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An Approach towards Automatic Abondoned Luggage Segmentation and Detection

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Abstract—*Tracking based methodologies for surrendered object location regularly get to the complex observation recording. We exhibit another system to vigorously and effectively recognize deserted and evacuated objects in light of foundation subtraction and foreground investigation with supplement of following to lessen false positives. In our framework, the foundation is demonstrated by three Gaussian blends. So as to handle complex circumstances and keeping a steady overhaul rate for video streams with various edge rates. At that point, the same Gaussian blend models utilized for foundation subtraction are utilized to identify static closer view districts without additional calculation expense. Besides, the sorts of setting data about the closer view veils, which altogether outflanks past edge-based methods. Taking into account the kind of the static areas and user defined parameters (e.g., object measure and relinquished time), a coordinating technique is proposed to distinguish surrendered and uprooted objects. A man location procedure is likewise incorporated to recognize static items from stationary individuals.*

Index Terms*: Anti-terrorism, background subtraction, foreground analysis, abandoned object, removed object, video surveillance*

1. INTRODUCTION-

The failed car bombing happened recently in Times Square at New York City demonstrated that effective and efficient detection of abandoned objects is very important to prevent attacks on landmarks, public transportation and at airports have been as of late proposed to consequently identify relinquished articles (stopped vehicles and left-gear) in video observation for various applications, for example, movement checking, open wellbeing, retail, and so forth. At train/tram stations, air terminals, huge urban areas, and other open spaces with high movement streams. Many methods turns out to be exceptionally trying for security officers and additionally video reconnaissance answers for rapidly distinguish objects that have been deserted. In spite of the fact that endeavors have been made to set up a few guidelines the issue is not very much characterized and still an open issue in video observation. For instance, Beynon *et al.* [4] characterized a relinquished bundle as any stationary bundle far from anybody considered in charge of it. Flying creature characterized a surrendered item to be a stationary article that has not been touching a man (somebody needed to abandon it) for quite a while limit. Ferrando *et al.* characterized a relinquished article as a static "non-human" item which parts from a "human". Spengler and Schiele characterized a surrendered object as a "non-human" forefront which keeps still over a specific timeframe and without people being close by. Every single above definition can't cover the mind boggling circumstances, all things considered. For instance, an auto/truck is stopped and afterward the driver leaves, or somebody just tosses a sack to a zone from long separation. Additionally, in exceptionally swarmed situations, it is hard to recognize the relationship of a deserted item and its proprietor, for example, somebody leaves a pack to his/her companion. We characterize a deserted article to be a stationary item that has not been in the scene some time recently, and an evacuated item to be a stationary item that has been in the scene before yet is not there any longer. To recognize relinquished and uprooted objects, we concentrate on the best way to identify static areas that have as of late changed in the scene and how to figure out if they compare to deserted or evacuated object.

2. RELATED WORK

Most of the proposed techniques for abandoned object detection rely on tracking information [1, 4] to detect drop-off events, while fusing information from multiple cameras. As stated by Porikli [3] these methods are not well suited to complex environments like scenes involving crowds and large amounts of occlusion. In addition, they require solving a difficult problem of object tracking and detection as an intermediate step. proposed a single camera, non-tracking-based system which makes use of two backgrounds for the detection of stationary objects. The two backgrounds are constructed by sampling the input video at different frame rates (one for short-term and another for long-term events). This technique, however, is difficult to set appropriate parameters to sample the input video for different applications, and has no mechanism to decide whether a persistent foreground blob corresponds to an abandoned object event or a removed object event. In many surveillance scenarios, the initial background contains objects that are later removed from the scene (e.g., parked cars or static people that move away). Correctly classifying whether a foreground blob corresponds to abandoned or removed objects is an essential problem in background modeling, but most existing systems neglect it. The Object Video surveillance system keeps track of background regions which are stored right before they are covered by an abandoned object. In case the same object is removed (i.e., the background is uncovered), the stored region can be matched with the current frame to determine that the object was removed. Clearly, this approach fails when the static object stays long enough in the scene, which makes the matching of the current frame with the stored background region more difficult due to differences in lighting. Another problem occurs when an object is already part of the initial background. For these cases, the Object Video system relies on analyzing the edge energy associated with the boundaries of the foreground region for both the current frame and the background model. The assumption is that the edge energy of the current frame is higher for abandoned objects and lower for removed objects. This method was originally proposed by Connell *et al.* [9]. Relying on edge energy to distinguish abandoned and removed objects works well for simple, homogeneous backgrounds. However, the edge energy assumption is clearly violated in complex scenes with cluttered backgrounds. Another big limitation of the edge energy based method is that only parts of the static objects are often detected due to the imperfect background subtraction in real surveillance systems for complex environment applications.

