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Anomaly Detection Techniques in Surveillance Videos

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***Abstract*—In recent years, a dramatically increasing number of surveillance cameras have been installed to monitor private and public spaces and areas. Video surveillance is seen as an effective way to ensure our security. Therefore, modeling activity patterns and human behaviors for detection or recognition of peculiar event is a critical technology which has attracted remarkable research interest in the last few years. Various methods have been developed to build intelligent vision systems, this article extensively explain the current improvement made toward video-based human abnormal activity detection and wide applications in various fields range from monitoring in public spaces to personal health rehabilitation.**

I. Introduction

Nowadays with the increasingly growing needs of protection for people and personal properties, video surveillance has drawn much concern in daily life. Considering these needs have led to the deployment of cameras almost every corner, video surveillance system can interpret the scene and automatically recognize abnormal behaviors which plays a vital role in intelligence monitoring. At present, using video in machine vision is an important research issue, one of the most active areas is activity understanding from video surveillance system. Being able to detect and classify targets of interest and analyze what they are doing both called activities understanding. One crucial aspect is to detect and report situations of special interests then notify operators or users automatically, in particular when unexpected things happen. In this case, video surveillance system can effectively improve safety and security for the management and control of public area or personal life. Besides, which aims to develop autonomous surveillance schemes to replace the traditional (human observer oriented) schemes also can relieve the workload of relative personnel.

Often times, the intention is to detect, recognize interesting events which literally may be defined as suspicious event, irregular behavior, uncommon behavior, unusual activity/event/behavior, abnormal behavior, anomaly and so on [1,2]. As blow Figure 1 shows some examples of abnormal and normal. In anomaly detection of automated surveillance process, data representing the behaviors of surveillance targets are collected by sensors in an environment where part of data is assumed to be anomalous. After a feature extraction process for these data, the resulting features become the input of a modeling algorithm, we can use this newly learned method to determine the normal or anomalous state of observed behavior. This procedure can be performed either in real time or offline.

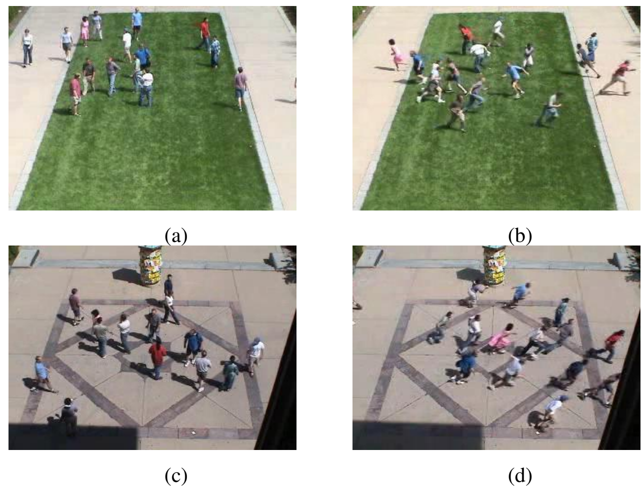

Fig. 1. Normal and Abnormal Frames: (a, c) normal frames in the UMN datasets; the individuals are walking in all directions; (b) UMN abnormal frame; the individuals are walking in all direction; (d) UMN abnormal frame; the individuals are running in the same directions.

There are many overviews related to anomaly detection [3- 10] in automated surveillance. In a review [3], Brezeale and Cook expatiated the relevant topic of categorizing the genre of produced video in 2008, while Lavee et al. [4] in 2009 addressed a more concrete topic of understanding particular events in video data. Buxton in [5] presented a survey on understanding dynamic scene activity, Dee and Hogg contributed a section reviewing anomaly detection in their survey of real-world surveillance [7]. Haering et al. also gave a general review of surveillance in 2008 [7], then in 2010, Raty produced a overview of the same topic[8]. Almost no previous reviews can adequately accomplish the task of detecting anomaly simultaneously covering these two fields: surveillance and anomaly detection. All the works on anomaly detection have the same methodology to accomplish the assignment of anomaly detection, whose flow chart is shown in Figure 2.

