DETECTING ABNORMAL ACTIVITIES FROM INPUT VIDEOS AND REPORTING TO AUTHORITIES.

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Abstract

In the context of pattern recognition, abnormal event detection plays an important role. Anomaly detection is an active area of research on its own. Previously known anomaly detection techniques are usually not object based, where objects are not recognized prominently. In this system we find optimized object aware anomaly detection technique, based on certain object categories focusing on mobile objects. Algorithm used performs block based foreground segmentation to restrict our analysis to moving objects and unrelated background dynamics. Object detector is used to discard unrelated objects on connected blocks. Histograms of block-motion trajectories are extracted and cluster them to represent normal events. This framework gives a relatively low computational complexity and high detection accuracy.

Keywords—*anomaly detection; block based foreground segmentation; object aware;*

Introduction

Recently, there is an increasing interest in automatic analysis of a video stream in order to generate alerts in real time when an "unusual" event happens. Such algorithms may be used as an attention mechanism, which with proper detection and false-alarm rates, will enable a single operator to effectively "watch" a large number of cameras [2].

Anomaly detection is an active area of research on its own. Various approaches have been proposed, for both crowded and non-crowded scenes. They can be broadly categorized according to the type of scene representation adopted. One very popular category is based on trajectory modeling. It comprises tracking each object in the scene, and learning models for the resulting object tracks [3]. Both operations are quite difficult on densely crowded scenes, for which these approaches are not very promising.

Abnormal event detection plays an important role in video surveillance and smart camera systems. Various abnormal activities have been studied, including restricted area access detection, car counting, detection of people carrying cases [5], abandoned objects , group activity detection , social network modeling, monitoring vehicles , scene analysis and so on. In this paper, we focus on modeling abnormal events in human group activities, which is a very important application for video surveillance.

Fig: 1 Example of Abnormal Event Detection

Based on socio-psychological studies, originally introduced Social Force model to investigate the pedestrian movement dynamics. The social force captures the effect of the neighboring pedestrians and the environment on the movement of individuals in the crowd. Later, Helbing published his popular [4] work in combining the collective model of social panic with social force model to create a generalized model. In this model, both psychological and physical effects are considered in formulating the behavior of the crowd.

Dense sampling has shown to improve results over sparse interest points for image classification. The same has been observed for action recognition in a recent valuation by Wangetal.[7],where dense sampling at regular positions in space and time outperforms state-of-the-art space-time interest point detectors. In contrast, trajectories are often obtained by the KLT tracker, which is designed to track sparse interest points [5]. Matching dense SIFT descriptors is computationally very expensive and, thus, infeasible for large video datasets. In this paper, we propose an efficient way to extract dense trajectories. The trajectories are obtained by tracking densely sampled points using optical flow fields. The number of tracked points can be scaled up easily, as dense flow fields are already computed [1]. Furthermore, global smoothness constraints are imposed among the points in dense optical flow fields, which results in more robust trajectories than tracking or matching points separately, see Figure 1. Dense trajectories have not been employed previously for action recognition. [7] Segmented objects by clustering dense trajectories. A similar approach is used in for video surveillance.

Related Work

Sr.No	Paper Title	Description	Pros	Cons
1	A framework for an event driven video surveillance system	Tenable optimization of event driven surveillance	Scalability	Works on tested interface only, Not compatible with current technology.
2	Automated Unusual Event detection in video surveillance	Automated approach for detecting falls of elderly people	More accuracy for fall detection using single static camera.	Failures may leads to unnecessary alarms.
3	Real Time Unusual Event detection using video surveillance for enhancing security	To detect an unusual events within the different bank.	Can detect overcrowding areas, Low Cost .	Low resolution, Not trained with dataset.
4	Abnormal detection using interaction energy potentials.	To detect abnormal behaviors in human group activities	Does not relied on individual human so it is more robust to errors	Cannot detect static object efficiently.
5	Action Recognition by dense trajectories	To model videos by combining dense sampling with feature tracking	More Robust, Improve performance and efficiency	More Complex model, Inconsistency

A framework for an event driven video surveillance system.
As analysis of huge volume of daily archived surveillance media is impossible to handle manually and some interested events may get missed. This paper uses an approach which helps in management of large store of surveillance media and optimizes the event detection. Here, Finite State Machine (FSM) is used to represent events considering it as state and change as state transition. This system provides improved Scalability due to client-server architecture. But, Not Compatible with current technology due to use of FSM. [8]