3. STATIC OBJECT DETECTION

In this section, we describe how to detect the static objects from the scene. Here the static objects are the changes of the scene that stay in the same position for relatively long time. These static objects can be classified as abandoned objects and removed objects. We employ the mixture of Gaussian method to detect scene changes due to its robustness and efficiency. We further extend the method to detect static objects by using different mixture models. The parameters for unmatched distributions remain the same. The parameters of the distribution which matches the new observation are The mixture of Gaussians method is robust to slow lighting changes, periodical motions from clutter background, slow moving objects, long term scene changes, and camera noises. However, it cannot adapt to quick lighting changes and cannot handle shadows well. A number of techniques have been developed to improve the performance of the mixture of Gaussians method. In order to make the mixture of Gaussians method work for quick lighting changes, we integrated the texture information to the foreground mask to remove the false positive areas by using the gradient features since the texture in the false positive foreground areas which are caused by lighting changes should be similar to the texture in the background, and the gradient value is less sensitive to lighting changes and is able to derive an accurate local texture difference measure. To remove the false foreground masks that are caused by shadows, the normalized cross-correlation of the intensities is calculated at each pixel of the foreground region between the current frame and the background image. Static Region Healing: Foreground fragments are usual for many background subtraction methods. In the mixture of Gaussians background subtraction (BGS) method, the different parts of a static region are often updated to the background model at different speeds based on the similarity of the pixel values between the static region and the background model. By pushing back the static region to the background model when the static region is biggest (i.e., before it starts shrinking), we can avoid the fragment of the foreground. To push the static region back to the background model, we reset the weight of the static region as the maximum weight which was defined in the program. The mean and variance of the 2nd Gaussian distribution is exchanged with the 1st Gaussian distribution for each pixel in the static region mask.

Updating BGS models at a fixed rate for video streams with different frame rate: most existing adaptive BGS methods update the background models based on input frames and a predefined update rate parameter. In this case, the background models are updated at different speeds for video streams with different frame rates although the parameter of the update rate is the same. In real surveillance systems which use live videos as inputs, the video frame rate often changes dramatically even for the same camera view due to multiple engines running on one machine and the complexity of the scenario. To detect abandoned objects and removed objects by the mixture of Gaussians method, the abandoned/removed time is directly related to the model update rate. To ensure stability from the time the object is abandoned or removed till the system detects the static region, we update BGS models based on time stamp instead of frame number. Setting two thresholds for foreground mask and static region mask: In order to avoid static region fragments, we employ two different weight thresholds for foreground mask and static mask. In the mixture of Gaussians BGS method, the different parts of a static region are often updated to the background model at different speeds based on the similarity of the pixel values between the static region and the background model. Some pixels in the static region are often updated to the background model before the static region is healed. We use a lower weight threshold for the static mask and a higher threshold for the foreground mask. Dual thresholding has also been exploited by Boult *et al.* [6] in the context of background modeling. More recently, Zhang *et al.* used this idea in a more general framework, arguing that "two thresholds are better than one" for vision applications.

4. ABANDONED AND REMOVED OBJECT DETECTION

After static regions are detected and healed (i.e., pushed into the background), we need to classify whether the healing corresponds to an abandoned or removed object event. In this section, we initially present a robust algorithm that classifies the static regions into abandoned or removed objects. Then we describe a method to reduce false static region classification based on the history of background regions.

Heal Type Detection Very few methods have been proposed in the literature to classify static regions into abandoned or removed objects. Existing techniques rely on the analysis of the intensity edges along the static region in the background image and the current frame. The intuition is that, in many cases, covering the background with an object will introduce more edges in the image due to the object boundaries (occluding contours). Based on this assumption, the static foreground region may be classified as abandoned object if the background image contains fewer edges than the current frame (along the static foreground blob) and conversely for removed items. Although these methods work well for simple scenarios with a smooth background, they are not suitable for complex environments involving crowds and occlusions. Below we depict two key limitations that arise under these conditions: The edge energy assumption is clearly violated when the background is cluttered with many intensity edges. • For scenes where the object is constantly occluded, it is possible that only part of the object is healed. In this case, the static region will not contain the occluding contours, potentially having fewer intensity edges. The key insight of our method to solve these problems is to exploit the surroundings (i.e., context information) of the static blob to classify it into abandoned or removed object. In fact, the surrounding image information has rich features to infer what is inside the blob, as it has been demonstrated by the impressive results obtained by image inpainting techniques

Image inpainting can be used to “fill up” the static foreground blob so that the resulting image could be compared to the background image to determine the heal type (abandoned or removed). However, this operation is computationally expensive and may fail for large regions with complex texture patterns. Rather than going from the surroundings to the interior of the blob as in inpainting, our strategy takes the opposite way. We start at the boundaries of the static blob and use a segmentation process to grow into the exterior, in order to verify how the static region is compatible with its surroundings. Our method is inspired in some sense by the work of Ramanan [26], which uses segmentation to verify object hypotheses in pattern classification. Assume that an object was abandoned in a cluttered background. We first erode the static foreground region to make sure its boundaries fall completely inside the object. Then, we use these boundary points as seeds in a segmentation process.The region growing stops at the boundaries of the object, leading to a smaller segmented region which is not compatible with its surrounding. If the background segmentation is larger than the current frame segmentation, then the foreground region is classified as abandoned object. Otherwise, it is classified as a removed item. If the segmented regions have similar sizes, the heal type is set to “unclear”, which may occur when the static foreground blob corresponds to lighting changes or other artifacts. Our approach is simple to implement, runs in real-time.

