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Detection of Left Object using Temporal Modelling via Static-Camera

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ABSTRACT: In this paper, a detection system is framed which is based on the Real-time capture of video via Camera and interpret the temporal flow of events related to abandonment of object. The video is captured on real time with the help of static cameras and same video is processed with the help of Image Processing. Our approach is framed to identify static foreground regions based on the temporal transition information which is based on the sequential pattern of each pixel. After detection it also analyses the previous frames by using back tracing methodology to identify and record the most likely luggage owners and raises an alarm. Therefore the proposed approach handles the problem of abandoned object very well using the dual rate background modelling methodology.

KEYWORDS: Abandoned object detection, object detection and tracking, visualSurveillance, Background Modelling, short-term background model and long-term background model

I. INTRODUCTION

Now-a day's security on public places has become a vital issue with concerns about terrorism on the rise. It is very important to identify the suspicious stationary object/items for the public security. The demand for reliable surveillance systems is increasing day by day, especially areas such as airports, railway and subway stations. Thus, video surveillance systems which can carry out automatic detection of security related events are gaining increasing interest.
But the main problem is though the cameras have installed at many places but the footage is only used after incident had taken place. However we can use those cameras in a smarter way that to prevent such incidents from occurring. As we know that there is no such type of object which falls under 'Abandoned' category, historic methods like training an object detector for a particular category fails in such case. Hence to make a way out of it, we are processing the real-time input and processing it with the help of image processing.
The camera which is mounted captures the video if a person is keeping any unknown object/item in the public place and leaving it there. In case if that person is just stepped away momentarily and visible within the scene, there is no concerned to be raised. But in case if the person is not found in the scene, it will raise an alarm and notification will sent to the security people.
In our approach we are also using back tracing methodology to look for the object owner. The system will inspect the previous frames captured in video checking when the left object was with the person who brings the object into the scene and sets it down there. The system will figure out the features of the object owner. These features are then utilised and get it matched with the features of the owner in the subsequent frames. If the features get matched, the alarm is diffused and if the match does not found out for a particular time period which is pre-defined the object is considered as Abandoned and alarm is triggered.
The solution of this problem is foreground and background techniques which are feasible to identify static foreground regions. We are combining the short-term background model and long-term background model to extract the foreground objects.
This Paper is organized as follows: Section II describes related works, Section III describes the proposed work in detail. Conclusions are given in section IV.

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II. RELATED WORKS

Automated surveillance systems are uprising drastically in the market like railway stations, airports, warehouses etc. Thus aiming towards the solution of the problem of detecting abandoned objects, many researchers proposed various techniques. The techniques which were proposed on abandoned object detection are based on tracking information to detect the left object event. However such techniques are not well-suited for crowded environments like railway stations etc.
F.Porikli and Y. Ivanov [1] suggested the double background models i.e. long-term and short-term for detecting a static foreground. They are dependent on the fast and slow learning rates the subtraction of two obtained foregrounds using these 2 learning rates results into static foregrounds. A single camera is used in this technique.
Auvinet [2] suggested the method of employing two cameras for the detection of abandoned objects and the planar homography between two cameras. They are used to foreground tracking results regulation.

Wu-Chih Hu [3], Chao-Ho Chen have proposed an effective method for detection and tracking of multiple moving objects from a video sequence captured by moving camera without additional sensors. Moving object detection is getting difficult for video capturing by a moving camera because the motion of camera and motion of object are mixed.
Bhargava et al. [4] represents the event of object abandonment by its constituent sub-events. The algorithm verifies the sequence of foreground observations by pre-defined event representation and temporal constraints.

Fan et al. [5] proposed a method which tracks the moving people nearer to the left object with the usage of a blob tracker. The movement information is gained which is given as an input to the ranking function.

Tian et al. [6] combines a human detector and blob tracker to track the owner of abandoned object

III.PROPOSED WORK

We proposed an approach which works on the detection of the abandoned objects in real time. It is based on background modelling and background subtraction. As we are using single camera in our system which detects static abandoned object, we will divide the image in short-term and long-term module according to its learning rates to extract the foreground objects. Each pixel of an input image is classified as a 2-bit code.Fig. 1 shows our system diagram

