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An Approach for Unattended Object Detection through Contour Formation using Background Subtraction

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Abstract

Any unattended object in public places is generally considered as a suspicious object. Identification of such objects in public places is one of challenging tasks in computer vision. Robust object detection system with prompt and accurate identification of safety breaches augments security measures at public places such as shopping malls, airports, railway stations, etc. This paper proposes a new and efficient approach for the detection of unattended objects in a well illuminated environment from video captured through a single camera. The proposed approach extracts foreground objects using background subtraction method. These foreground objects are further categorized into static and moving objects by comparing their respective coordinates of centroid in consecutive frames. The foreground object is classified as an unattended object if that object is static over a predefined period of time and its size lies in the predefined range. The performance of the proposed approach is evaluated by conducting the experiments on ABandoned Objects DAtaset (ABODA) dataset and also on few real time videos recorded by the authors. The results are derived for evaluating the experiments using Correct Object Detection Rate (CODR), Object Success Rate (OSR), and False Alarm Rate (FAR) metrics. The CODR & OSR rates so attained for the proposed approach with static background are 100% each while FAR is 0%. Average CODR, average OSR, and average FAR of static and dynamic background are found to be 70.83%, 67.25%, and 35.41% respectively for the proposed approach. The proposed approach updates/replaces the original background frame to minimize the scope of false alarm rate in case of dynamic background. It is generic and can be efficiently used for object detection in various public scenarios.

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Keywords: Suspicious activities, Unattended object detection, Background subtraction, Canny Edge detector, ABODA dataset;

1. Introduction

Video surveillance is one of the most demanding research areas in the field of computer vision because of its broad applicability in real life applications [1]. Some of the applications are theft detection, unattended object detection,

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fight detection, intrusion detection [2], human detection [3], etc. In view of increased security threats & breaches, and limitations of human surveillance, video surveillance is the prime mandate.

Common security issues in public places are theft, fight, snatching, explosives hidden in abandoned luggage, etc. All these incidents are centered around human activity. Therefore, in addition to object detection, a video surveillance system is required to identify suspicious human behavior [4] in public places. With existing surveillance systems, the cause of any incident is determined after it has happened. Security personnel analyze the captured videos for suspicious activities/objects [5] which is a passive approach. Thus, there is a need of an active surveillance mechanism to enhance the safety of persons/objects in public places by detecting potential suspicious situation and generating automatic alerts accordingly.

An object is an unattended object if it is intentionally left at some place and is untouched/unused over a period of time. These objects may or may not be suspicious. Increased security concerns drive the necessity for efficient surveillance systems that can detect and recognize such suspicious objects in public places. Security alerts help the security personnel to take security measures timely. Unattended object detection is one such system which can detect one or more unattended objects by analyzing sequence of video frames. A significant challenge in the object detection technique is to segregate an abandoned or intentionally left object from several other objects that exist in the scene.

When a person leaves a bag or any similar object at any place, proposed system analyzes it, determines the most likely position of the object and detects it as unattended. In the proposed approach, foreground objects are extracted by background subtraction method. Thereafter, Canny Edge detector is used to detect edges and contour finding algorithm is used to find closed contours. By comparing the current frame with few previous frames, our system identifies the position and size of left over object and confirms that it is unattended. The proposed system also assists security personnel by providing situational awareness and enables them to respond efficiently for that situation. The main contributions of this research are:

- A method for the detection of unattended objects through a probe of ‘k’ consecutive video frames followed by generation of alert.
- Provides the facility to differentiate the unattended object as suspicious or non-suspicious with the help of human input and if found to be non-suspicious then exclude it from being decided as an unattended object in future runs.

The performance of the proposed approach is tested on the ABODA dataset and on few real time streaming videos captured through webcam in our lab.

Rest of the paper is organized as follows: In section 2, related work is presented. In section 3, we explain the methodology of the proposed approach. Experimental analysis with different datasets and conclusion are presented in section 4 and section 5 respectively followed by references.

