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Speedy Detection Module for Abandoned Belongings in Airport Using Improved Image Processing Technique

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Abstract

Recently, in computer vision and video surveillance applications, moving object recognition and tracking have become more popular and are hard research issues. When an item is left unattended in a video surveillance system for an extended period of time, it is considered abandoned. Detecting abandoned or removed things from complex surveillance recordings is challenging owing to various variables, including occlusion, rapid illumination changes, and so forth. Background subtraction used in conjunction with object tracking are often used in an automated abandoned item identification system, to check for certain pre-set patterns of activity that occur when an item is abandoned. An upgraded form of image processing is used in the preprocessing stage to remove foreground items. In subsequent frames with extended duration periods, static items are recognized by utilizing the contour characteristics of foreground objects. The edge-based object identification approach is used to classify the identified static items into human and nonhuman things. An alert is activated at a specific distance from the item, depending on the analysis of the stationary object. There is evidence that the suggested system has a fast reaction time and is useful for monitoring in real time. The aim of this study is to discover abandoned items in public settings in a timely manner.

Keywords: Image processing, object detection, video surveillance, edge detection, public safety, computer vision

1. Introduction

There are a plethora of uses for computer vision in today's environment. Character recognition, medical scan categorization, and autonomous car object identification are a few examples. Automated systems may now do tasks that formerly required a person to complete

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them, possibly lowering the likelihood of human mistakes and/or reducing the number of hours of labor. Computer vision might substantially assist in the monitoring of surveillance footage however, object and activity recognition in surveillance video is still a problem for computer vision. It is a physically taxing job where long hours can lead to errors, and is expensive to employ a person to continuously oversee security footage. An automated system that alerts a person if unusual behavior or an unusual item is discovered would be much more effective [1-5].

This application is more complex because of the different characteristics of surveillance video. For example, each scenario has a distinct set of camera angles and varying video resolutions depending on the camera type. It may have a wide range of variations, both in terms of the foreground and backdrop of the images, as well as the activities that are deemed regular. Furthermore, the system should have a low false-negative rate and a low false-positive rate so that it does not constitute a security risk [6-9].

The implementation of cutting-edge and intelligent surveillance systems has become a necessity in light of ever-increasing security concerns. They should be able to keep a close eye on the region under surveillance while also automatically detecting and alerting everyone in the vicinity of potential hazards. It is also important to have intelligent systems that can detect and track items in detail. For instance, if an item is thrown into a monitoring area, it should be detected immediately and tracked. This is an important feature that must be included in any intelligent system, given the dangers that unattended items represent to security. Especially in populated locations like train stations, airports, and shopping malls, these abandoned things might contain anything that could be dangerous to the general population [10].

The use of video surveillance enables us to keep an eye on everything, including people, from afar. To prevent crime, the use of video surveillance cameras in public places such as ATMs, shops, schools, buses, metro stations, conference halls, and airports has expanded significantly over the last several years. Automated surveillance video anomaly detection technologies have become more important to assist security personnel. The abandoned item detection system is only one of the many systems that have been developed [11-13].

Attacks on public transit and other vital infrastructure may be prevented by detecting and removing abandoned items. Detecting items left behind in high-traffic areas may be difficult for the security staff and video surveillance systems. It is also unreliable in complicated surveillance recordings because of issues such as occlusions, illumination changes, and other difficulties in tracking down abandoned objects [14].

When it comes to abandoned objects, they may be described as stationary items that have not previously been in the scene, whereas a removed object can be defined as a fixed object that has previously appeared in the backdrop but is no longer there. Hence, the goal is to identify areas of the image that have recently changed to decide whether they are abandoned or deleted items by subtracting the background and analyzing the foreground using user-specified criteria [15].

This research article has been constructed with several sections that contain the complete novel work. Section 2 brings current research on object detection in various public places. Section 3 delivers the proposed work for an efficient framework of abandoned belongings detection. Section 4 discusses the experimental test of the proposed model. Finally, it concludes with possible exploration.