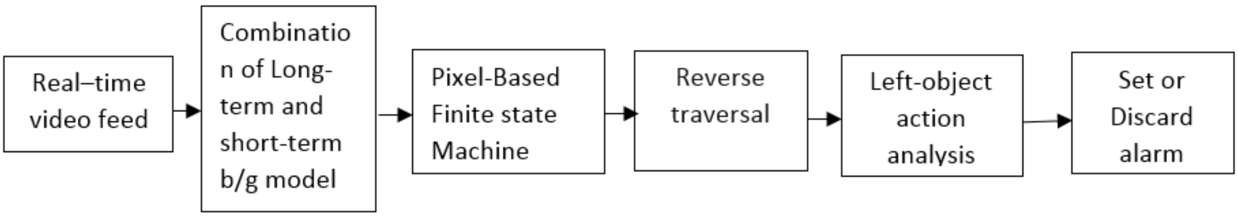

FIGURE 1 :THE PROPOSED SYSTEM OVERVIEW

The system involves three main steps: i) Static Foreground detection using Long-term and short-term background model and Pixel-based finite state machine ii) Reverse traversal verification iii) left object action analysis iv)abandoned and removed object alert detection. An algorithm involves a specialized mixture of Gaussian (MOG) background model to analyse the foreground as abandoned object. Various thresholds are applied to obtain the static region masks for stationary objects.

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The vital contributions of our work are listed as follows:

1) Enhanced dual rate background modelling can identify the foreground pixel and background pixel effectively using the short-term and long-term background model at different learning rates
2) The pixel-based finite state machine model identify the stationary foregrounds more accurately using temporal transition information based on sequential pattern of each pixel
3) Our back-tracing algorithm can verify the event of left luggage efficiently.

A] Enhanced Background Modelling

Background modelling/subtraction is very crucial step being the first ever step in detecting and identifying objects/items in the videos. A pixel-based model of the background is built and analysis of each pixel of an image is carried out.A pixel's deviation in colour and/or intensity values i.e. features are used to determine whether the pixel belongs to the background or the foreground. This information is then grouped together to form regions in the image. Once the pixel is identified as a background pixel, the features of the pixels are utilised to update the background model.
Consider if the sequence of images It ($t \in N$) of size m×n, in this case background modelling can be applied as:
B(x, y) - background model
(x, y) – Pixel of an incoming image
It- Incoming image

Step i) Background model **B**(x, y) for each pixel (x, y) is initialized where $0 \leq x \leq m-1$, and $0 \leq y \leq n-1$.
Step ii)If $I_t (x, y) \in \mathbf{B}(x, y)$ for every pixel of incoming image *It, then* pixel (x, y) is declared as background pixel.
In other case, pixel (x, y) is declared as foreground pixel.
Step iii) Going forward, for every new pixel of an incoming image which is considered as background pixel as per step(ii), the background model B(x, y) is updated considering the pixels of incoming image It (x, y) as a sample.
Step iv) $t \leftarrow t + 1$, go to Step ii).

B] Short term model and long term model usage

We have utilised long-term and short-term models in our approach for detecting static foreground. The short-term background model Bs consists of the most recent background samples. It adapts to changes at faster speed. Let us consider the small learning rate λS which updates the background modelBs at a faster speed and takes less time. Consider Fsas a binary foreground image obtained through Bsshort-term background model. It contains more false positives.
The long- term model Blconsists of B background sample values taken from a larger window than the short-term model. It adapts to changes slowly but provides the stable image of the background. This model updates the background at slower speed λL.Fl denotes the binary foreground image obtained using the long-term model. It does not contain the most recent background samples and hence contains more false negatives.
To overcome this problem, we combine the result of these two background models i.e. a short- and a long-term model and take the best features of both the models.
In our approach, when a person is dropping an object/item, the long-term model detects the object as a Foreground object whereas short-term model detects it as a background object due to faster updating rate. Thus, a pixel of 2-bit code $Pi$is represented as a combination of long-term and short-term backgrounds.

$$P_i = F_L(i) F_S(i),$$
$$P_i \in \{0, 1\} \text{ –Binary value of pixel i of foreground images}$$

The short-term and long-term background model is used in our approach as the short-term background model detects the moving objects which are introducing in the video at faster rates and which cannot get detected in long-term model as they are moving at faster rate. The long-term model is helpful as and when the abandoned object is kept, short –term model considers it as a background object because of its faster speed of updating background, however long-term model considers it as a foreground object due to its large learning rate.

