Crowd Anomaly Detection In City Crime Video

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1. Abstract

Anomaly analysis is of great interest to diverse fields, including data processing and machine learning, and plays a critical role during a wide selection of applications, like medical health, mastercard, fraud, and intrusion detection. Recently, a big number of anomaly detection methods with a spread of types are witnessed. This paper intends to supply a comprehensive overview of the prevailing work on anomaly detection, especially for the info with high dimensionalities and mixed types, where identifying anomalous patterns or behaviours may be a nontrivial work. Specifically, we first present recent advances in anomaly detection, discussing the pros and cons of the detection methods. Then we conduct extensive experiments on public datasets to guage several typical and popular anomaly detection methods. the aim of this paper is to supply a far better understanding of the state-of-the-art techniques of anomaly detection for practitioners. Finally, we conclude by providing some directions for future research.

A framework and design that is suitable for anomaly detection in crowded videos is represented by three properties. Modeling of appearance and physical properties of such scene, Temporal abnormalities, Spatial abnormalities. The proposed model for normal crowd behavior is based upon the dynamic texture and outliers. The probability of event handling in temporal anomalies is very low as compared to spatial anomalies. We can handle these events using discriminant salience. Our consist of hundreds videos and five well-defined abnormality categories in which we experiment and evaluate.

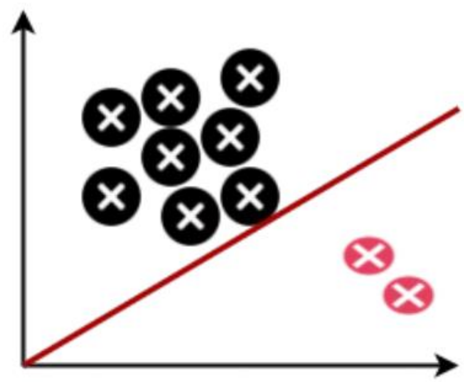
2. Introduction

Crowd Detection anomaly detection has been an important Research problem in recent years. Because video Monitoring is the detection of abnormal events such as Robbery, Murder, etc. The video Anomaly detection plays an important role in city surveillance video.

The main challenge for automatically classifying anomalies is the feature extraction and feature set and the technique that can be replicated. Video monitoring has been recently applied for safety concern but generally it requires lots of human operators to monitor the screens which often leads to fatigue and inattention and fails to identify the occurrence of abnormal events. Many more challenges arise in video monitoring like back-up of video data and to read that data manually is time-consuming and extremely tedious.

What are anomalies?

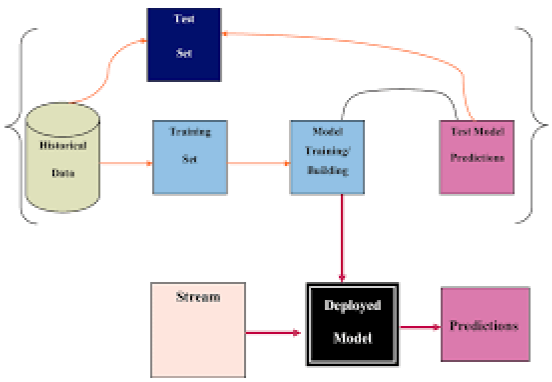
An anomaly is a pattern that does not follow expected patterns shown in Fig.1.



Representation of anomalies in graph. Here black cross represent as normal and Red Cross represent as anomalies.[1*]*

*"*Anomalies in city crime videos are like robbery, bankruptcy, thefting, beating, assault, stealing etc. "shown in Fig.2 [26]

The Scope of the study should cover the nature of input data, feasibility of supervised/unsupervised learning, types of anomalies, suitability of the techniques, anomaly detection outputs and evaluation criteria.



"This survey presented from above perspectives. A typical anomaly detection framework is presented" in Fig. 3 [27]

In this framework first we extract feature/data from input this is called as shown in Fig. 4. The normal behaviour is represented in terms of rules, models, or data repository. Specific anomaly detection techniques are used for detecting anomalies using anomaly scoring and labelling mechanism

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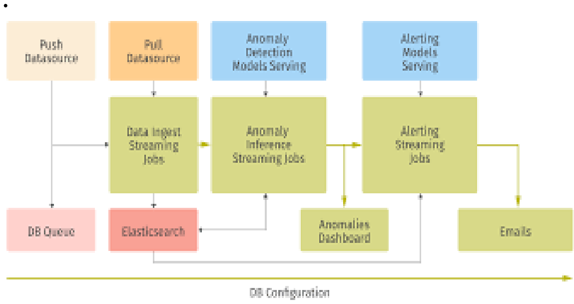

"DB Configuration" Figure:4 [28]

3. Related Work

Here we provide summary of recently published good research papers. What approaches they used and their model performance. All these research are from AI City challenge.

A Two-stream-based model to handle the anomaly event detection problem using the RGB and two flow neural network (ConvNets) to extract video features. RGB stream performs anomaly event detection from video frames, while the Flow stream is trained to detect anomalies from motion-based on dense optical flow. Later on instead of only considering RGB features for MIL models we also propose a model known as TAEDM that can leverage information of both RGB and two flow modalities. The information from RGB modality is the static features of still images, such as the colour, shape, and appearance of objects or people in the event. The information from the Flow modality is the motion features of the event. As a result, TAEDM can capture the complementary information on the RGB stream from still images and motion between images in one video sufficiently. We will evaluate the developed approach on a scale benchmark data sets i.e UCF-Crime. Now here are some surveys which contains computer vision-based methods in surveillance

References	Focus	RESEARCHED AREA
Morris (2008) [7]	Video trajectory-based scene analysis	Scene modelling: Tracking interest of point study, path learning (normalization and dimensional reduction), clustering approaches.

