**JOURNAL OF ALGEBRAIC STATISTICS**
Volume 13, No. 2, 2022, p. 1294 - 1303
https://publishoa.com
ISSN: 1309-3452

# Suspicious Loitering detection using a contour-based Object Tracking and Image Moment for Intelligent Video Surveillance System

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## Abstract

Video surveillance provides for the safety of the people in the public environment by monitoring unusual events. This system only monitors the scenario but don't detect the suspicious events occur and not to prevents unusual activities. Hence, this system is essential to upgrade and adapt the intelligent techniques that automatically track and detect the suspicious loitering person in the surveillance. The aim of this paper is to propose a technique for loitering detection based on the contour features and contour-based tracking method. First, foreground objects are segmented using the frame difference method. Identify the static objects from detected objects and thereby compute the centroid using image moments. The frame threshold detects the loitering person by tracking the trajectory of the centroid coordinates through a certain period of time. The benchmark dataset and the real-time own dataset videos are utilized for testing to evaluate the efficiency of the system. The experimental result shows that the proposed method archives high detection rate.

**Keywords:** Loitering detection, centroid, image moment, contour, video surveillance, suspicious events.

## 1. Introduction

In the modern era of security, video surveillance is an essential tool for the investigation and prevention of crime. Over the past few years, video surveillance systems are most important for the security of the community in public and private places. It is used to monitor and capture video footage as critical forensic evidence for identifying the person involved in the crime once the events have occurred[1]. However, there is no mechanism available to prevent crime at the time and alert authorities if event is suspected. It is used only for hug storage of videos which is very complex to analyze and retrieve the video footage for any suspicious activities are occurred[2]. Therefore, due to the significance and complexity of the location under surveillance, an intelligent system should be integrated with the automatic video surveillance.[3] This will support the security officer in detecting and preventing crimes.

The term Loitering can be defined as a person standing in a particular location in the public environment for a long period[4]. A human loitering behavior can lead to criminal activities such as theft, terrorist attacks, and bank robberies[5]. Hence, there is a growing demand for intelligent

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video surveillance (IVSS)[6][7] for loitering detection.This system an early detection and notification of loitering a person in a specific area helps prevent many crimes.

This paper proposes the vision-based Loitering Detection System (LDS) to overcome the above mentioned issue and accomplish intelligent video surveillance. The LDS includes four states such as foreground object detection, object tracking, identifying the static object and loitering detection[8][9].

Rest of this paper is organized as follows: Section 2 describes the related works to LDS. Section 3 elaborates the methodology of the proposed Method static object identification, trajectory analysis and loitering detection. Section 4 present experimental result and discussion, and section 5 gives the conclusion and future research work.

## 2. Related Works

There are various approaches to Loitering detection techniques are proposed by many researchers. Most of the methods used as object detection and tracking information of the objects to detect Loitering person stay at the long period in the same location. Sandesh Patil et al.[10] proposed the suspicious movement detection used semantics-based approach for human behavior recognition and objects are tracked using blob matching technique for classified either object or human. H´ector F. G´ omez A. rt al. [11] present identified the loitering common behavior using micro-patterns of the elderly people loitering profile in video surveillance. Wenring Li et al.[12] proposed trajectory object detection analyzes the time and angles variation to detect the loitering behavior. Rashmiranjan Nayak et al.[5] proposed LDS includes object detection, tracking and loitering re-identification(ReiD).In this system used YOLO3 and DeepSORT methods for loitering person. Tiemei Huang et al. [13] proposed a new perspective used pedestrian activity area classification for automatic loitering detection. The pedestrian behaviors are three categories like sector, ellipse, and rectangle used to calculate the area of pedestrian activity.

## 3. Proposed Method

The purpose of the proposed model is to detect suspicious loitering persons in real-time video surveillance. It includes five stages such as foreground object detection, object tracking, extract the contour features, static object identification and classify the suspected loitering detection as shown in Figure 1.