2. Related Work

Abandoned object detection techniques are proposed in the literature by many researchers [6, 8, 9, 10]. All these techniques use tracking information of objects to detect an unattended object at a particular place. Borker et al. [6] propose a video surveillance system for automatic detection of suspicious activity. The proposed approach tracks whole body of a moving person with a bag or abandoned bag in consecutive frames, but the system fails in handling the occlusion problem correctly. Singh et al. [7] propose a system which identifies and tracks a human object in real time surveillance scene. Smith et al. [8] present a two-tiered solution to identify the left-luggage object using Markov Chain Monte Carlo (MCMC) tracking model. This model tracks the person and luggage for a scene of the video. The output of the model is passed to a bag detection process that determines whether the luggage is left by any person or not. Guler et al. [9] present a new method for abandoned object detection by combining background subtraction based tracking and a stationary object detection algorithm. A system is proposed to detect and track the moving objects by using the cross-correlation method and wavelet transform based techniques by Nagmode et al. [10].

Porikli et al. [11, 12] propose a non-tracking but single camera-based method which uses two backgrounds for the detection of stationary objects. Tian et al. [13] propose a novel solution to detect abandoned or removed objects by detecting both background and foreground objects. They use mixture of Gaussians to detect the background object while background subtraction method is used to detect the static foregrounds. An intelligent vision-based analyzer is proposed [14] for semantic analysis of unattended objects for a monocular surveillance video. This video is captured by a consumer camera through cluttered environments. Venetianer et al. [15] demonstrate efficiency of "ObjectVideo VEW" and "OnBoard" intelligent video surveillance system through experiments. This approach keeps track of background regions that are stored right before an abandoned object that covers them. It fails when the static object stays for a long duration in the scene because matching of the current frame with the stored background frame becomes difficult with differences in illumination. In the next section, a methodology of the proposed approach is explained in detail.

3. Proposed Approach

In this section, we propose an automated unattended object detection system based on object tracking method. Fig. 1 depicts the architectural design of the proposed approach. In our system, objects that are to be detected may be static or dynamic. Firstly, stream of frames is extracted from the input video and one frame is chosen as the background frame. The background frame may be either the first frame or any intermediate frame in the streams. Each frame is preprocessed to adjust the contrast and to remove the noise.

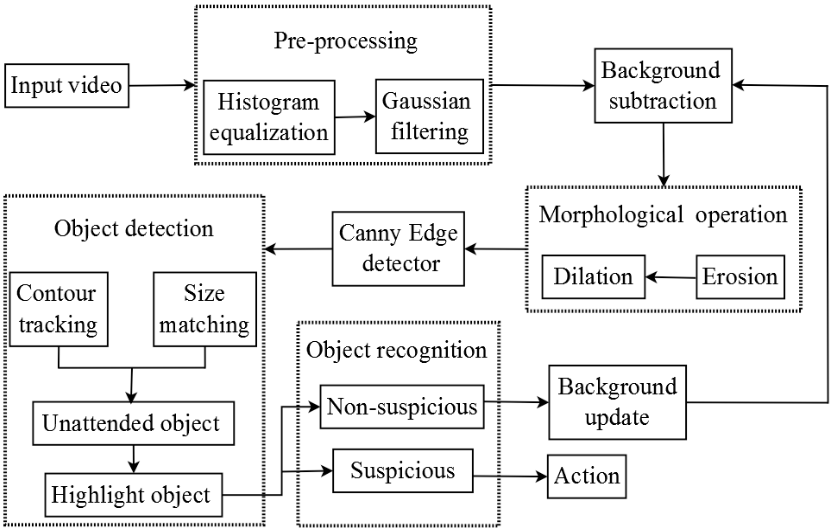

Fig. 1. Block diagram of the proposed approach

After preprocessing, foreground objects are extracted by using background subtraction method. In this method, pixel difference between the current frame and background frame is calculated. After extracting the foreground objects, we apply morphological operations multiple times to get a well defined shape of the detected objects. The two morphological operations used for this purpose are dilation and erosion. Dilation operation is used to expand the image by adding pixels in the image boundary while the erosion operation is used to shrink the image by removing pixels in the image boundary. Next, Canny Edge detector algorithm is applied on the obtained foreground objects to find the edges of each object. Canny Edge detector algorithm performs four operations: smoothing, finding the intensity gradient of the edge, non-maximum suppression, and hysteresis thresholding to detect the edges in image.