In this paper, a more focused research is being striven towards creating on anomaly detection in automated surveillance. Thus, we will be able to address further understanding and application in this field. In Section 2 to Section 5, we will talk about kinds of methods to detect abnormal behaviors. Then draw a conclusion and discuss about the future work of

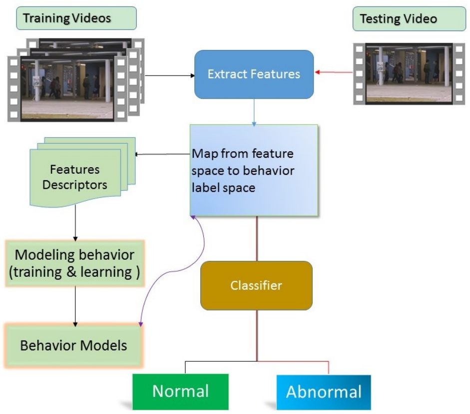

Fig. 2. General process of anomalies detection in video sequences.

this topic at Section 6.

II. Classification-based Anomaly Detection Techniques

Classification [37, 38] is firstly to learn a model from a set of labeled training data, then use the learned model to classify a test input data into one of the classes. Classification based anomaly detection techniques are supervised methods and also can be regard as semi-supervised ones, which perform in a similar two-phase mode. Firstly, to learn a classifier using the available labeled training data, then to classify a test instance as normal or anomalous by the classifier have learnt at the first phase.

Classification-based anomaly detection techniques can be generally divided into two prominent categories: oneclass and multi-class anomaly detection techniques. In the following subsections, we expound kinds of classifiers built by different classification algorithms in anomaly detection techniques.

A. Support Vector Machines-based Techniques

Vapnik and Lerner [26] originally proposed the support vector machine for classification or regression. Xinyi Cui et al. [20] proposed a new method in 2012, they use interaction energy potential function to represent the current behavior state of a subject based on the positions/velocities of a subject itself and its neighbors, then the social behaviors can be captured by the relationship between interaction energy potential and its action. Based on these, they use SVM to determine the Uncommon Energy-Action patterns as anomaly. Their method has a pretty good robustness to detection errors which are introduced by detection or segmentation techniques for no dependency on human detection or segmentation. Their method takes advantage of the relationship between present status of a person and his/her reactions. The information of interaction energy potential and the related peoples reactions contain comprehensive information, which is enough to model abnormal behavior among a group of people. In addition, this method does not depend on human detection or tracking algorithm, so it performs better effectiveness than Social Force [15] and Optical Flow [21] on tboth UMN dataset and the BEHAVE dataset. The optical flow features also can be taken advantage of to detect abnormal behavior. Surveillance usually relies on tracking, but if the scenario is crowded, the tracking method will be unreliable [14]. Lots of researches have demonstrated that the histogram of the optical flow orientation descriptor is suitable for describing movement information under global scenario such as video frame and foreground frame [22-25], but performs not that well in sparse scene.

Recently, Tian Wang et al [54] use a kind of framework for representation and analysis which is based on optical flow to extract visual features without object tracking. Then they use one-class support vector machine (SVM) [29] and principal component analysis (PCA) [27, 28] to detect abnormal behaviors. They are supervised learning methods because they need learning the normal behaviors beforehand. This algorithm mainly consists of three procedures. Firstly, calculate the optical flow of each frame by the HornCSchunck (HS) optical flow [21] method in gray scale. Secondly, the histogram of optical flow orientation (HOFO) of each frame should to be calculated. It is noteworthy that the optical flow in the background is zero as the HOFO descriptor is computed on the foreground image. So it is timesaving for the background area not considered. Ultimately, they use the above two classifiers to classify feature samples from surveillance video. We have tested their methods on the UMN dataset and PETS scene. The results show that one-class SVM and KPCA classification methods can achieve high accuracy without the state transition restriction strategy. The limitations of these algorithms are in a relative high false alarms rate and can not to train the samples online. Above all, there are various kinds of normal examples, so to learn the training samples in one batch is really hard in realistic scenarios. Moreover, their method only focuses on detecting global abnormal events, so it is also necessary to develop their method to detect abnormal events both globally and locally.

B. Neural Networks-based Techniques

Neural networks can be applied to anomaly detection both in multi-class and one-class settings. Neural networks-based anomaly detection technique in multi-class operates in two steps. First, to use the normal training data to train a neural network to learn different normal classes. Second, put each test instance into this neural network, then can judge the acceptability of the network, the one accepted is regarded as normal and vice-versa [39, 40]. Different types of neural network techniques have been proposed to detect abnormal events, such as Replicator Neural Networks can be used for one-class anomaly detection [41], Multi layered perceptron, auto associative networks, Hopfield Networks, Oscillatory Networks and so on. Its notable that the deep learning techniques, especially for the applications of Convolutional Neural Networks (CNNs) have already made some breakthrough in computer vision field, which have achieved high recognizing accuracy and is faster than almost all the state-of-the-art algorithms, one of the key techniques is using the tremendous parallel processing power of GPUs [52]. Recently, pioneering work to exploit encoding techniques to generate video representation ground on CNN descriptors, which is extracting the frame level CNN descriptors with the Caffe toolkit [53], then the second step can be done by generating video level vector representations [51]. Their massive experiments have proved that this approach have improved the performance of video representation by more than 0.3 compared with most advanced video representation on the large scale MED dataset.