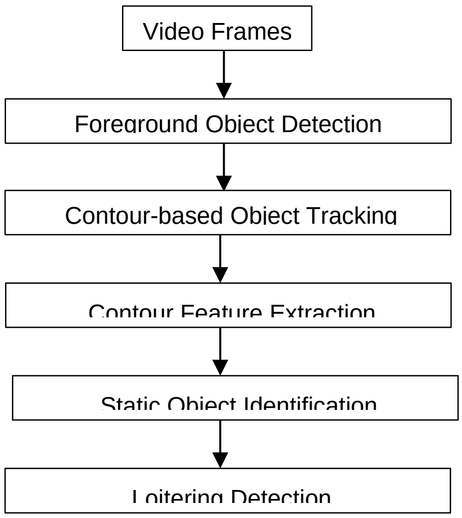

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Figure 1. Proposed Model

## 3.1.Foreground Object Detection

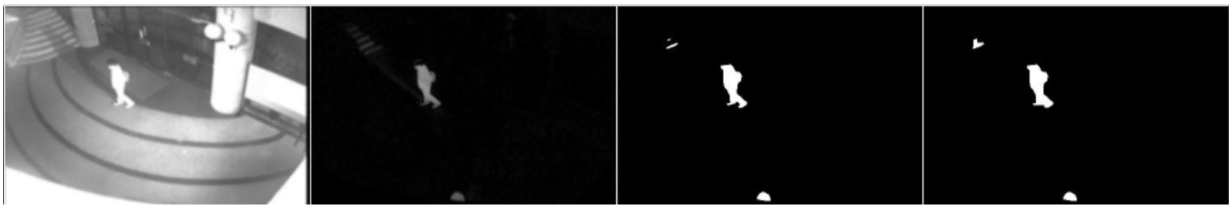
### 3.1.1. Pre-Processing

The preprocessing is an essential and standard step used to remove unwanted noise and smooth the image in the video frames. And also helps to improve the performance and avoid the wrong detection.

First step in this proposed method input video frames convert to gray scale image. After that applied the Gaussian Blur method[14] for image smoothing and reduce the noise as shown in Figure 2(a).

### 3.1.2. Object Detection and Segmentation

Foreground object detection and segmentation is the important main task in the proposed algorithm. Step two creates the reference model from the initial input frame from the video sequence. The frame difference technique[15] is viral role to detects the foreground objects in the video scene by the pixel-wise difference between the reference model frame and current frame. The FD computed by using Eq.1.



(a) (b) (c) (d)

Figure 2. (a) Preprocessing frame (b) Detected moving object (c) segmented binary image frame (d) Object noise removed frame

$$FD(x,y)=\begin{cases}1,\left|f_k(x,y)-f_{k-1}(x,y)\right|\geq T\\0,\left|f_k(x,y)-f_{k-1}(x,y)\right|<T\end{cases} \tag{1}$$

Where, k is current and k-1 is previous frame and T is the threshold. The Frame difference method is better accuracy compare to other methods as shown in Figure 2(b).

Image thresholding is the popular segmentation technique[16] for separating the object from the background scene. The detected objects are segmented using a simple threshold method to create a binary image from the gray scale image see Figure 2(c). To get better result assign the threshold value between 25 and 35. Final step, closing morphological operation applies multiple iterations until it reaches a noise-free shape of the detected objects see in Figure 2(d).

## 3.2. Contour-based Object Tracking

Contour-based object tracking algorithms[19] are employed to represent the shape and motion of segmented objects, as well as to track the path and trajectory of their position of the centroid (Eq.4) and shape in subsequent frames see Figure 3(c) and (d). However, contour-based tracking is generally more robust than region-based object tracking algorithms, since it can be adapted to deal with partial occlusions and contour information is generally less sensitive to variations in illumination[20].