Contour finding algorithm [16] is applied on the detected edges to obtain closed contours. Thereafter, to confirm whether the object is static or not, we compare the centroid of contours between k^{th} & $(k-50)^{th}$ frames, k^{th} & $(k-100)^{th}$ frames and k^{th} & $(k-190)^{th}$ frames. These frames are taken randomly for this purpose. If the object is found to be static then the size of this contour is compared with the size of specified unattended object. If the size of contour lies within the range (here, range is taken as 300 to 10000 pixels), then this contour is considered as an unattended object. To highlight the detected unattended object, a message "unattended object" is displayed with a red rectangular bounding box. Algorithm 1 presents the pseudo code of the proposed "unattended object detection" technique.

Algorithm 1 Algorithm for unattended object detection

INPUT: Video V containing N number of frames.
OUTPUT: Alert message is generated for unattended object present in the video.
Ensure:

(1) bg_b is a background frame.
(2) c is the maximum index of the list.
(3) c_1 & c_2 are the no. of rows and columns respectively in the kernel matrix.
(4) After c_3 no. of frames system start detecting unattended object.
(5) m no. of erosion and dilation operations are performed.
(6) p is the total no. of contours present in a frame of input video.
(7) $k_1, k_2,$ & k_3 are three distinct random integers (($k_1, k_2,$ & k_3)< c_3)
(8) $area(.)$ calculates contour area.
(9) Assumed size of unattended object is in the range pl_1, pl_2.

```
Procedure UODetection(V)
F_1, F_2, ... F_N = readVideo(V)          ▹ Converting input video into sequence of frames.
for i ← 1 to N do
    cf = rgb2gray(F_i)                    ▹ Converting input frame from rgb scale to gray scale.
    cf_h = equalizeHist(cf)               ▹ Equalizing the histogram of gray image.
    cf_b = filter(cf_h)                   ▹ Applying filtering operation on gray image.
    fg = absDiff(cf_b, bg_b)              ▹ Applying background subtraction method to extract frame having foreground objects only.
    bw = g2b(fg)                          ▹ Converting fg from gray scale to binary scale.
    kernel = ones(c_1, c_2)               ▹ Creating a matrix of dimension c_1Xc_2 having values of each element = "1".
    for j ← 1 to m do
        ew = erosion(bw, kernel)          ▹ Applying erosion operation on bw image.
        dw = dilation(ew, kernel)         ▹ Applying dilation operation on ew image.
        bw = dw
    end for
    e = edgeDetector(bw)                  ▹ Detecting the edges of the image.
    cnt_i[1...p] = findCountour(e)        ▹ Extracting p contours from the i^th frame.
    for k ← 1 to p do
        f_i[i%c] = centroid(cnt_i(k))     ▹ Storing centroid of k^th contour of i^th frame.
        if (i > c_3) then
            if (centroid(cnt) == [{f_i(i-k_1)%c} && {f_i(i-k_2)%c} && {f_i(i-k_3)%c}]) then
                if ( pl_1 < area(cnt_i(k)) ≤ pl_2) then
                    drawBoundingBox(cnt_i(k))            ▹ Draw bounding box
                    putText("unattended object")          ▹ Display alert message
                end if
            end if
        end if
    end for
end for
end procedure
```

The detected objects may or may not be suspicious. Our proposed approach relies on human input for confirming the suspicious nature of the object. Once confirmed as non-suspicious/harmless, the object is considered a background object for all future detection. This feature makes the proposed approach suitable for real-time video surveillance.