5. ABANDONED/REMOVED OBJECT ALERT DETECTION

In this section, we describe the process of abandoned/removed object alert detection which includes 3 parts: 1) Human detection method, 2) system interface, and 3) occlusion handling by keeping track the abandoned/removed items during a time period specified by the user.

A. Human Detection: In order to distinguish stationary human or non-human objects in the static regions, we developed a learning framework for human detection based on adaptive local features. This framework can be applied to detect humans in near-field, mid-field, and far-field surveillance scenarios, which deal with images with different levels of detail. In order to account for these differences, for each scenario we designed a human detector in a scale specifically tailored to the available resolution which can be configured for different camera views by users.

B. System Interface: After a static region is healed and classified as an abandoned or removed object, some conditions need to be verified before triggering an alert. If both human and non-human object classes are selected for abandoned and removed object detection, the human detection process is skipped. The conditions based on size, object class, and regions of interest are trivial to implement. For the time condition, we need to keep track of the healed static region and check whether it is persistent during the time period specified by the user. Since we use the 2nd Gaussian distribution to detect the static regions, the time from the object has been abandoned/removed till it has been healed to the background model is determined by the model update rate, weight threshold, and the similarity of the object and the background models. This time is also counted in the alert detection. In crowded scenes, the abandoned object (or the ghost due to object removal) may be constantly occluded.

C. Matching under: Occlusions In order to verify the persistence of the abandoned and removed object in the scene during the time period specified by the user, we use the healed static region as a template and apply cross-correlation in each incoming frame to detect the object (or the ghost) at that specific image location. Occlusions are clearly a problem here, as they lead to low correlation scores. Let Static Time be the time duration specified by the user and OccTimeThr be the maximum allowed continuous occlusion time. After the static region is healed, in case the object is not detected (low correlation score) for a continuous time duration greater than OccTimeThr, we terminate the process and no alert is triggered. In case the object is detected, we check whether the current time since the region became stationary is greater than Static Time Thr, in which case we trigger the alert indicating an abandoned or removed item. This process handles occlusions quite quite well in crowded environments, while meeting the user specified time conditions. This matching process is also important to bring a spatial, region-based analysis into the pixel wise background adaptation model. Pixel wise adaptation is very useful for handling multimodal backgrounds (like waving trees, etc.), but may also lack higher-level information about the object shape. As an example, healing may occur if different objects with different shapes but same color frequently cross a specific image location. In this scenario, the region-based matching process is essential to eliminate false stationary regions.

6. DISCUSSION AND CONCLUSION

We have presented a new framework to robustly and efficiently detect abandoned and removed objects in complex environments for real-time video surveillance. The mixture of Gaussians background subtraction method is employed to detect both background and static foregrounds by using the same Gaussian mixture model. Then the static foregrounds were classified into abandoned or removed objects by segmenting and comparing the surrounding areas of the background model and the foreground image. Our method can handle occlusions in complex environments with crowds. Furthermore, in order to reduce false alarms, we have employed tracking information in a small temporal window to provide an additional cue to filter out the impact of spurious and noisy trajectories for abandoned object detection. The testing results which are based on different scenarios have proved that our approach can be successfully applied in real.

REFERENCES

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

[2] M. Bertalmío, G. Sapiro, V. Caselles and C. Ballester, “Image Inpainting”, Proceedings of SIGGRAPH 2000, New Orleans, USA, July 2000.

[3] A. Bevilacqua and S. Vaccari, “Real Time Detection of Stopped Vehicles in Traffic Scenes”, IEEE International Conference on Advanced Video and Signal-Based Surveillance, London , UK , September 2007.

[4] M. Beynon, D. Hook, M. Seibert, A. Peacock, and D. Dudgeon, “Detecting Abandoned Packages in a Multi-camera Video Surveillance System”, IEEE International Conference on Advanced Video and Signal-Based Surveillance, 2003.

[5] N. Bird, S. Atev, N. Caramelli, R. Martin, O. Masoud, N. Papanikolopoulos, “Real Time, Online Detection of Abandoned Objects in Public Areas”, IEEE International Conference on Robotics and Automation, May, 2006.

[6] S. Boragno, B. Boghossian, J. Black, D. Makris, and S. Velastin, “A DSP-based system for the detection of vehicles parked in prohibited areas”, IEEE International Conference on Advanced Video and SignalBased Surveillance, London , UK , September 2007 .

[7] S. Guler and M. K. Farrow, “Abandoned object detection in crowded places,” in PETS, 2006, pp. 99–106.

[8] S. Guler, J. A. Silverstein, and I. H. Pushee, “Stationary Objects in Multiple Object Tracking”, IEEE International Conference on Advanced Video and Signal-Based Surveillance, London , UK , September 2007

[9] M. Harville, “A Framework for High-level Feedback to adaptive, perpixel, Mixture-of-Gaussian Background Models”, Proceedings on ECCV, 2002.