2. Related Works

Three phases are often included in the process of spotting abandoned baggage on surveillance video: The candidate's abandoned suitcase goods are found in the video in the first step. For future probabilistic reasoning, a trajectory is established by finding and tracking the baggage owner. In the last step, data from the preceding phases are used to calculate a likelihood or confidence level for the occurrence of baggage abandonment. In each of the three phases, there is a wealth of relevant literature. Various steps of an algorithm are applied in different approaches.

Using foreground masking, Liao et al. described a technique to locate items. Due to the difficulty of detecting objects in congested areas, use of background tracks have been proposed here [16]. Porikli et al. presented an extraction approach for static regions based on a pixel-based dual foreground [17]. This is comparable to Bhargava et al. who presented a tracking method for detecting abandoned things [18].

Pan et al. suggested the use of a single camera within the region and two backdrops to identify stationary objects in a non-tracking-based system. The input video is sampled at two different frame speeds to create the two backdrops [19].

A further issue arises if an item is already present in the background. Object video analyses the foreground and background model's edge energy to determine the foreground region's borders in certain situations. A common assumption is that the edge energy of the structure is greater for abandoned items than for removed objects. Connell et al. first suggested this approach. Accurate tracking of the foreground was regulated by the planer homography between the two cameras for further good accuracy [20].

2.1 Research Gap

In order to make surveillance analysis faster, accessible, and efficient, it is suggested here to use a combination of edge and object detection methods called improved image processing. The particular problem it addressed and fast detection is found by simple and modified image processing method. The scenes are captured in video frames from surveillance footage of a specific location. Detecting and providing an alarm to the owner if a picture contains an abandoned bag is the primary goal of this research study.

3. Methodologies

3.1 Pre-processing state

A pixel-based model of the backdrop is learned by analysing multiple photos. The backdrop pixel is defined and the background model is updated by viewing these photographs. The background modelling and subtraction are used in the proposed strategy. Camera and video surveillance systems rely on background removal to identify moving objects. Figure 1 shows this proposed technique’s entire framework.

3.2 Background review in the image

It is critical to evaluate the effectiveness of object identification algorithms in order to accurately track numerous items in a scene. So, object detection relies heavily on the ability to distinguish between foreground and background items. When developing a new product, object detection is often the initial stage. Surveillance cameras use object tracking to better comprehend the events they capture [21-25].

3.3 Object detection

Multiple targets that overlap one another in congested locations provide a barrier for this stage. Item Classification (Object Classification) is used to categorize the properties of the object, including color and form, so that it may be identified (Object Recognition).

