Real Time System for Unattended Baggage Detection

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Abstract - *Video Surveillance is one of the integral part of security systems at public places including airports, bus stops, railway stations, marketplaces etc. Video Surveillance requires more robust and effective automated technical advancements. In this paper we propose an abstract framework for real time system to detect unattended baggage at public places from surveillance videos. The initial stage of proposed system is background subtraction. The background subtracted frames are used by later stages for foreground static region detection followed by object type identification & performing thresholding validation. Confirming to previous stages, the object is termed as unattended & alarm is issued to alert the authority. The work also compares previous work done in this problem domain and provides a review and comparison between various strategies to detect unattended baggage at public places.*

Key Words: Video Surveillance, public places, background subtraction, identification, thresholding, unattended baggage.

1. INTRODUCTION

With world security concerns being at high stakes, automated techniques to detect unattended baggage from CCTV surveillance cameras requires more effective advancements. Unattended baggage at public places could lead to serious security issues & can impose as a threat to security parameters. Detecting unattended baggage by analysing frames from the video in real time reduces manual observation & reduces security risks to its minimum. The proposed system is capable of localizing the candidates of unattended object & identify whether the object is of interest to us, we perform further steps after the object is identified, it then performs thresholding parameters check to validate it against the definition of unattended baggage. The baggage is checked for certain conditions: (a) whether it has remained unattended for a time period, exceeding to which is a possible candidate, (b) its owner is not within scope of baggage proximity. Fulfilling to both the conditions the baggage is termed as unattended. The system is divided into five stages: (1) Background subtraction, (2) Static foreground region detection, (3) Object identification, (4) Thresholding & (5) Triggering alarm. The object once termed static by initial stages is processed by later stages for object identification & thresholding to validate its unattended condition. Final stage involves alert triggering, if the object has been determined as unattended baggage by its previous stages, a boundary box is now created around the object and an alarm will be raised to alert authorities with the localized location of that object.

2. PREVIOUS WORK

Previous work done in this problem domain uses different techniques at different stages. Most of the work include background subtraction as basis for approach. [4] uses foreground mask sampling for foreground region detection & background subtraction, which creates a mask of foreground pixels. Tian et al. [3] performs background subtraction using Gaussian mixture model given by Stauffer & Grimson. Complementary background modelling is given by [5], which uses short-term and long-term background models to identify foreground static pixels. A mixture of Gaussians is taken into account by [3] to extract foreground static regions. Smeureanu et al. [7] applies Static Object Detection (SOD) pipeline by subtracting motion mask from foreground mask & perform IoU (Intersection over Union) on bounding boxes. Liao et al. [4] implements Selective tracking & motion prediction is performed on owner to compute probabilistic score. This score is compared with predetermined confidence score to declare object as abandoned with a probability certainty. Tian et al. [3] detects static region type by region growing segmentation. Background subtraction performed in [6] compares every frame with background frame & determines object as unattended through time thresholding. A pixel based finite state machine model is presented in [5] to use sequence of state transition pattern as a reference to stationary foreground pixels. A Cascade of CNN is employed by [7] to recognize abandoned luggage in object tracks.

3. PROPOSED SYSTEM

The proposed system divides the video into frames & works on individual frames. Fig. 1 depicts the workflow of proposed system. The first stage is background subtraction. The frame is processed for three types of objects: (a) background objects, (b) static foreground objects which were not in earlier frames, but are introduced later & has remained static for a certain time duration and (c) dynamic objects which change their relative location with time. We employ effective Gaussian mixture learning algorithm given by Lee [2] based on Stauffer & Grimson's adaptive background mixture model [1] to get background subtracted frame. Foreground mask sampling is performed on this frame, which results in a foreground static mask. A convex hull is created for this mask which represent the candidate of unattended object. In next stage we employ a cascade of CNN proposed by Smeureanu et al. [7] to identify objects that interest us. Object identification is then applied on mask-hull from previous stage & only objects identified positive candidates are forwarded and other frames are discarded. Frame with identified static baggage is forwarded for thresholding where validation is done for certain conditions of time threshold and distance threshold (owner's distance from luggage); fulfilling to which it is termed unattended. The system then raises an alarm for the event.

3.1 Background subtraction

Gaussian mixture model introduced by Stauffer & Grimson is widely used to detect background regions. We employ a mixture of 3 Gaussians to model the system.

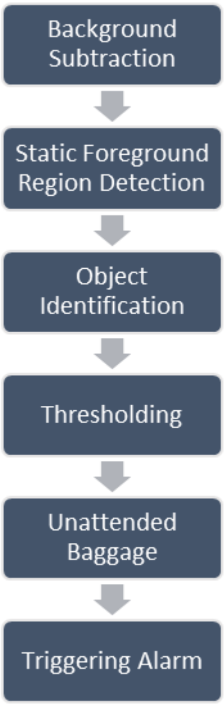

Fig. 1. Proposed System Diagram

An effective learning algorithm proposed by Lee [2] with improved convergence rate and estimation accuracy over the standard method is used. 1st Gaussian represent persistent pixels or background region. 2nd Gaussian update pixels with variations at a slow rate or relative stationary region & 3rd Gaussian stores pixels with variations at higher rate. In our system, if the value of 2nd Gaussian for a pixel is larger than the threshold, the pixel belongs to the static region.

