u_i for pixel x_i and suppose u_j is known for all neighbors x_j. Let denote the label field obtained as follows:

$$u_i = \begin{Bmatrix} u_{BG} \text{ if } u_i = 0 \\ u_{AO} \text{ if } u_i = 1 \end{Bmatrix} \tag{8}$$

We can denote the decision rule for the configuration of u_i, to calculate the prior probabilities of the label at x_i as follows:

$$\frac{\Pr\{x_i \mid u_{BG}\}}{\Pr\{x_i \mid u_{AO}\}} \underset{AO}{\overset{BG}{\gtrless}} \eta \frac{\Pr\{E = u_{AO}\}}{\Pr\{E = u_{BG}\}}, \tag{9}$$

where η is cost term and is set to 2.5 in our experiments, and E is MRF, with realization u_{AO} and u_{BG}. Furthermore, we now assume that the probability on the left-hand side is conditionally independent. That is,

$$\Pr\{x_i \mid u_i\} = \prod_j \Pr\{x_j \mid u_j\} \tag{10}$$

In the proposed scheme, $\Pr\{x_i \mid u_{BG}\}$ and $\Pr\{x_i \mid u_{AO}\}$ can be further simplified by:

$$\frac{\Pr\{x_i \mid u_{BG}\}}{\Pr\{x_i \mid u_{AO}\}} \equiv \frac{\Pr_{BG}\{x_i\}}{\Pr_{AO}\{x_i\}}. \tag{11}$$

For right-hand side of (9), since we define the field as MRF, following Geman [6] the a priori probabilities of Markov Random Field E as denoted below:

$$\Pr\{E = u\} = \frac{1}{Z} \exp\left(\frac{-1}{T} \sum_{c \in C} V(c)\right), \tag{12}$$

where Z and T are normalization and natural temperature constants, respectively. We use a first-order MRF, where each 2-pixel clique consist of x_i and one of its neighbors, and has the likelihood $e^{-V_{ij}(u_i, u_j)}$. The potential function as follows:

$$\sum_{c \in C} V(c) \equiv \sum_{\{j,i\} \in C} V(j,i) \tag{13}$$

We use 8-neighborhood (N_8) in our system, thus with clique structure defined above, the sites x_j correspond to the eight immediate neighbors (adjacent pixels) of x_i. Since the labels L are binary (either 0 or 1), we opt to apply similar function that Geman and Geman [6] used, called Ising potential function,

$$V(i,j) = \begin{Bmatrix} 0 \text{ if } u_i = u_j \\ 1 \text{ if } u_i \neq u_j \end{Bmatrix} \tag{14}$$

The potential function in (14) will count the number of dissimilar neighbors of x_i for each circumstance. We can denote the number of background and abandoned/left neighborhood pixel as $N_{BG}[i]$ and $N_{AO}[i]$ respectively. Then the new equation becomes:

$$\frac{\Pr_{BG}(x_i)}{\Pr_{AO}(x_i)} \underset{AO}{\overset{BG}{\gtrless}} \eta . \exp\left(\frac{1}{T}(N_{AO}[i] - N_{BG}[i])\right), \tag{15}$$

where the constant $1/T$ is a threshold variance, which in our experiments is set to about 0.5. The u_i is said to be *BG* if probability on the left-hand side is greater than priori probabilities of MRF on the right-hand, and conversely to be *AO*. Since our existing model is based on GMM, we can then convert it to MRF and define $\Pr_{BG}(x_i)$ and $\Pr_{AO}(x_i)$ from (15) simply as follows:

$$\begin{gathered} \Pr_{BG}(x_i) = \underset{i}{\arg\min} \left\{ \frac{(x_{ri} - m_{ri})^2}{\Sigma_{ri}} + \frac{(x_{gi} - m_{gi})^2}{\Sigma_{gi}} + \frac{(x_{bi} - m_{bi})^2}{\Sigma_{bi}} \right\} \\ \Pr_{AO}(x_i) = \theta^2 \end{gathered} \tag{16}$$

θ is a threshold to represent the distance from the mean (to cover 2.5 standard deviations of the inliers to a Gaussian, θ =2.81). Finally, similar to [38] we enhance the quality of *AO* detection and MRF convergence by implementing iterated conditional modes (ICM) [38]. Having applied ICM, we obtain the satisfied result of detection after 5 iterations.