JOURNAL OF ALGEBRAIC STATISTICS
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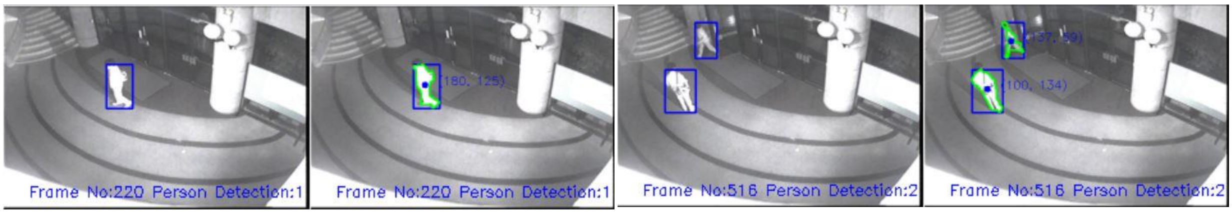
### 3.3. Contour Feature Extraction

Contours and boundaries play a major role in the representation of non-rigid objects[17]. A contour tracing algorithm[18] is used to find the contour shape of the segmented objects(ROI) as shown in Figure 3 (a) and (b). In the main part of the proposed method, image moments are used to calculate contour mass area and centroid of the objects[14].

Image moment ($M_{ij}$) is able to calculate the grey scale image pixel intensities by following Eq. 2.

$$M_{ij} = \sum_{x}\sum_{y} x^i y^j I(x, y) \tag{2}$$

Where x and y indicate the row and column of pixel position, and the pixel intensity of current location is I(x, y).




(a) (b) (c) (d)

Figure 3. (a) Detect the person (b) Tracking the person and extract contour feature centroid (c) Detect and Tracking multiple persons (d) Extract multiple contour feature centroid

The contour area (A) of the silhouette objects is computed using Eq. 3 and also the centroid position coordinates of $C_x$, $C_y$ of the contour pixels in the blobs are calculated using Eq.4.

$$A = \sum_{x=0}^{w}\sum_{y=0}^{h} f(x, y) \tag{3}$$

where w, h represents the contour boundaries width and height.X and Y denotes pixel location.

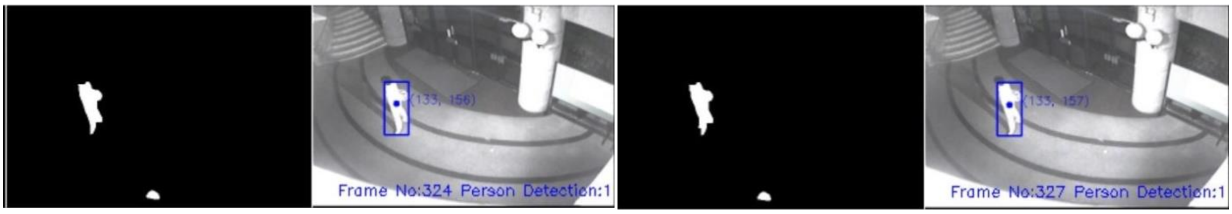
$$C_x, C_y = \sum_{x}\sum_{y} (x - \bar{x})^p (y - \bar{y})^q f(x, y) \tag{4}$$

$$\bar{x} = \frac{M_{10}}{M_{00}} \; and \; \bar{y} = \frac{M_{01}}{M_{00}}$$

Where the centroid of pixels p, q at the location of x, y in the region of interest.

### 3.4. Static Object Identification

The majority of proposed approaches for object detection and identification tend to be based on moving objects. In this case, the lottery detection is based on non-moving




(a) (b) (c) (d)

JOURNAL OF ALGEBRAIC STATISTICS
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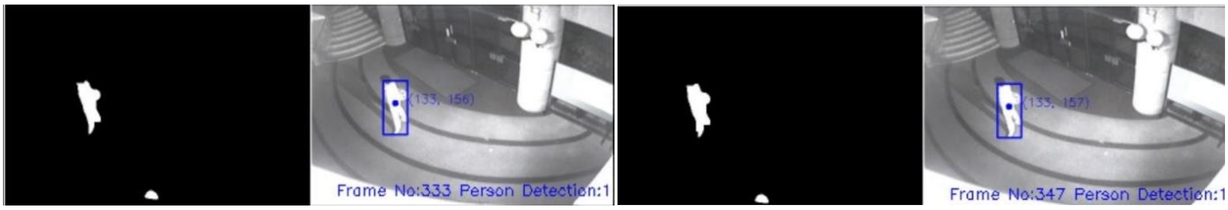