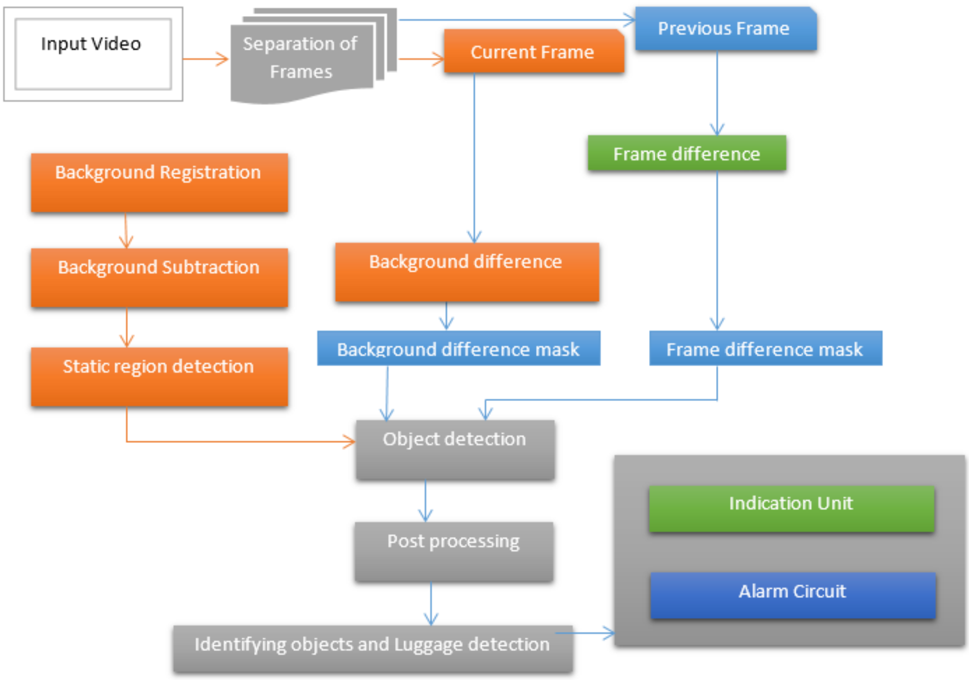

Figure 1. Proposed architecture of object and abandoned luggage detection

3.4 Identifying object and luggage detection

A Kalman filter is used to identify foreground items, such as people and their belongings. First, the pixels of interest are recognized, and blobs are created using the background model learned using the first 500 frames. Each blob has a distinct shape, size, and position (a color histogram). To merge and divide blobs, an association value depending on the overlap between the blob and the object's bounding boxes is assigned. Once the blobs are formed, and all the blob merging and splitting is completed, the baggage is identified and found based on its movement. Since baggage that has been monitored is less likely to wander off, this feature is a must. While the blob tracker has some flaws, it is still an excellent tool. It is impossible for the tracker to distinguish a human object that has already been combined into one. Misidentification might occur if objects are detected based on their movement [26, 27].

3.5 Owner tracking

The human tracker is a reduced version of Wu and Nevada's work, and is just intended for tracking people. Full-body detectors (left, front/rear, and right) are used to scan the picture using three trained full-body detectors. The detectors' angles vary from 0° to 45°. The multi-view person detection will be the result of the scanning data being combined. Then, utilising a data (frame detection result) association style approach, the discovered human objects are monitored in 2D. Although the trained detectors are in the 0°– 45° range, the detection of people becomes less accurate when the angle is quite large. By integrating these two trackers, each of their shortcomings are alleviated. The next step is to create an event model for each scenario that might occur so that the event can be recognised. Bayesian inference is used because it is important to deal with each ambiguity in the event specification [28,29].

3.6 Indication unit

When the abandoned baggage is identified and recognized, an alert notice is sent after the development of these phases. There are two parts of this system for identifying abandoned luggage: a low-level tracking module and a high-level event detection module. There are two tracking modules in this system: one that tracks the movement of blobs and the other that tracks the movement of humans. There is a difference between an event and a connected cue becoming proof. If any of these things happen, an alert or warning will go out since there is a good chance that abandoned baggage will be found. The prototype phase is the simplest of all the prototype stages. A picture of the suitcase is all that is required for the system to work. The item and the backdrop remain stationary in the first phase. The system can categorize the baggage at this point. Instead of a single picture, the input for the second prototype phase is a succession of images. However, the backdrop should remain static for both the items and the passengers. After this stage is completed, the system that tell the difference between people and their belongings is obtained.

4. Results and Discussion

The foreground of the picture must be removed before the area of interest can be retrieved. In this approach, background information is no longer necessary for further processing. The accuracy of object identification will be affected by the results of the foreground removal. Image acquired for the purpose of analysing it, using the suggested enhanced version of the image processing technique [30] is shown below. Figure 2 shows human and luggage identification by the proposed improved image processing method. The distance between the owner (x_1) and the luggage (x_2) is found by Euclidean distance formula between the owner and abandoned luggage.

$$\boldsymbol{d(x_1, x_2)} = \sqrt{(\boldsymbol{x_1} - \boldsymbol{x_2})^2}$$

Figure 2. Human and object detection area by proposed algorithm

Table 1. Performance metric for various methods

Methods	Total frames in videos	Processing time of each frame (s)	Total Processing Time (s)	Responding Time (s)	Results observation
Extended Edge detection Method	69	0.129	8.901	15.98	Slow Process
Object detection method	69	0.112	7.728	13.874	Slow process
Improved Image Processing	69	0.008	0.552	0.991	Speedy Detection

4.1 Object tracker

Keeping track of items in the scene in the given input image is critical to the proposed system's ability to analyse the photos received from the video surveillance. For the classification of distinct behaviours, each processed frame's data are used. Recognizing and analysing an object's motions in relation to its environment allows the determination of its behaviour. According to these proposed monitored objects' activities, the recognised behaviour is divided into two categories: normal and suspicious behaviour. It is preferred to do this using pattern recognition and neural networks, among other ways. Velocity, distance from other objects, and so on are used to categorise behaviour. Furthermore, the suggested image processing method has a shorter execution and response time than the existing algorithms. As a result, it has been shown that rapid detection of abandoned bags is associated with great response time. Figure 3 depicts a performance chart for the suggested method, as well as a time measurement for the algorithm.

