VIDEO BEHAVIOR PROFILING FOR ABNORMALITY EXPOSURE

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ABSTRACT

The goal of this study is to solve the challenge of modeling video behavior acquired in surveillance cameras for online normal behavior recognition and anomaly detection applications. Without any manual labeling of the training data set, a novel framework for automatic behavior profiling and online anomaly sampling/detection is established. The framework is made up of the following essential elements: 1) Using discrete-scene event detection, a compact and effective behavior representation approach is devised. The similarity of behavior patterns is assessed using a Dynamic Bayesian Network to model each pattern (DBN). 2) A unique spectral clustering approach with unsupervised model selection and feature selection on the eigenvectors of a normalized affinity matrix is used to uncover the natural grouping of behavior patterns. 3) A composite generative behavior model is built that can generalize from a short training set to account for changes in normal behavior patterns that aren't visible. 4) To detect abnormal behavior, a runtime accumulative anomaly measure is introduced, but normal behavior patterns are detected when adequate visual evidence is present using an online Likelihood Ratio Test (LRT) technique. This ensures that anomalies are detected and typical behavior is recognized in the shortest time feasible. Experiments with noisy and sparse data sets obtained from both interior and outdoor monitoring scenarios illustrate the usefulness and robustness of our approach. In particular, it is demonstrated that in detecting abnormality from an unseen video, a behavior model trained using an unlabeled data set outperforms those trained using the same but labeled data set. Our online LRT-based behavior identification strategy outperforms the commonly used Maximum Likelihood (ML) method in distinguishing ambiguity among different online behavior classes, according to the results.

Index Terms—Behavior profiling, anomaly detection, dynamic scene modeling, spectral clustering, feature selection, Dynamic Bayesian Networks.

INTRODUCTION

THERE is an increasing demand for automatic methods for analyzing the vast quantities of surveillance video data generated continuously by closed-circuit television (CCTV) systems. One of the key objectives of deploying an automated visual surveillance system is to detect abnormal behavior patterns and recognize the normal ones. To achieve this objective, previously observed behavior patterns need to be analyzed and profiled, upon which a criterion on what is normal/abnormal is drawn and applied to newly captured patterns for anomaly detection. Due to the large amount of surveillance video data to be analyzed and the real-time nature of many surveillance applications, it is very desirable to have an automated system that runs in real time and requires little human intervention. In the paper, we aim to develop such a system that is based on fully unsupervised behavior profiling and robust online anomaly detection. Let us first define the problem of automatic behavior profiling for anomaly detection. Given a 24/7 continuously recorded video or an online CCTV input, the goal of automatic behavior profiling is to learn a model that is capable of detecting unseen abnormal behavior patterns while recognizing novel instances of expected normal behavior patterns. In this context, we define an anomaly as an atypical behavior pattern that is not represented by sufficient samples in a training data set but critically satisfies the specificity constraint to an abnormal pattern. This is because one of the main challenges for the model is to differentiate anomaly from outliers caused by noisy visual features used for behavior representation. The effectivenessof a behavior profiling algorithm shall be measured by

1) how well anomalies can be detected (that is, measuring specificity to expected patterns of behavior) and

2) how accurately and robustly different classes of normal behavior patterns can be recognized (that is, maximizing betweenclass discrimination).

To solve the problem, we develop a novel framework for fully unsupervised behavior profiling and online anomaly detection. Our framework has the following key components:

1. A scene event-based behavior representation. Due to the space-time nature of behavior patterns and their variable durations, we need to develop a compact and effective behavior representation scheme and to deal with time warping. We adopt a discrete scene event-based image feature extraction approach [8]. This is different from most previous approaches such as [24], [16], [14], [3] where image features are extracted based on object tracking. A discrete eventbased behavior representation aims to avoid the difficulties associated with tracking under occlusion in noisy scenes [8]. Each behavior pattern is modeled using a Dynamic Bayesian Network (DBN) [7], which provides a suitable

means for time warping and measuring the affinity between behavior patterns.

2. Behavior profiling based on discovering the natural grouping of behavior patterns using the relevant eigenvectors of a normalized behavior affinity matrix.Anumber of affinity matrix-based clustering techniques have been proposed recently [25], [23], [30]. However, these approaches require a known number of clusters. Given an unlabeled data set, the number of behavior classes is unknown in our case. To automatically determine the number of clusters, we propose to first perform unsupervised feature selection to eliminate those eigenvectors that are irrelevant/uninformative in behavior pattern grouping. To this end, a novel feature selection algorithm is derived, which makes use of the a priori knowledge on the relevance of each eigenvector. Our unsupervised feature selection algorithm differs from the existing techniques such as [12], [6] in that it is simpler, more robust, and thus able to work more effectively even with sparse and noisy data.

3. A composite generative behavior model using a mixture of DBNs. The advantages of such a generative behavior model are twofold:

a) It can accommodate well the variations in the unseen normal behavior patterns in terms of both duration and temporal ordering by generalizing from a training set of a limited number of samples. This is important because in reality, the same normal behavior can be executed in many different normal ways. These variations cannot possibly be captured in a limited training data set and need to be dealt with by a learned behavior model.

b) Such a model is robust to errors in behavior representation. A mixture of DBNs can cope with errors that occurred at individual frames and is also able to distinguish an error corrupted normal behavior pattern from an abnormal one.