Automated unusual event detection in video surveillance.
Fall is an unusual activity and serious problem among elderly people causing high risk to life. This paper presents an automatic approach for detecting and recognizing falls of elderly people in the home environment and report to family members. Here, Object detection followed by feature extraction is done and then decision tree is used for classification. Even though single static camera is used, accuracy is more. Failure may leads to unnecessary alarms. [9]

Real time unusual event detection using video surveillance for enhancing security.
There is increasing in number of suspicious actions at ATM booths. This uses low resolution videos for analysis. This is used to detect unusual events such as overcrowding situations and fights in banks or at ATM booths. Here, background subtraction is followed by connected component labeling algorithm and detected events are extracted. There is no need to use classifier and high computational scheme to convert low resolution to high resolution videos. But, therefore not trained with datasets [10].

Abnormal detection using interaction energy potential.
This paper is used to detect abnormal behavior in human group activities. The relationship between current state of subject and corresponding actions is used to distinguish between normal and abnormal patterns. The interaction energy potential is used to model the relationship among group of people; this is calculated using position and velocity of people. This technique is more robust to detecting errors. But, cannot detect static object efficiently due to no interaction. [5]

Action recognition by dense trajectories.
Feature trajectories have shown to be efficient for representing Videos. This paper uses an approach to describe videos by dense trajectories. Here, sampling of dense points from each frame is done and tracking them based on displacement information from a dense optical flow field. This technique provides efficient solution to remove camera motion by computing motion boundaries descriptors. Dense Trajectories are more robust and calculate motion information efficiently and thus improves performance. But, More Complex model and some Inconsistencies are there. [7]

Proposed Methodology:

[A]Image processing:

- Image processing the analysis and manipulation of a digitized image, especially in order to improve its quality.
- Input video is taken from the database which will be converted into continuous frames.
- Continuous frames are used for further processing.

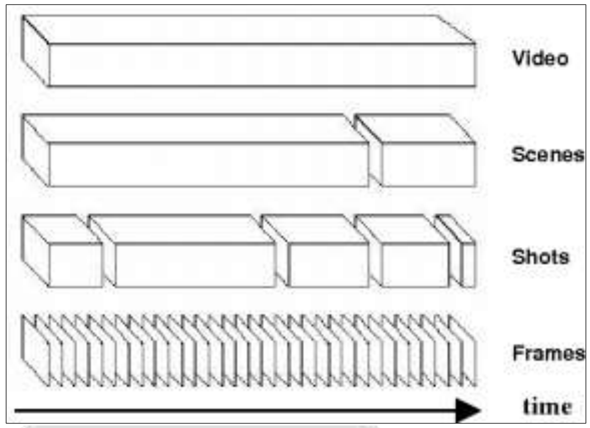

Fig:3 Image Processing

[B]Foreground Detection:

- Input frames from the image processing step are converted into grey frame.
- Consider grey frame size P*Q, now frames are converted into blocks, where each block size p*q.
- Number of Blocks in frame can be represented as m*n, where m=P/p, n=Q/q.

$$b_{s,t} = \sum_{i=1}^{p} \sum_{j=1}^{q} p_{i,j},$$

- Calculate feature value for each block where it is summation of pixel values in each block.
- Obtain foreground block by measuring difference between the adjacent frames.

$$b_{s,t}^{\psi} = \frac{1}{\iota} \sum_{i=1}^{\iota} b_{s,t}^{\phi_i} \quad (\phi_i \in \Psi)$$

Where,

$$|b_{s,t}^{\phi_i} - b_{s,t}^{\phi_{i-1}}| < \varepsilon_1 \quad (i \in [1, \iota])$$

- Reduce the average of pixel values from original grey frame

$$\varphi_{s,t} = \begin{cases} b_{s,t}^{\phi_i} & |b_{s,t}^{\phi_i} - b_{s,t}^{\phi_{i-1}}| \geq \varepsilon_1 \ \cup \ |b_{s,t}^{\phi_i} - b_{s,t}^{\psi}| \geq \varepsilon_2 \\ 0 & \text{Otherwise} \end{cases}$$

- Form the sparse matrix which represents the foreground.

