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Abandoned Object Detection

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ABSTRACT

Now a day, security cameras have been installed at a high rate in places where there are extensive grounds and large crowd is there. Surveillance system has become an important aspect in security and a necessity to keep proper check. There was a time when video surveillance was mostly used by the government and big companies. But now the scenario has changed. Presently the use of surveillance camera has increased andit is increasing more. The number of cameras installed for security has been increasing year by year. The main reason is security enhancement including the prevention of incidences of terrorism. Therefore, we proposed a method which detects abandoned objects and algorithms can be used to assist security officers monitoring live surveillance video by directing their attention to a potential area of interest.

KEYWORDS: *Object detection, infrequently moving objects, visual attention, visual surveillance, background model*

I. INTRODUCTION

In video surveillance tasks, many times it is required to isolate foreground objects of interest, from background [1]. Based on the extracted foreground objects, high-level tasks, like identifying target objects [2] and distinguishing activities from videos, can be addressed more effectively. Assuming that the camera is stationary, motion plays a major role in video-based foreground/background separation: foreground objects are usually moving while the background is relatively static. Many approaches, like optical flow and background subtraction, have been developed to track the motions of foreground objects, based on which the foreground and the background can be separated. Optical flow requires that the foreground objects move all the time. However, in practice, foreground objects may show sporadic motions, i.e., objects stay static for a long time and have short-duration motions occasionally, e.g., abandoned objects [3], removed objects [4], and persons stopping for a while and then walking away [5], [6]. Background subtraction is another type of effective approaches that have been widely used to identify the moving foreground objects from a clean background [7], [8], [9], [10],[11],[12]. In this paper, we target to monitor the objects. It is assumed that there are abandoned objects such as a bag or a box. Then there is a possibility where things are intentionally left behind. It can be explosive materials which aim at public facilities. If we can detect them, it is possible to prevent the terrorism. For instance,"Detecting unattended packages through human activity recognition and object association". This study uses fixed point camera. However, fixed point camera cannot detect far objects. Assuming that the camera is stationary, motion plays a key role in video- based foreground/background separation: foreground objects are usually moving while the background is relatively static.

So, to guard from any unpredicted situations from occurring we need the surveillance system to

be more advanced and accurate. That is how the idea of abandoned object detection through video surveillance came up. With the help of which we can detect if any suspicious package is left by anyone and then raises an alarm. It is challenging to detect an object when the color of the object almost matches the color of the background. Here, the object will still be successfully detected in our project.

II. Problem Statement

The possible approach to image registration is first to extract distinctive features from each image, to match these features establishing a global correspondence, and then to estimate the geometric transformation between the images. The goal is to track an abandoned object in a crowded place.

Here, we have used Background Subtraction algorithm to track the abandoned object where we are recording the initial frame as the background. We have also assigned a region of interest (ROI) where the possibility of object abandonment is high.

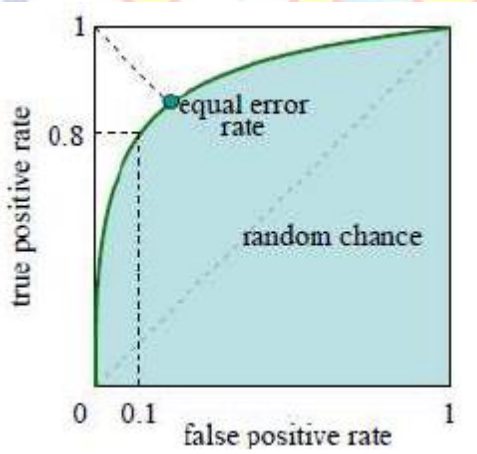

Fig. 1ROC curve and its related rates [4]
(Ideally, TPR should be close to 1, while FPR is close to 0)

III. Work Flow

A. Video acquisition

Video acquisition is the process of converting an analog video signal to digital video. The resulting digital data are computer files referred to as a digital video stream, or more often, simply video stream. From videos, certain frames are extracted and given to next stage. Image segmentation is the process of partitioning a digital image into multiple segments (set known as super-pixels).

B. Segmentation

The goal of segmentation is to simplify and/or change the representation of an image into something that is more meaningful and easier to analyze. Image segmentation is typically used to locate objects and boundaries (lines, curves, etc.) in images. More precisely, image segmentation is the process of assigning a label to every pixel in an image such that pixels with the same label share certain characteristics.

C. Template matching

Template matching is a technique used for finding small parts of an image which match a template image. It can be used in manufacturing as a part of quality control, a way to navigate a mobile robot, or as a way to detect edges in images. If the template image has strong features, a feature-based approach may be considered; the approach may prove further useful if the match in the search image might be transformed in some fashion.

D. Object identification

Object identification technique used for finding and identifying objects in an image or video sequence. Humans recognize a multitude of objects in images with little effort, in spite of the fact that the image of the objects may vary somewhat in different viewpoints, in many different sizes and scales or even when they are translated or rotated. Objects can be recognized when they are partially obstructed from view. This task is still a challenge for computer vision systems.