IV. Experimental Results

The proposed method will be evaluated by demonstrating the quantitative result. We select famous CAVIAR test case specifically "***Leaving bags behind***" scenario. In addition, to provide more comparison, we also use outdoor scenario to compare with our previous method in [12].

A. CAVIAR Test Case [21]

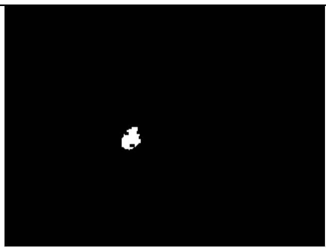
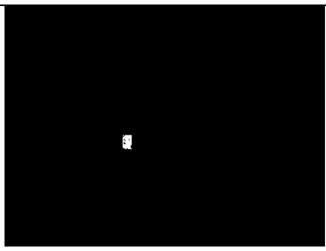
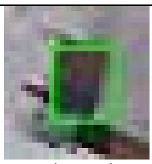
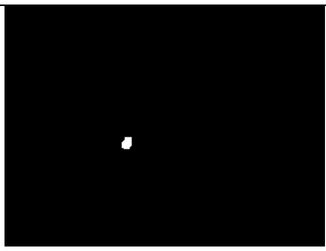
Frame Number	644
 a. Original [12]	
 b. Original with Shadow Removal	
 c. Enhanced using MRF and Shadow Removal	

Fig. 1. Comparison using CAVIAR "***Leaving bags behind***" scenario (Source: LeftBox.avi).

B. Outdoor Test Case

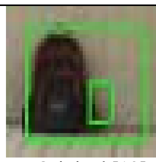
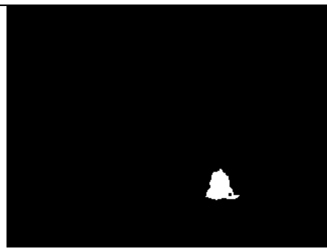
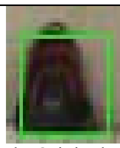
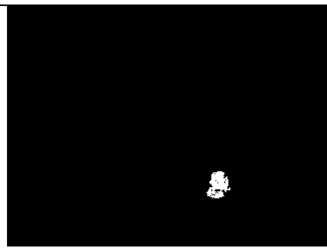
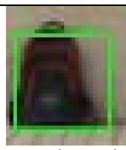
Frame Number	644
 a. Original [12]	
 b. Original with Shadow Removal	
 c. Enhanced using MRF and Shadow Removal	

Fig. 2. Comparison using outdoor test case (Source: Outdoor.avi).

Fig.1 shows a sample scenario of *AOD*. One person brings one box and leaves it, and then after successive frames our method detects it as "abandoned/left" object. The comparison in Fig.1.a shows our previous method still incorporate the shadow as part of the object. On the contrary Fig.1.b can clearly cast the shadow but still have aperture problem. Finally in Fig.1.c, by combining shadow removal and MRF, our proposed method can obtain much outperformed result.

Unlike Fig.1 which demonstrates the indoor scene, subsequent scenario (Fig.2) present the outdoor case when one person leave his bag and detected as "abandoned/left" object. Apart from shadow issue, outdoor case is also prone to illumination changes and noise. Since our method employs probability approach using Gaussian Mixture Model, those issues can be relatively figured out and less affect the result. As shown in Fig.2.c, the *AO* can be obtained accurately and cast the shadow completely.

V. Conclusions

We have demonstrated our enhanced-framework to detect *AO* accurately and outperform other methods. We propose *AOD* through background modeling by utilizing color and texture model. By using Gaussian mixture and texture approach, the *AO* can be detected robustly and resist to illumination changes without post-tracking method needed. Finally, for casting the shadow in *AO* and producing clean segmentation, we propose new concept of shadow removal and MRF combination in this field. Next challenges in this research field is how the framework can encounter more complex scene; consist of multiple abandoned objects, overlapping object and very crowded environment.