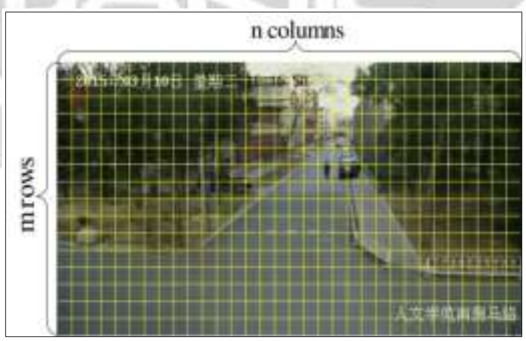

Fig: 4 Foreground Detection

[C]Extract Interested Objects:

- Remove the uninterested blocks from the sparse matrix.
- Traversing row wise in matrix, create groups of sequencing blocks based on the movement done.
- Allocate blocks to the groups if group is already created else create new group.
- Generate rectangles as per groups.
- Apply Deformable Part Model (DPM) to detect objects.
- By applying this, we get fine foreground matrix.

$$\bar{\varphi}_{s,t} = \begin{cases} \varphi_{s,t} & \varphi_{s,t} \in \text{pedestrian} \\ 0 & \text{Otherwise} \end{cases}$$

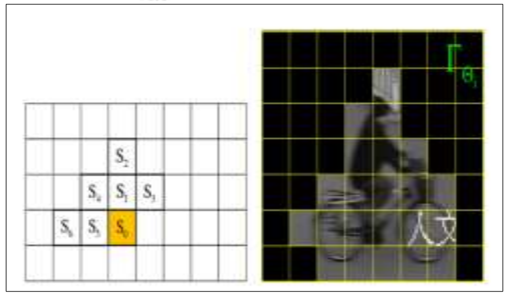

Fig: 5 (a) order of blocks to be searched (b) Rectangle picture

[D]Track Foreground Block of Interested Objects:

- Track block of interested objects to get trajectories (directions).
- Divide trajectories into different partitions (4 or 9) and generate histogram for each partition.
- Each frame is represented by one vector or concatenation of 4 or 9.

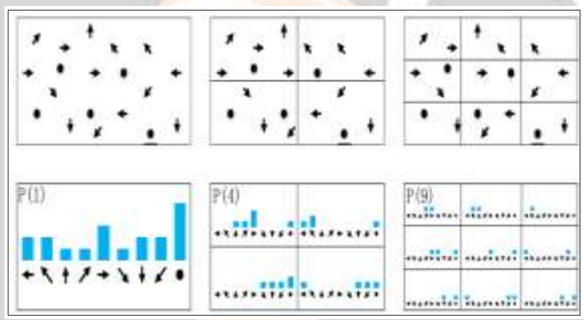

Fig: 6 Partition-Trajectory Histogram

[E]Abnormal Event Detection:

- Construct feature vector.
- Apply K- means algorithm to calculate threshold value which represents distance between centroid and feature vector.
- We get abnormal clip for each video.
- Detection result may have several clips which have continuous abnormal frames.
- Choose longest one and record its start frame and end frame.
- Finally, abnormal activity is detected.

Fig: 7 Detecting Interested object

[F]Reporting to Authorities:

- After detecting abnormal activity, we report to the respective authority to take proper actions regarding the activity.

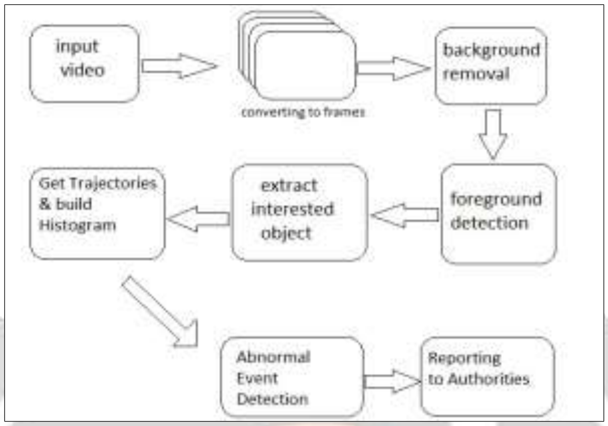

Fig:8 System architecture

Video containing abnormal activities is taken as input by system, which may be captured using common cameras or already stored in datasets. This video is then converted into frames by image processing which improves the quality. Then frame is analyzed to identify foreground and thus remove irrelevant background. From that foreground object of our interest is extracted. These objects are then represented using trajectories and then histogram is build. Thus doing comparative analysis, abnormal events are detected and finally reporting it to respective authorities.

Conclusion

In this paper, uniform framework for object aware abnormal activity detection is used. Here, we used, block based foreground segmentation and method to represent spatio-temporal features of human behavior using histogram. As this system is object-based, more uninterested objects are eliminated before abnormal activity detection. As a result, this system gives a low calculus complexity and high detection accuracy. After detecting abnormal activity, we report to the respective authority to take proper actions regarding the activity.

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