(e) (f) (g) (h)

Figure 4. (a) (c) (e) (g) static object in binary images (b) Static object detected in Frame# 324 centroid (133,156) (d) Static object detected in Frame# 327 centroid (133,157) (f) Static object detected in Frame# 333 centroid (133,156) (h) Static object detected in Frame# 347 centroid (133,157)

objects conditions that are the static object. Hence static object identification is more important than the segmented object. In this situation, the Frame Difference method is a vital role in accurately detecting the moving and static objects in the subsequent frames. The contour features and contour-based tracking are used to identify static objects based on that ROI information (contour area and centroid). Figure 4(b),(d),(f),(h) show that person standing within a particular area continuously.

### 3.5. Loitering Detection

The core work of the proposed method is once the static object is detected and tracked then the loitering of a person should be detected based on the activity in long duration time on the same location and when it is moved trajectory around a particular place. [5][21]. When view at the path of an area through a camera, the path is indicated by the lines that are shown figure 5(a) which indicate the direction a person should travel. As same that Figure 5(b) indicate which line paths are suspected spot in the area. Furthermore, the detection of suspicious loitering is determined based on the frames time threshold and the static object centroid coordinates values.

A person's presence in a particular area for a longer time than a given frame number is known as a frame time threshold. Found and kept in the detected contour centroids

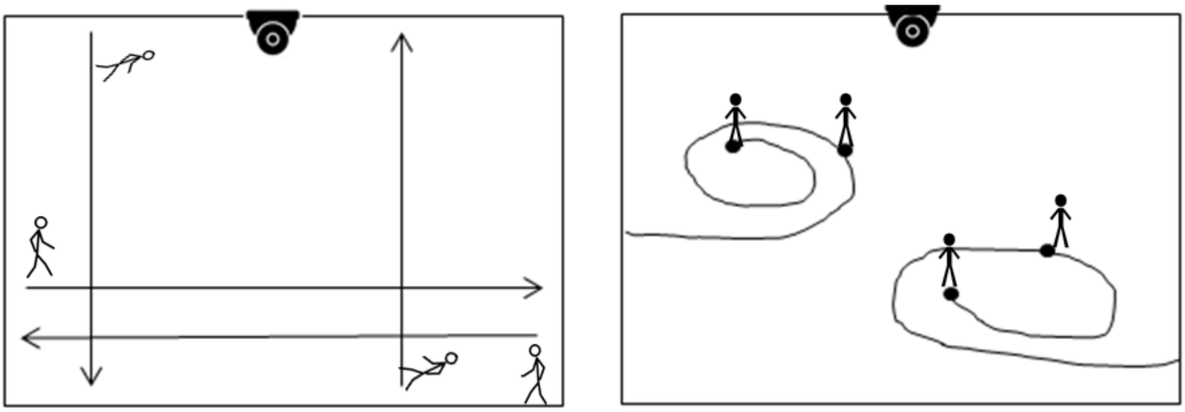

Figure 5: Trajectory Model Map (a) Ground truth direction of pedestrian Trajectory (b) Suspicious spot of pedestrian trajectory

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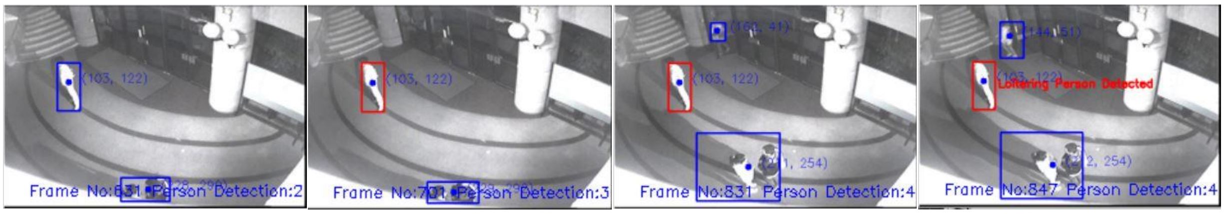