4. Simulation and Results

The proposed approach is implemented by using OpenCV [17] with python. Performance of the proposed approach is evaluated on ABODA dataset. ABODA dataset [18] contains eleven videos recorded at both indoor and outdoor environments. Some of these videos have been recorded in natural light, while others, in the room ambience. The videos that are used from ABODA dataset have different ambient illumination.

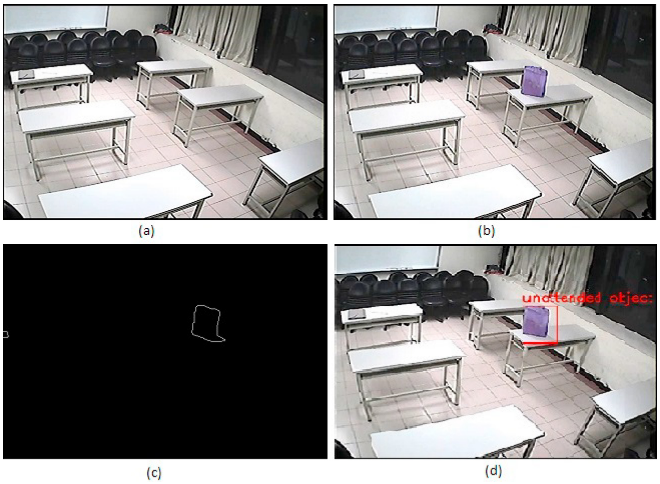

Fig. 2. (a) Background frame; (b) an unattended object is present in the current frame; (c) obtained contour from subtracted frame; (d) correctly identified unattended object.

This dataset also includes crowded scenes as found at airports and railway stations, varying illumination, and day and night time recordings. To observe real time response of the proposed approach, few experiments are performed on the live videos. These live streaming videos are taken through webcam in our lab. Fig. 2 show the intermediate results of the proposed approach. These experiments confirm the effectiveness of the proposed approach in this paper, elaborated further in section 4.1.

To measure the performance of the proposed approach, three objective parameters: Correct Object Detection Rate (CODR), False Alarm Rate (FAR), and Object Success Rate (OSR) are also computed. CODR is the proportion of correctly identified unattended objects to the actual number of unattended objects. FAR is the proportion of wrongly identified unattended object to the total number of identified unattended objects. Therefore, Object Success Rate of this method is defined in terms of CODR and FAR. CODR, FAR, and OSR are calculated using equation 1, 2 and 3 respectively [6, 10].

$$CODR = \frac{TP}{TP + FN} \tag{1}$$

$$FAR = \frac{FP}{TP + FP} \tag{2}$$

$$OSR = \frac{CODR}{CODR + FAR} \tag{3}$$

True Positive (TP) is the total number of correctly identified unattended objects while False Positive (FP) is the total number of wrongly identified unattended objects. False Negative (FN) is the total number of unattended objects that are not detected.

4.1. Results and Discussion

We conduct our experiments on all eleven videos of ABODA dataset and first frame of each video is taken as the background frame.

Fig. 3 shows the frames of video1 recorded at indoor environment having artificial light. Here, two persons are interacting with each other and one person has a bag (Fig. 3(a)). Later, one of the two persons drops his bag (Fig. 3(b))