3.2 Static Foreground Region Detection

The pixels belonging to static region (p_i) from previous stage are sampled foreground mask sampling given by Liao et al.[4] to create a foreground mask. A foreground mask M is a Intersection over Union of static region mask S_k where k=1 to n.

$$S_k = p_1 \cup p_2 \cup \dots \cup p_i,$$

$$M = S_1 \cap S_2 \cap \dots \cap S_n$$

Filtering is performed on foreground mask M to remove irrelevant & noisy pixels. Connected component analysis is done later. The foreground mask is then used to obtain a convex hull which contains the object boundary within itself. This convex hull represents static foreground region.

3.3 Object Identification

The mask obtained is passed through a cascade of CNN introduced by Smeureanu et al.[7]. The first CNN is pre-trained with type of objects that will be termed as baggage. The mask is passed through filters, whose intersection gives feature information which is compared from ground truth tables. A bounding box is created around objects tested positive. A second CNN is applied to image samples tested positive by first CNN. The bounding box is scaled with twice the height & thrice the width of previous bounding box obtained after first CNN. The new bounding box checks whether the owner is within bounding area or neighbourhood of object. The owner is assumed to be the last person that was in contact with the object before it became static. This information is stored as an object-owner key pair. This key differentiates owner from other person & performs selective tracking on the owner. In condition when a person other than the owner comes in neighbourhood of object after it was termed unattended, it will remain unattended until the owner comes back in neighbourhood region of object. The sign transfer function will then be applied to transform the scores for an object track into class labels.

3.4 Thresholding

Thresholding is applied to samples tested positive by previous stages. We check conditions for object to be termed as unattended according to the following two rules, which are defined by PETS2006 [8].

1) Temporal Rule: The luggage is termed as an unattended object when the luggage was left by its owner, and was not re-attended in a time-period ***T***= 30 seconds.

2) Spatial Rule: The unattended luggage is termed as an abandoned object when its owner leaves it. When the distance between owner and luggage is larger than a predefined distance ***D***= 3 meters, then it is the point to trigger an alarm event.

We modify spatial rule with the distance equal to new bounding box region obtained after applying second CNN in previous stage. In certain conditions, occlusion created in crowded scene violates these rules. To remove uncertainties occurred from occlusions in a crowded scene, we use two time threshold parameters given by Tian et al. [3]:

A. Static Time Threshold: Time specified by temporal rule.

B. Occlusion Time Threshold: Maximum allowed occlusion time.

If object is not detected by previous stages for a continuous time period greater than *Occlusion Time Threshold*, 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 Threshold* in which case we trigger the alert.

3.5 Triggering Alarm

If all the above stages mark object to be positive as a candidate for unattended baggage, the system will create a boundary box around the object and will trigger an alarm with object in the boundary box and the time for which it has remained unattended to alert the authorities.

4. RESULT COMPARISON & DISCUSSION

We identified different strategies used in previous work & their impact on performance measures. The methods used for background subtraction, & determining the object definition of unattended baggage incorporates various problems which hamper the performance of the system. A number of datasets are available: PETS2006, PETS2007, AVSS2007.

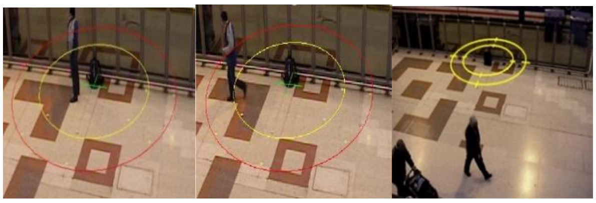

Fig. 2. Unattended Baggage Detection Event [8]

TABLE I. SUMMARY OF LITERATURE

	Work Details		
	Method Used	***Problems Identified***	***Data Set & Performance***
[7]	Unattended luggage is identified by a cascade of CNN.	To calculate metrics for determining performance, all videos are manually annotated with ground-truth bounding boxes, since the data sets do not provide such annotations.	Data Set: PETS2006 Precision: 95.67%, Recall: 83.74%; Data Set: AVSS2007 Precision: 97.48%, Recall: 66.59%.
[6]	Uses Background subtraction & Static region detection.	-Relationship of object with owner is not taken into consideration. -In presence of occlusions, system does not consider object to be as unattended. -Sudden lightning changes in a challenging issue.	Data Set: PETS2006, Accuracy: 85.71%
[5]	A Finite-state-machine model is introduced to extract stationary foregrounds	-Does not accurately identifies owner of unattended baggage. -Temporary occlusion hinders the performance of system.	Data Set: AVSS2007, Precision: 1.0, Recall: 1.0
[4]	Abandoned baggage are first identified and localized by proposed foreground-mask sampling technique.	Too many abrupt changes in speed and direction of owner makes difficult for the motion prediction algorithm to successfully follow.	Data Set: AVSS2007, Precision: 1.0, Recall: 1.0.
[3]	Uses Gaussian mixture model for static foreground region detection.	-Does not classify between objects. -Sudden lighting changing is an issue. -Detects static person as a possible candidate.	Data Set: Big On-City Test, Detection Rate: 87.5%

5. CONCLUSION

We have proposed a system to detect the unattended baggage by capturing frames from video surveillance cameras in real time. Our system works well under occlusions & sudden lightning changes & also removes noisy or irrelevant pixels. We apply CCNN procedure to identify those objects that are of interest to us, hence not considering human as a static object. Our system rightly identifies the owner through key-pair with last intersection assumption & perform Selective Tracking. The proposed system removes the drawbacks of previous works given in Table. I & we detect the unattended baggage more efficiently with improvised technical method combinations & directives. The futuristic expansion of work will involve more effective identification of owner to increase the accuracy of system. Also, the proposed system can be scaled up for more number of objects being incorporated.

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