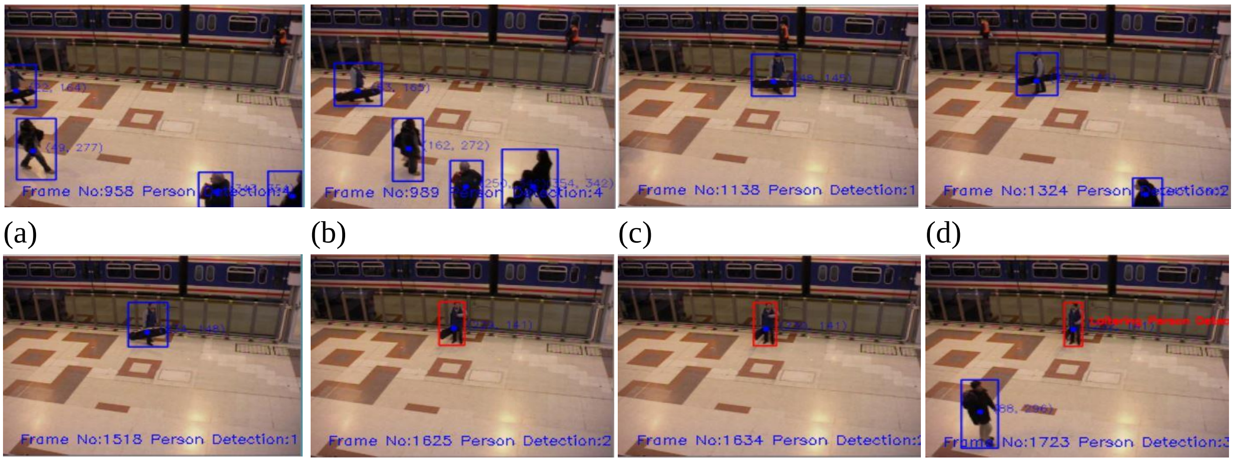

(a) (b) (c) (d)

Figure 6. (a) standing person are detect and tracked in blue mark boundary (b) Detection of a loitering person mark the red boundary (c) centroid status continue the frames number 831(d) prolong the frame threshold is to be confirmed the loitering detection.

using Eq.4 in every frame. The frame time threshold T[frame] is decided based on real-time locations like a bus stop, shopping mall, railway station, etc. The criterion for lottery detection requires comparing with static contour centroid in the threshold T [frame-60] frames. Afterward, to confirm the detection is to verify the T [frame-90] frames as shown in Figure 6 (a) to (d).

## 4.Implementation of Results and Analysis

The Loitering Detection system (LDS) is implemented in Python using OpenCV libraries. This system tests loitering detection on PETS2006 dataset[22] scenario, ABODA dataset[23] scenario and Real-time IP camera's own dataset video sequences. The video defines loitering as a person entering a scene, staying there, and loitering especially around the surveillance area spending more time period.




(a) (b) (c) (d)

(e) (f) (g) (h)

Figure 7. (a) Several persons enter the scene and all are detected (b) Persons move in the direction to exit the scene. (c) All persons exit in the scene expect one person (d) the person returns back to the same side (e) Again move forward (f) and (g) loitering person detected (h) prolong the frame time threshold is to be confirmed the loitering detection.

The experiment performed PETS 2006 benchmark dataset scenario S5 is 400 x 300 video streams of 3200 frames at a rate of 25 fps and avi file format. In this video scenario, several persons enter both sides of the scene and entered persons are detected and marked as blue boundaries (frame number 958) see Figure 7(a). After time running in the frames, entire people exit from the scene (frame number 1138) except one person as shown in Figure 7(c).