ACKNOWLEDGMENT

This work was supported by National Science Council, Taiwan, under Grants NSC 101-2221-E-468-021.

REFERENCES

[1] E. Auvinet, E. Grossmann, C. Rougier, M. Dahmane, and J. Meunier, "Left-luggage detection using homographies and simple heuristics," *PETS*, pp. 51-58, 2006.

[2] A. Bevilacqua and S. Vaccari, "Real time detection of stopped vehicles in traffic scenes," *Proc. IEEE Int. Conf. Adv. Video Signal-Based Surveillance*, London, U.K., pp., Sep. 2007.

[3] M. Beynon, D. Hook, M. Seibert, A. Peacock, and D. Dudgeon, "Detecting abandoned packages in a multi-camera video surveillance system," *Proc. IEEE Int. Conf. Adv. Video Signal-Based Surveillance*, pp. 221, 2003.

[4] N. Bird, S. Atev, N. Caramelli, R. Martin, O. Masoud, and N. Papanikolopoulos, "Real time, online detection of abandoned objects in public areas," *Proc. IEEE Int. Conf. Robot. Automation*, pp. 3775 - 3780, May, 2006.

[5] S. Ferrando, G. Gera, and C. Regazzoni, "Classification of unattended and stolen objects in video surveillance system," *Proc. IEEE Int. Conf. Adv.Video Signal-Based Surveillance*, pp. 21, 2006.

[6] S. Geman and D. Geman, "Stochastic Relaxation, Gibbs Distributions, and the Bayesian Restoration of Images," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 6, no. 6, pp. 721-741, 1984.

[7] S. Guler and M. K. Farrow, "Abandoned object detection in crowded places," *PETS*, pp. 99-106, 2006.

[8] S. Guler, J. A. Silverstein, and I. H. Pushee, "Stationary objects in mul-tiple object tracking," *Proc. IEEE Int. Conf. Adv. Video Signal-Based Surveillance*, London, U.K., pp., Sep, 2007.

[9] P. T. N. Krahnstoever, T. Sebastian, A. Perera, and R. Collins, "Multiview detection and tracking of travelers and luggage in mass transit environments," *PETS*, pp. 67-74, 2006.

[10] L. Li, R. Luo, R. Ma, W. Huang, and K. Leman, "Evaluation of an IVS system for abandoned object detection on PETS2006 datasets," *Proceedings of 9th IEEE Intl. Workshop on Performance Evaluation of Tracking and Surveillance*, New York, USA, pp. 91-98, 2006.

[11] S.-N. Lim and L. Davis, "A one-threshold algorithm for detecting abandoned packages under severe occlusions using a single camera," *CS Dept., University of Maryland, College Park, CS-TR-4784*, pp., Feb, 2006.

[12] C.-Y. Lin, C.-S. Chan, L.-W. Kang, and K. Muchtar, "Left-object detection through background modeling," *International Journal of Innovative Computing, Information and Control*, vol. 9, no. 4, pp. 1373-1388, 2013.

[13] C. Y. Lin, C. C. Chang, W. W. Chang, M. H. Chen, and L. W. Kang, "Real-time robust background modeling based on joint color and texture descriptions," *Proceedings of The Fourth International Conference on Genetic and Evolutionary Computing*, Shenzhen, China, pp. 622-625, 2010.

[14] F. Lv, X. Song, B. Wu, V. K. Singh, and R. Nevatia, "Left luggage detection using Bayesian inference," *Proceedings of 9th IEEE Intl. Workshop on Performance Evaluation of Tracking and Surveillance*, New York, pp. 83-90, 2006.

[15] J. Martinez-del-Rincon, J. E. Herrero-Jaraba, J. R. Gomez, and C. Orrite-Urunuela, "Automatic left luggage detection and tracking using multi-camera UKF," *Proceedings of 9th IEEE Intl. Workshop on Performance Evaluation of Tracking and Surveillance*, New York, USA, pp. 59-66, 2006.