Here is the representation of pixels in 2-bit code Piwhich can be expressed in 4 states:

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Pi	Indication by *Bl* and *Bs*
00	Background pixel
01	An uncovered background pixel ->temporarily occluded by an object and then exposed in a recent image.
10	Static Foreground pixel
11	Moving foreground pixel

Table 1: Pixel classification from long-term and short-term background model

C] Pixel-Based Finite State Machine (PFSM)

To reflect the situation discussed in above section B] i.e. whenever the object was left by the owner, it will be detected as foreground by the long-term model. On the other hand, due to the faster learning rate, the left luggage would be classified as background by the short-term model. To represent this situation, as shown in the Table 1, we are representing a single pixel as 2-bit code. To get the better results, we are using temporal transition information to find the stationary objects based on a sequential pattern of each pixel instead of using recognizing the pixel status based on a single frame which can create noise or can be inaccurate due to imperfect background subtraction results.
Suppose that the *t* is the time at which the state of the pixel is changed from one state to another state at time *t+1*via background subtraction. We can illustrate the behaviour of each pixel by constructing the pixel-based Finite state machine.

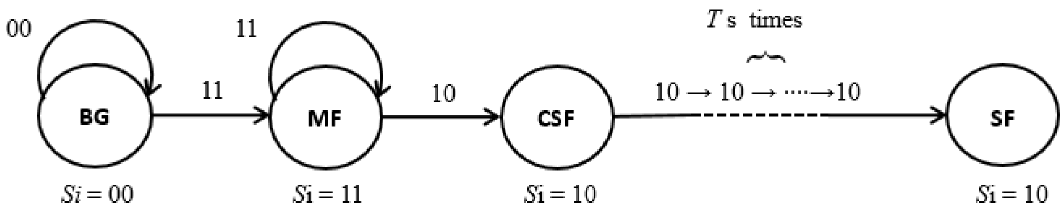

FIGURE 2: Pixel –Based Finite state machine

BG- state of Background
MF-Moving foreground
CSF-candidate static foreground
SF- static foreground
Ts is the finite transition times for changing state from 10 to 10.

The above PFSM states shows that –

1) *Si* = 00, which indicates that the particular position at pixel i remains background at first.
2) When a person comes and brings the luggage to that position, pixel i is occluded by a foreground region and thus *Si* = 11.
3) Then, when the luggage carried by the person is considered as abandoned, the short-term model updates the object into its background model but the long-term model does not, and thus the status of this site becomes *Si* = 10.
4) Finally, when the status of *Si* = 10 remains for a sufficient time, at that time the decision is made that the pixel i is in foreground region i.e. the object is abandoned.

Only this transition pattern (*Si*=10) is considered as static foregrounds.

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D] Reverse traversal using a video summary

This procedure is used to check whether the object is placed casually for a short time by a person or it is placed in public place intentionally. The system verifies whether the person/owner is nearby to the object and if it is not the case, the object is marked as Abandoned if owner does not returns to the object within specific range of period.
At the moment when the object is considered as abandoned at time‘t’ and no other moving foreground objects are within its neighbour region of radius D, the system traces back through previous frames to search the moment $t_0 = t - T_s$ when the object was first brought to and put down the object where T_s is the transition-time constant employed in our PFSM model. The event of the owner dropping down the object increases the chances of the owner’s presence in the neighbourhood of the object and, as a result, provides the system with the best timing for collecting the owner’s appearance model.Let *‘p’* be the position where the object is left. Window $\boldsymbol{W_0}$ is considered which is of size (r2, δ), where r specifies the radius of a circle centered at p, and δ denotes the time interval[t0, t0 + δ].For Window $\boldsymbol{W_0}$, background subtraction algorithm identifies all foreground blob which are present in that window $\boldsymbol{W_0}$ and among those one is selected that is much closer to the shape of human by using the height/width estimator and the human detector which helps us in filtering out the static foregrounds which could be human.

E] Left-object Action Analysis

There can be two types of actions/rules once the object is declared as abandoned:-

- First type is when the object is left by the owner and the object is not attended in the next 60 seconds, the object is declared as an unattended object and an alarm is triggered.
- Second type is when the owner left the object and the distance between the owner and luggage is greater than a predefined distance D= 3 m, then an alarm is triggered.

For getting the alarm trigger, both the above rules should get fulfilled.

IV. CONCLUSION

This project presents a temporal consistency model combining a reverse traversal algorithm for abandoned object detection. The proposed algorithm is very simple and effective on real time video input and can be implemented on public safety. The enhanced background modelling which uses short-term and long-term background model is more effective than single-image based double background modelling. Thepixel-based finite state machine is used to achieve temporal transition information in sequential pattern. The reverse traversal algorithm is used to get the traceability of the owner of the object which runs iteratively to check the left object moment.

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