The experiment performed ABODA dataset in sequence of video5 is 720 x 480 video streams of 3297 frames at a rate of 29 fps with avi file format. The low lighting conditions in this video

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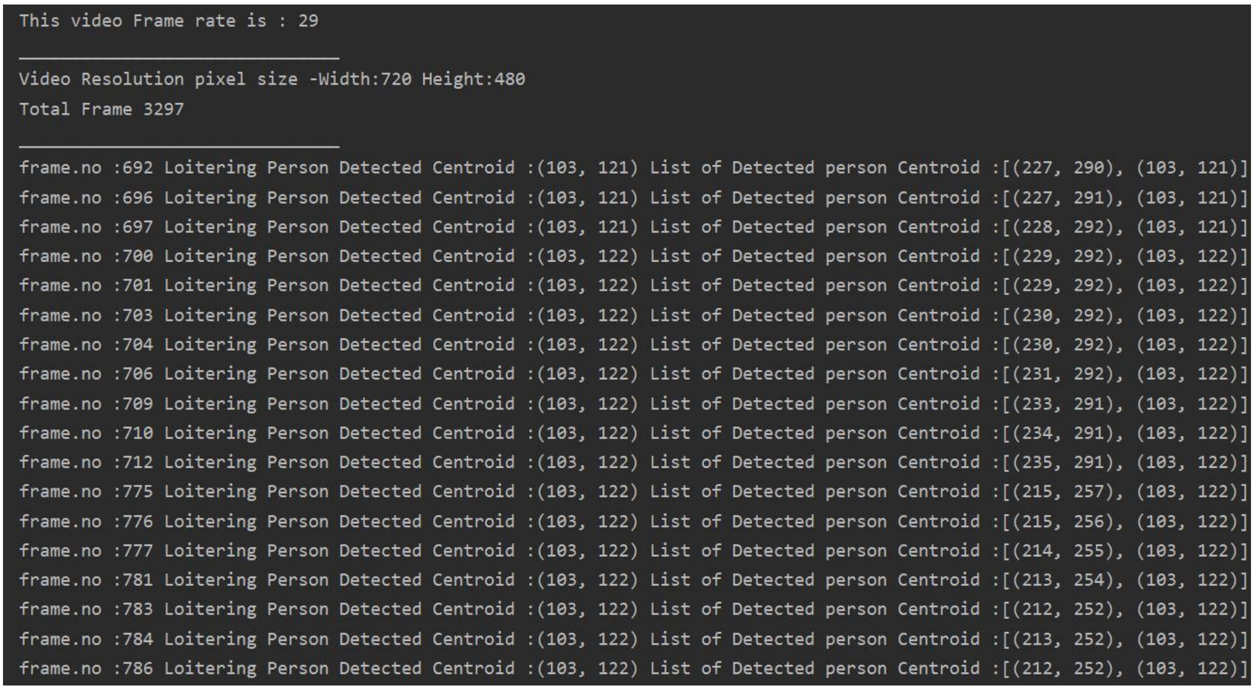
sequence and the camera focus from the top angle create shadow issues throughout the scene. Thus, correct foreground object detection can be a challenging task. Some proposed works face difficulties in the scenarios and have a lot of false detection[24]. The above image frames step by step explain loitering detection scene as shown in Figure 4 and 6. As a result, Figure 8 loitering detection verifies centroid coordinates in the list of centroid coordinates detected in successive frames.



```
This video Frame rate is : 29
_____________________________
Video Resolution pixel size -Width:720 Height:480
Total Frame 3297
_____________________________
frame.no :692 Loitering Person Detected Centroid :(103, 121) List of Detected person Centroid :[(227, 290), (103, 121)]
frame.no :696 Loitering Person Detected Centroid :(103, 121) List of Detected person Centroid :[(227, 291), (103, 121)]
frame.no :697 Loitering Person Detected Centroid :(103, 121) List of Detected person Centroid :[(228, 292), (103, 121)]
frame.no :700 Loitering Person Detected Centroid :(103, 122) List of Detected person Centroid :[(229, 292), (103, 122)]
frame.no :701 Loitering Person Detected Centroid :(103, 122) List of Detected person Centroid :[(229, 292), (103, 122)]
frame.no :703 Loitering Person Detected Centroid :(103, 122) List of Detected person Centroid :[(230, 292), (103, 122)]
frame.no :704 Loitering Person Detected Centroid :(103, 122) List of Detected person Centroid :[(230, 292), (103, 122)]
frame.no :706 Loitering Person Detected Centroid :(103, 122) List of Detected person Centroid :[(231, 292), (103, 122)]
frame.no :709 Loitering Person Detected Centroid :(103, 122) List of Detected person Centroid :[(233, 291), (103, 122)]
frame.no :710 Loitering Person Detected Centroid :(103, 122) List of Detected person Centroid :[(234, 291), (103, 122)]
frame.no :712 Loitering Person Detected Centroid :(103, 122) List of Detected person Centroid :[(235, 291), (103, 122)]
frame.no :775 Loitering Person Detected Centroid :(103, 122) List of Detected person Centroid :[(215, 257), (103, 122)]
frame.no :776 Loitering Person Detected Centroid :(103, 122) List of Detected person Centroid :[(215, 256), (103, 122)]
frame.no :777 Loitering Person Detected Centroid :(103, 122) List of Detected person Centroid :[(214, 255), (103, 122)]
frame.no :781 Loitering Person Detected Centroid :(103, 122) List of Detected person Centroid :[(213, 254), (103, 122)]
frame.no :783 Loitering Person Detected Centroid :(103, 122) List of Detected person Centroid :[(212, 252), (103, 122)]
frame.no :784 Loitering Person Detected Centroid :(103, 122) List of Detected person Centroid :[(213, 252), (103, 122)]
frame.no :786 Loitering Person Detected Centroid :(103, 122) List of Detected person Centroid :[(212, 252), (103, 122)]
```