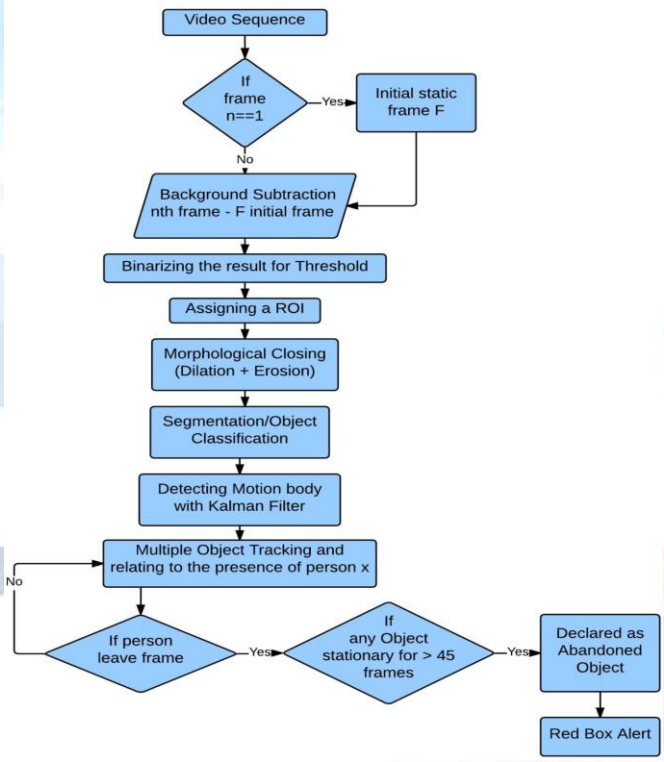

Fig. 2 Work flow of project

E. Region of interest

A region of interest (ROI) is a selected subset of samples from a dataset identified for a particular purpose. A ROI is a form of annotation, often associated with categorical or quantitative information (e.g., measurements like volume or mean intensity), expressed as text or in structured form. Morphological operations are also employed to fill broken boundaries. The combination of gradient and contour-based features is an additional class of descriptors that has been extensively used. Their efficacy relies on the robustness of gradient-based descriptors to illumination changes and noise induction.

F. Object detection

Object detection is the process of finding instances of real-world objects such as faces, bicycles, and buildings in images or videos. Object detection algorithms typically use extracted features and learning algorithms to recognize instances of an object category.

G. Background Initialization

From this section, we introduce the proposed method for background modelling and background subtraction, starting from an input long streaming video. For a long streaming video, there may be intermittent, abrupt background changes, such as those caused by sudden illumination change or camera shake. In this paper, we first divide the long video into a set of super-clips so that each super-clip does not contain abrupt background change. In this way we can perform background modelling for each super-clip independently [13]. Specifically, the super-clips are constructed as follows. First, the input long video is uniformly divided into short video clips Ci, i 2 {1, 2, · · · ,M}, with a predefined length of N frames for each video clip. A key frame ci is then selected from each video clip Ci as its representative. In this paper, we simply pick the middle frame fi⌊N/2⌋ as the key frame ci for the i-th clip Ci = {fij}, j 2 {1, 2, · · · ,N}. Starting from clip C1, the key frame c1 is compared to each ci(i > 1) sequentially until reaching a clip Cp with |RoD(c1, cp)| larger than a threshold, which we empirically choose to be half of the image area. We then merge all the clips Ci(1< i < p) into the first super-clip. The second super-clip is generated similarly starting from Cp. This process is repeated until it gets to the last clip CM. The number of super-clips is further reduced by merging nonadjacent super-clips if their temporally nearest key frames are sufficiently similar, which is set to be true if the total area of their estimated RoDs is smaller than 20% of the image area. This merging process is very useful for the temporary background change, e.g., for outdoor videos, the illumination may get darker for a while and then get back to normal, and the super-clips before and after the illumination change can be merged into a longer super-clip [18].

Each constructed super-clip consists of a sequence of non-overlapped and fixed-length short video clips, each of which needs a background image to accommodate the possible slow background variations within the super-clip. For each video clip Ci, the key frame ci, which is the middle frame of Ci in this work, is employed as its initial background image bi such that bi = ci. In the next section, we introduce a propagation algorithm to update the initial background image bi for each Ci, by identifying foreground regions from bi and replacing them with underlying background regions found from other key frames.

IV. RESULTS

Fig. 3 Object Identification

Fig. 4 Object Detection

Fig. 5 Object Thresholding

V. Conclusion

Our thesis has described an efficient system for security surveillance with high accuracy of detecting multiple abandoned object. Our work also keeps track of the carrier of the object and shows alarm when the carrier leaves the frame in this way the false alarm has been minimized.

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