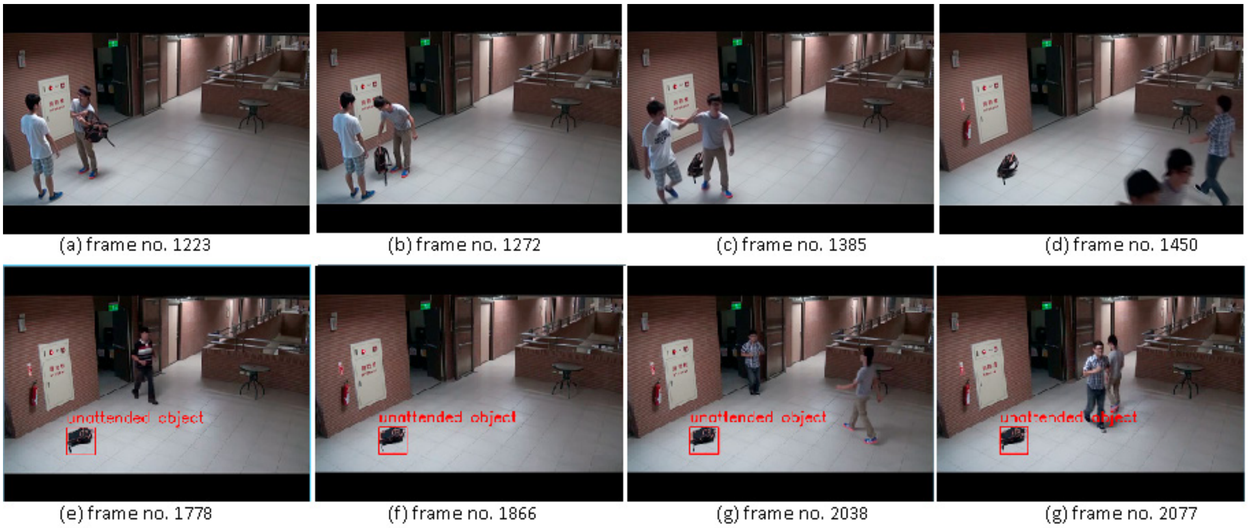

Fig. 3. (a) to (d) show the sequence of frames of video1 where a person drops his bag and moves away from the place; (e) to (h) show the detected unattended object.

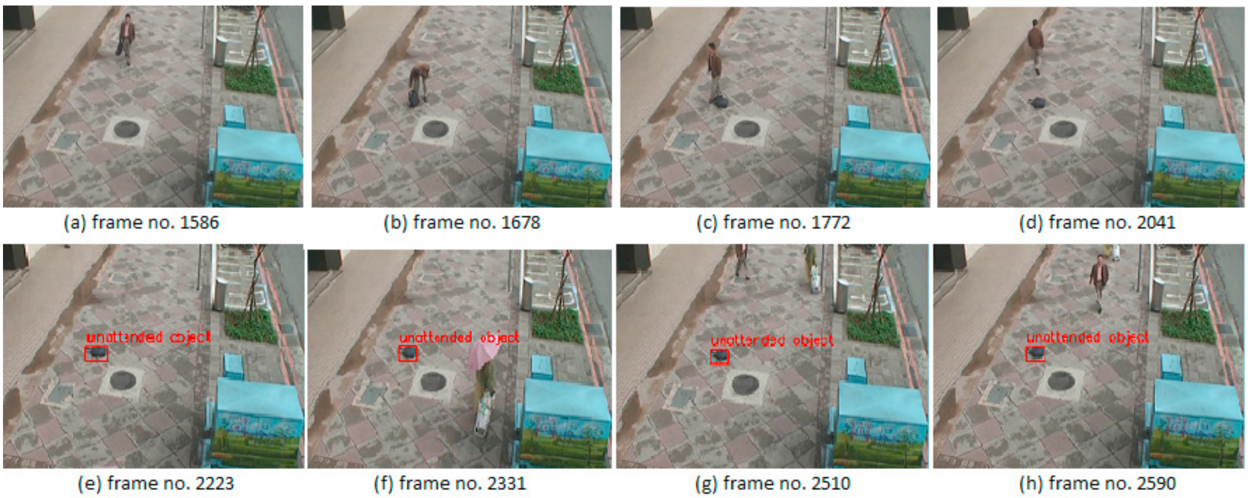

Fig. 4. (a) to (d) show the sequence of frames of video3 where a person drops his bag and moves away from the place; (e) to (h) show the detected unattended object.