Figure 8: Loitering detection person centroid coordinates in detected person centroid list in the frames.

The experiment is carried out using real time IP Camera own dataset captured in outdoor natural environment which consists video sequences of 1280 x720 video streams frame at a 24 fps. In this situation a person enters the scene with the bag and loitering the surrounding area. This system was correctly detect the person in the scene (Figure 9(a)) and also detected loitering with red bounding box (Figure 9(b)).

(a) (b)

Figure 9: The result on the real-time IP Camera own dataset: (a) Detect the person's continuous frames (b) Loitering detection a person stays in the same location

The above dataset contains different scenarios like walking, loitering, and standing events which are utilized for testing. The quantitative performance analysis presented in table1 that shows the detection rate achieved by the proposed method with different dataset. The performance measures like TP, TN FP and FN are used for computing the detection rate. TP (True Positive) means correctly detecting the loitering person. TN (True Negative) means correctly detecting the walking person. FP (False Positive) means incorrectly detecting a normal behavior. FN(False Negative) means missed the correct loitering detection.

Table1 : Loitering Detection Rate

| **Dataset** | **Video Scenarios #** | **Detection Rate (%)** |
|---|---|---|
| PETS2006 | 3 | 97.5% |
| ABODA | 3 | 95.4% |
| IP Camera - Own | 4 | 94.7% |

## 5. Conclusion

In this research paper, a simple and efficient method is proposed to detect the suspicious loitering person in the public environment. Most of the existing methods detect the loitering by behavior activities classifier with pre-trained data. These methods may detect falsely or missed to detect the loitering, take a long time for execution, and it is difficult to implement in intelligent system. The proposed method effectively and rapidly detects a loitering person based on contour-based tracking and centroid features without utilizing any pre-trained data and classifiers. Since this method took less processing time and reduced the cost for loitering detection.

In future, the work may enhance to identify the motivation of loitering in a particular area and try to detect the post loitering activities. It will helps to prevent the unexpected events.

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