[16] F. Porikli, "Detection of temporarily static regions by processing video at different frame rates," *Proc. IEEE Int. Conf. Adv. Video Signal-Based Surveillance*, London, U.K., pp., Sep, 2007.

[17] F. Porikli, Y. Ivanov, and T. Haga, "Robust abandoned object detection using dual foregrounds," *EURASIP J. Adv. Signal Process.*, vol. 2008, no., pp. 30, 2008.

[18] A. Prati, I. Mikic, M. M. Trivedi, and R. Cucchiara, "Detecting moving shadows: algorithms and evaluation," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 25, no. 7, pp. 918-923, 2003.

[19] H. Rowley, S. Baluja, and T. Kanade, "Neural network-based face detection," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 20, no. 1, pp. 23-38, Jan, 1998.

[20] C. Sacchi and C. Regazzoni, "A distributed surveillance system for detection of abandoned objects in unmanned railway environments," *IEEE Trans. Veh. Technol.*, vol. 49, no. 5, pp. 2013-2026, Sep, 2000.

[21] C. T. C. Scenarios, "EC Funded CAVIAR project/IST 2001 37540 http://homepages.inf.ed.ac.uk/rbf/CAVIAR/."

[22] V. K. Singh, P. K. Atrey, and M. S. Kankanhalli, "Coopetitive multi-camera surveillance using model predictive control," *Springer J. Mach. Vision Appl.*, vol. 19, no. 5-6, pp. 375-393, Oct, 2008.

[23] K. Smith, P. Quelhas, and D. Gatica-Perez, "Detecting abandoned luggage items in a public space," *PETS*, pp. 75-82, 2006.

[24] M. Spengler and B. Schiele, "Automatic detection and tracking of abandoned objects," *Proc. IEEE Int. Workshop VSPETS*, pp., 2003.

[25] C. Stauffer and W. E. L. Grimson, "Adaptive Background Mixture Models for Real-Time Tracking," *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, Fort Collins, Colorado, USA, pp. 246-252, 1999.

[26] C. Stauffer and W. E. L. Grimson, "Learning Patterns of Activity Using Real-Time Tracking," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 22, no. 8, pp. 747-757, 2000.

[27] E. Stringa and C. S. Regazzoni, "Real-time video-shot detection for scene surveillance applications," *IEEE Transactions on Image Processing*, vol. 9, no. 1, pp. 69-79, 2000.

[28] Y. Tian, R. S. Feris, and A. Hampapur, "Real-time detection of abandoned and removed objects in complex environments," *Proc. IEEE Int.Workshop Visual Surveillance (in conjunction with ECCV' 08)*, Marseille, France, pp., 2008.

[29] Y. Tian, R. S. Feris, H. Liu, A. Hampapur, and M.-T. Sun, "Robust Detection of Abandoned and Removed Objects in Complex Surveillance Videos," *IEEE Transactions on*

Systems, Man, and Cybernetics-Part C: Applications and Reviews, vol. 41, no. 5, pp. 565-576, Sept, 2011.

[30] P. L. Venetianer, Z. Zhang, W. Yin, and A. J. Liptop, "Stationary target detection using the objectvideo surveillance system," *Proc. IEEE Int.Conf. Adv. Video Signal-Based Surveillance*, London, U.K., pp., Sep, 2007.

[31] P. Viola and M. Jones, "Rapid object detection using a boosted cascade of simple features," *Proc. IEEE Conf. Computer Vision Pattern Recognit.*, Kauai, Hawaii, pp. I-511-518, 2001.

[32] J. Wang and W. Ooi, "Detecting static objects in busy scenes," Department of Computer Science, Cornell University, Technical Report TR99-1730 1999.

[33] H. Zhao, H. Yang, S. Zheng, H. Liao, J. Chang, and L. Chen, "A localized approach to abandoned luggage detection with foreground-mask sampling," *Proc. AVSBS08*, pp. 132-139, 2008.