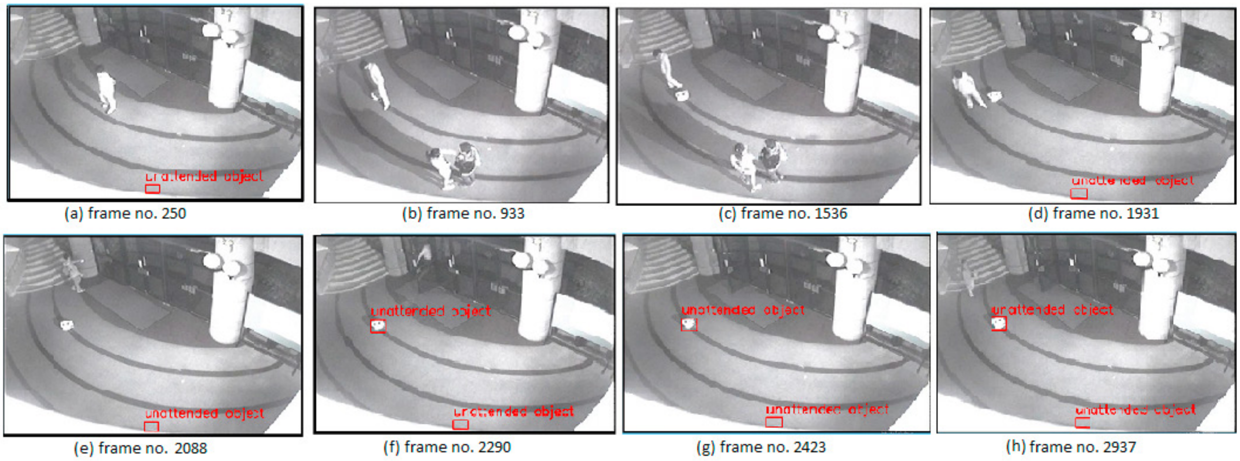

Fig. 5. (a) to (e) show the sequence of frames of video5 where a person drops his bag and moves away from the place; (a), (d) and (e) show the false detection; (f) to (h) show both the unattended object and false detection.

and moves away from the scene (Fig. 3(c), Fig. 3(d)). Our proposed approach correctly detects the unattended object and highlights a message around the detected object (Fig. 3(e), Fig. 3(f), Fig. 3(g) and Fig. 3(h)).

Fig. 4 shows the frames of video3 recorded at outdoor environment, having natural light. In this video, a person carrying a bag (Fig. 4(a)) drops it on the way (Fig. 4(b), Fig. 4(c)) and walks away (Fig. 4(d)). Our proposed approach correctly detects it as an unattended object in both conditions: either a person is in the frame (Fig. 4(f), Fig. 4(g) and Fig. 4(h)) or not (Fig. 4(e)). From Fig. 3 and Fig. 4 it can be concluded that the proposed approach accurately detects the unattended object in natural light as well as in artificial light when background is static.

Fig. 5, Fig. 6, and Fig. 7 show the frames of video5, video11, and video12 respectively. Video5 is recorded at outdoor environment having low illumination, video11 is recorded at crowded places in artificial light and video12 is recorded in our lab.

Fig. 6. (a) to (f) show different frames obtained through video11 recorded in crowded environment; (d), (e) and (f) show the false detection of an unattended object.

Fig. 7. (a) to (h) show different frames obtained through real time video recorded through webcam in our lab; (a) placing a box; (b) placed box; (c) to (e) box is detected as an unattended object (d) placing a bag on the chair; (f) and (g) detected both bag and box as unattended object; (h) only bag is detected as an unattended object after updating the background frame.