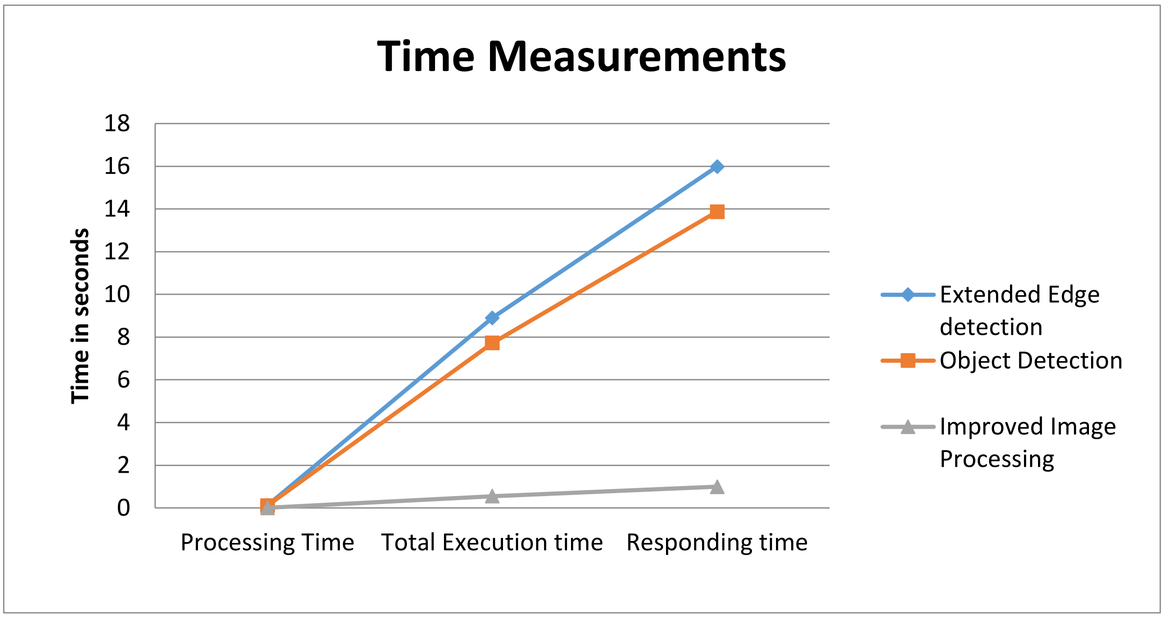

Figure 3. Overall performance chart for various methods

4.2 People and luggage recognition

In order to grasp the meaning of the extracted foreground, this method must be able to discern between the numerous items in the picture. People, baggage, and other items in motion are included in this category. There are a number of steps that need to be taken before any recognition occurs. Shapes, textures, and colors are examples of these characteristics. In the end, the rules established by the knowledge-based system is used to categorize different types of things.

5. Conclusion

The real-time bag identification algorithm developed in this research is found to be effective even in densely populated environments. For the real-time video surveillance, a novel framework has been developed that can reliably and quickly identify abandoned and removed items. Occlusions in densely populated areas can be handled with this technique. It uses the current iteration of the project to mark the areas of the video where it seems like a baggage has been abandoned. In order to make it more useful, it may be expanded so that the baggage can be tracked throughout time in order to identify the person who is accountable for it. Tracking the person's actions across a dataset might be a further expansion. Segmentation and temporal models might be used in combination to accomplish this. Finally, feeding the output of this model to a faster R-CNN based network might be extended to item localization, which can be used to generate scene graphs, count, and characterize abandoned baggage.

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Author's biography

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