In the multi-class setting,Bayesian networks also can be applied for anomaly detection. As for a univariate categorical data sets, after being given a test data instance, the basic technique is to use Bayesian network to estimate the posterior probability of a observed class label from a set of normal class labels and the abnormal class labels. Then to chose the class label with largest posterior as the predicted class for the given test instance. As for multivariate categorical data sets, the basic technique is to aggregate the per-attribute posterior probabilities of each test instance and to use the polymeric value to portion a class label to the test instance.

C. Nearest Neighbor-based Techniques

Nearest neighbor analysis has been applied in several anomaly detection techniques. The most important idea is to calculate the distance or similarity measure between two data instances[55]. There are different ways to compute it. We can use Euclidean distance for the continuous attributes and simple matching coefficient is mostly used for categorical attributes. The distance or similarity of each attribute can be combined for multivariate data instances.

Therefore, some techniques that use the distance between data instances in a different manner can be used to detect anomalies. In a given data set, nearest neighbor based method comes out of a definition that the abnormality score of a data instance is determined by the distance between its Kth nearest neighbor ant itself. But this method is not appropriate for scenes that have various density modes. Advantages and disadvantages of classification-based techniques are showed as follows.

1) Advantages: (a) Classification-based techniques, especially the multi-class techniques, can take advantage of robust algorithms to distinguish kinds of instances under different classes. (b) Classification-based techniques has fast speed and high accuracy in detecting many categories of known abnormal phenomena in testing phase.

2) Disadvantages: (a) Require both accurate labels from normal and anomaly classes, but this is often not possible. (b) Potential high false alarm rate - previously legitimate (or unseen) scenarios have the potential to be recognized as anomalies.

III. STATISTICAL-BASED DETECTION TECHNIQUES

Shandong Wu et al. [11] proposed an approach for crowd flow modeling and anomaly detection in both coherent and incoherent scenarios. The originality of their work is showed in three aspects. First, use particle trajectories to model crowded scenarios [12, 13], this is a new and efficient trajectories representative method for modeling arbitrarily complicated crowd flows. Second, regulate a batch of chaotic invariant features with a intention of introducing chaotic dynamics to characterize complicated crowd motions, which has been proved to be responsibly calculated and applied to detect abnormal events. Third, anomaly detection and localization is archived by a probabilistic framework. Using Lagrangian particle dynamics approach is a new method [11] of detecting and localizing deviances in relatively crowd sequences, together with chaotic invariants modeling can get better performance. A new representative trajectories in crowd flows is defined to serve as a compact, informative, modeling elements. No matter how the scene is extremely crowded or sparse, representative trajectories always be effective, and performs very well. Besides, time series data obtained by representative trajectories also can be effectively be applied in chaotic modeling of a scene. For probabilistic abnormity detection and localization, they also possess a representative chaotic feature set to completely acquire the chaotic dynamics of representative trajectories. There are also many other methods use the concept of statistical to achieve the same task. For example, Borislav Antic et al. have newly proposed that spatio-temporal video parsing also can be employed to abnormality detection [35]. The destination of abnormality detection is to find abnormalities in a large body of test data without actually knowing what they are, but unfortunately the abnormal training samples which can be available are not enough. Beyond that, the prevailing concept of the field is to retrieve individual abnormal local patches or image regions independent of another directly. To solve this problem, they proposed the spatio-temporal video parsing method to jointly detection of abnormalities in videos after foreground/background segregation by the means of robust background subtraction algorithms [36]. Video parsing has a goal of to find a set of indispensable normal spatio-temporal object hypotheses which jointly explain all the foreground pixels of a video. Meanwhile, all the hypotheses are supported by normal training samples as they can be learnt from training data. As a result, they decide to avoid a direct detection of abnormalities and indirectly discover them as those hypotheses which are needed for covering the foreground without finding an explanation for themselves by normal samples, so that they can indirectly discover all abnormal objects present in a scene and neednt to know what to look for. In addition to this, they use maximum a posteriori (MAP) approach to yield a set of hypotheses that best explain the foreground, and they efficiently solve abnormalities localization by MAP inference in a graphical model which can be formulated as a convex optimization problem. Their experiment results show that spatio-temporal video parsing algorithm has improved over the state-of-the-art on all standard and challenging benchmark sets both in terms of abnormality classification and localization.