Fig. 5 (a) & Fig. 5 (d) to Fig. 5 (h) show the false detection of an unattended object while Fig. 5 (f) to Fig. 5(h) show the correct detection of an unattended object present in the frames. Fig. 6 (d) to Fig. 6(f) show the frames where an unattended object is falsely detected by the system at different locations. Fig. 7(c) to Fig. 7(h) show the frames where the system correctly detects single as well as multiple unattended objects placed at different locations. From Fig. 5(f) to Fig. 5(h) and Fig. 7 (c) to Fig. 7(h), it can be concluded that the proposed approach efficiently detects the unattended objects that are present in the scene. From Fig. 5 (a) & Fig. 5 (d) to Fig. 5 (h) and Fig. 6 (d) to Fig. 6(f), it can be concluded that some false alarms are also generated by the system due to lighting effect or presence of shadows, etc.

Image results provided above well depicts the scenarios of unattended objects at public places. The detection of these objects is experimented with efficient outcomes. The quantitative analysis of the same is also presented in the Table 1. Table 1 summarizes the correct object detection and false alarm measures for all the test cases in the experiment. From the computed values we draw following inferences:

- Both Correct Object Detection Rate (CODR) and Object Success Rate (OSR) are 100% while False Alarm Rate (FAR) is 0% for all the videos of static background.
- The Average values of CODR, OSR and FAR for static and dynamic background are 70.83%, 67.25%, and 35.41% respectively. Here average value is the average of all values under respective column of Table 1, for all twelve videos.

These results establish that in either cases - indoor and outdoor, if background frame is static i.e., video is recorded through fixed camera and in the absence of variation in illuminations then the unattended object is correctly detected with the help of proposed approach. In case of dynamic background i.e., video is recorded through moving camera or in the presence of variation in illuminations, the proposed approach may or may not detect the unattended objects and may generate false alarms. In a similar work, Borkar et al. [6] propose an approach for abandoned bag detection in real time. However their system has no provision for updating/replacing the background frame, if the detected unattended object is confirmed as harmless. If the detected object is harmless and object detection system does not update the background frame, then the false alarm rate may increase in future detections. Our proposed approach overcomes this limitation.

Table 1. Results of unattended object detection in ABODA dataset and recorded video.

Video sequence	Scenario	Illumination effect	Unattended object	TP	FP	FN	CODR (%)	FAR (%)	OSR (%)
Video1	Indoor	No	01	01	00	00	100	00	100
Video2	Outdoor	No	01	01	00	00	100	00	100
Video3	Outdoor	No	01	01	00	00	100	00	100
Video4	Outdoor	No	01	01	00	00	100	00	100
Video5	Outdoor	Yes	01	01	01	00	100	50	67
Video6	Outdoor	Yes	02	01	03	01	50	75	40
Video7	Indoor	Yes	01	00	04	01	00	100	00
Video8	Indoor	Yes	01	00	03	01	00	100	00
Video9	Indoor	Yes	01	01	00	00	100	00	100
Video10	Indoor	Yes	01	01	00	00	100	00	100
Video11	Indoor	Yes	01	00	03	01	00	100	00
Video12 (recorded in the lab)	Indoor	No	02	02	00	00	100	00	100

5. Conclusion and Future Work

In this paper, we present an efficient approach for the detection of unattended objects in public places. The proposed approach uses background subtraction for object detection with the facility for updating the background frame if the detected object is found non-suspicious/harmless. We test our object detection algorithm on ABODA dataset as well as on live video footages recorded through the webcam in real time. Experimentally, it is found that Correct Object Detection Rate and Object Success Rate are 100% while False Alarm Rate is 0% for static background in all the scenarios. Average Correct Object Detection Rate, average Object Success Rate and average False Alarm Rate of the static and dynamic background are 70.83%, 67.25 %, and 35.41% respectively. The performance of this approach is high in terms of accurate detection of objects in normal day and night environments, and in low lighting effect scenarios. However, in videos with very high illumination, the glare of light blurs the boundary of the background object (i.e., dynamic background). Due to which, the unattended objects may or may not be detected. As future research, we aim to extend our method to incorporate object detection in more complex scenarios such as videos with varying lighting effects, overly crowded scenarios, etc.

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