Tian (2011) [8]	Video processing techniques applied for traffic monitoring	Background modelling, non-background modelling, shadow detection and removal, vehicle tracking, traffic incident detection and behaviour understanding
Li (2017) [15]	Spatial-temporal interested point(STIP) detection algorithm	STIP Algo: Detection challenge Application: Human activity detection, anomaly detector, video summarization and content based retrieval.
Mabrouk (2018) [16]	Abnormal behavior recognition	Modeling framework and classification method, scene density and object interaction.

4. Stabilizing Motion Crowd

In order to detect anomalous behaviour in crowd, the moving objects/targets should be stabilized. Due to background disturbances it becomes more difficult to detect anomalies in the video scenes using old or traditional methods. We apply filters visualizing technologies and subtracted in order to get better image of anomalies and easy identification of the flow.

Optical Flow method is one of the most effective and used method to present motion of crowd in vector field. It is more important to identify the target motion and the background once identification is done than motion and background are represented and smooth texture and rough texture respectively. With the help of roughness the background and motion of pedestrians is distinguished more accurately.

5. Analysis of Crowd Behaviour Pipeline

No matter what approach macroscopic or microscopic, there are basically four stages mentioned below:

1. Stage of detection: In this stage the main objective is to identify or the position of crowd or individual in every respective frame.
2. Stage of Tracking: In this stage the objective is to identify trajectories of specific crowd or an individual in sequence of frames. Mainly, the dominant flow of movement of crowd is tracked.
3. Stage of extraction Feature: In this stage when different motions of crowd or individual are studied independently or when a group of individuals are studied then they are considered as unique entity.
4. Stage of crowd anomaly detection: On the basis of previous stage of feature , this stage focuses on particular behaviour or anomalous in crowd video. Basically there are two main approaches for this stage i.e., supervised and unsupervised but the behaviour classification mainly confront the task in supervised manner.

Macroscopic vs Microscopic

There are basically two approaches for the distinction of individuals in relation to the crowd which they belong. These two approaches are:

Macroscopic: In this approach the crowd is treated as a whole single entity, tracking each individual without the need of individually segmenting.

Microscopic: In this approach the crowd is treated as a collection of individuals. element of crowd is studied individually.

Usually, according to previous studies microscopic approach is considered better than macroscopic approach as it provides better aspects of situation where individuals can be tracked properly. So we follow macroscopic approach to achieve our goal.

6.Dataset

Previous

In this section we review the previously taken video anomaly detection . The like UCF-Crime, they contain several different staged video where generally people walk slowly randomly starts running in different direction. The anomaly is detected by only running action. contain 37 videos. In this videos are short and some of the anomalies are unrealistic. BOSS is taken from a camera of local train which contain some videos like robbery, smuggling, dancing and much more. All activities were performed by actors.

Our Dataset

Due to the of previous we found a large scale to evaluate or method. It several untrimmed long video of robbery, abuse, arrest, fighting, action, explosion, harassment.

Training and Testing:-

We divided our into two sections training section of 800 normal and 810anomalous videos and the testing section consists 150 normal and 140 anomalous videos. Both section contains anomalies. Some of the videos have anomalies.

7. Result

Instead of just retrieving the misclassified components as suspected anomalies, an inventory of the components ranked by their importance score was created. A threshold for the anomaly score was set to >0.7, to only take the foremost anomalous cases. This gave 1265 anomalous cases, 65% of the entire test set. This threshold is straightforward to vary and provides you with different lengths of lists to see. If it's set to >0.9, the suspected anomalies are instead 242, and you've got instead 11% of a complete. However, as this data set consists of components with different Status another selection might be made during this last step. Hence, if the edge with 0.7 is kept, but only these statuses are evaluated, 314 components are found, which is 15% of the test set having a high risk of being anomalous. This is comparable with the 11% UCF- crime found in their investigation in 2014 with an equivalent status condition. This method is flexible and provides a classy way of choosing the components to see. it's a worthy approach since probabilities are more interesting than rough classifications.

8.Conclusion

The main contributions of our work are summarized as follows:

(i) A novel two-stream-based anomaly event detection model is proposed for anomaly detection in surveillance videos. Furthermore, a dense feature extraction method is proposed to obtain video-level feature.

(ii) Proposed models will using benchmark UCF-Crime.

In the proposed model, video segments that obtained high anomaly scores will be marked as anomaly event. video will be split into equal number of non-overlapping segments. The video containing anomaly segment is labelled as positive bag and a video without any anomaly segment is labelled as negative bag (as shown in figure). These bags will later used as instances in MIL. Using ranking method, anomaly scores for each and every video segment can be obtained and the video segments obtained high anomaly scores is seen as anomaly event.
Our model is formulated as a regression problem, which means that we consider a certain segment as an abnormal event based on regression prediction score. we use two branch feature extraction method. Concerning about the feature extraction is chosen as backbone because it is superior and effective Code.

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