IV. CLUSTERING-BASED DETECTION TECHNIQUES

Clustering-based methods have attracted many investigation to address anomaly detection problem [31-34]. These approaches hold the methodology that normal events appear frequently and dominate the data, while anomalies are deviate from the commonality and appear infrequently. Therefore, to identify those events clustered into dominant (e.g., large) groups as normal, those cannot be represented by the normal rules are identified as anomaly. Because several clustering-based techniques need distance calculation among a couple of instances, they are similar to nearest neighbor-based techniques. But the main difference between these two algorithms is that clustering-based techniques appraise each instance with respect to their cluster, but nearest neighbor-based techniques break down each instance refer to its local neighborhood. Even though clustering-based approaches can detect anomaly successfully, still some limitations exist. Most clustering approaches evaluate a video event as the motion trajectory of one single object, which often cause neglect of important information like spatial and temporal context. For one thing, video anomaly may not correspond to the whole trajectory, only to a part of it, for another thing, an anomaly can arise due to the inappropriate interactions among multiple objects (i.e., multiple trajectories), in spite of their individual behaviors are normal. Thus, trajectory clustering-based anomaly methods can cause miss detections. R. Mehran, et al. use the Social Force model which was proposed at the year of 1995 to detect and localize abnormal behaviors in crowd videos [16]. There are some researchers have developed Social Force Model to a novel social attribute-aware force model [17-19], this technique has advantages that the anomaly behavior can be detected and localized without tracking of objects in high density crowds which successfully avert typical problems in tracking, such as extensive clutter and dynamic occlusions. This model used to provide more information to perform clustering on.

V. Other Uncommon Detection Techniques

There are still some other techniques not as frequently be used as what we have reviewed above, such as information theoretic techniques and spectral techniques. Information theoretic techniques analyze the information content of a data set using different information theoretic measures such as Kolomogorov Complexity [43], entropy [44], relative entropy [30] and so on. The basic concept of information theoretic techniques is: Anomalies in data induce irregularities in the information content of the dataset. In information theory, entropy is also usually used to measure the uncertainty and disorder in a random variable [45, 46]. Based on these concepts, we summarize that the entropy usually is related to measure the disorder. In [47, 48], they use the distribution of the particles in the frame to simulate the distribution of the individuals in the crowd, and the velocity of the individuals in the crowd also can be simulated use the speed of the particles in the frame, such that they propose a particle entropy approach which can represent the crowd distribution information effectively. The main idea of this method is that the larger the particle entropy is that the higher, the disorder/anomaly will be. Information theoretic anomaly detection techniques have an advantage that it can be implemented in an unsupervised mode, but requires an information theoretic measure sensitive enough to detect irregularity generated by very few outliers. Spectral techniques hold the idea that data can be embedded into a lower dimensional subspace where normal instances and anomalies appear significantly different. A combination of attributes that capture the volume of variability in the data can be used to find an approximation. Thus the general approach of spectral anomaly detection techniques is to determine if anomaly can be easily identified in such subspaces (embedding, projections, etc.) [49]. The advantage of spectral anomaly detection techniques is that they can operate in an unsupervised mode, and their disadvantage is that they are based on the assumption that anomalies and normal instances are distinguishable in the reduced space, so have to project data into a lower dimensional space by the means of Principal Component Analysis [50].

VI. Concluding Remarks and Future Work

Various methods to detect the anomaly have been analysed above, considering various set of variants show improved performance than the others. Representation trajectories can be varied according to the position and size. Anomaly localization using frame level ground truth and pixel level ground truth shows good performance in crowded scenes. One direction for future work is to make these methods more robust to low quality videos, such as occlusion or shaking, faster in dealing with high resolution surveillance videos. Other direction is to develop frameworks that will effectively cope with the scenarios of extendibility of video analysis especially in the cluttered real world where environments have many moving objects and activities. In addition, a particularly promising direction for future direction is to develop more advanced deep learning techniques to probe into the hierarchical and temporal relationships for better behavior localization and detection.

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