4. Online anomaly detection using a runtime accumulative anomaly measure and normal behavior recognition using an online Likelihood Ratio Test (LRT) method. A runtime accumulative measure is introduced to determine how normal/abnormal an unseen behavior pattern is on the fly. The behavior pattern is then recognized as one of the normal behavior classes if detected as being normal. Normal behavior recognition is carried out using an onlineLRTmethod, which holds the decision on recognition until sufficient visual features have become available. This is in order to overcome any ambiguity among different behavior classes observed online due to insufficient visual evidence at a given time instance. By doing so, robust behavior recognition and anomaly detection are ensured at the shortest possible time, as opposed to previous worksuch as [2], [8], [16], which requires completed behavior patterns to be observed. Our online LRT-based behavior

recognition approach is also advantageous over previous ones based on the Maximum Likelihood (ML) method [31], [8], [16].AnML-based approach makes a forced decision on behavior recognition at each time instance without considering the reliability and sufficiency of the accumulated visual evidence. Consequently, it can be error prone. Note that our framework is fully unsupervised in that manual data labeling is avoided in both the feature extraction for behavior representation and the discovery of the natural grouping of behavior patterns. There are a number of motivations for performing behavior profiling using unlabeled data: First, manual labeling of behavior patterns is laborious and often rendered impractical given the vast amount of surveillance video data to be processed. More critically though, manual labeling of behavior patterns could be inconsistent and error prone. This is because a human tends to interpret behavior based on the a priori cognitive knowledge of what should be present in a scene rather than solely based on what is visually detectable in the scene. This introduces a bias due to differences in experience and mental states. It is worth pointing out that the proposed framework is by no means a general one, which can be applied to any type of scenarios.

Existing system:

However, these approaches require a known number of clusters. Given an unlabeled data set, the number of behavior classes is unknown in our case. To automatically determine the number of clusters, we propose to first perform unsupervised feature selection to eliminate those eigenvectors that are irrelevant/uninformative in behavior pattern grouping. To this end, a novel feature selection algorithm is derived, which makes use of the a priori knowledge on the relevance of each eigenvector. Our unsupervised feature selection algorithm differs from the existing techniques such as in that it is simpler, more robust, and thus able to work more effectively even with sparse and noisy data.

PROPOSED SYSTEM:

This introduces a bias due to differences in experience and mental states. It is worth pointing out that the proposed framework is by no means a general one, which can be applied to any type of scenarios. In particular, the proposed approach, as demonstrated by the experiments presented in Section, is able to cope with a moderately crowded scenario thanks to the discrete event-based behavior representation. However, an extremely busy and unstructured scenario such as an underground platform in rush hours will pose serious problems to the approach. This will be discussed in depth later in this paper.

ADVANTAGES:

- It can accommodate well the variations in the unseen normal behavior patterns in

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terms of both duration and temporal ordering by generalizing from a training set of a limited number of samples. This is important because in reality, the same normal behavior can be executed in many different normal ways.

- Such a model is robust to errors in behavior representation. A mixture of DBNs can cope with errors that occurred at individual frames and is also able to distinguish an error corrupted normal behavior pattern from an abnormal one.

DISADVANTAGES:

- Let us first define the problem of automatic behavior profiling for anomaly detection.
- However, an extremely busy and unstructured scenario such as an underground platform in rush hours will pose serious problems to the approach. This will be discussed in depth later in this paper.
- This problem is addressed by the approaches proposed. However, in these approaches, all the previously observed normal behavior patterns must be stored either in the form of histograms of discrete events or ensembles of spatiotemporal patches for detecting anomaly from unseen data, which jeopardizes the scalability of these approaches.

SYSTEM ARCHITECTURE

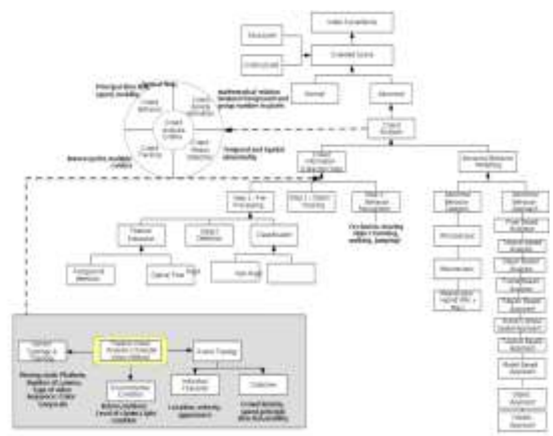

Figure: System Architecture for detecting abnormal behavior

MODULES:

Closed circuit television:

THERE is an increasing demand for automatic methods for analyzing the vast quantities of surveillance video data generated continuously by closed-circuit television (CCTV) systems. One of the key objectives of deploying an automated visual surveillance system is to detect abnormal behavior patterns and recognize the normal ones. To achieve this objective, previously observed behavior patterns need to be analyzed and profiled, upon which a criterion on what is normal/abnormal is drawn and applied to newly captured patterns for anomaly detection.

Due to the large amount of surveillance video data to be analyzed and the real-time nature of many surveillance applications, it is very desirable to have an automated system that runs in real time and requires little human intervention. In the paper, we aim to develop such a system that is based on fully unsupervised behavior profiling and robust online anomaly detection.

Dynamic bayesian network:

Due to the space-time nature of behavior patterns and their variable durations, we need to develop a compact and effective behavior representation scheme and to deal with time warping. We adopt a discrete scene event-based image feature extraction approach. This is different from most previous approaches such as where image features are extracted based on object tracking. A discrete event based behavior representation aims to avoid the difficulties associated with tracking under occlusion in noisy scenes. Each behavior pattern is modeled using a Dynamic Bayesian Network (DBN), which provides a suitable means for time warping and measuring the affinity between behavior patterns.

A composite generative behavior model using a mixture of DBNs:

The advantages of such a generative behavior model are twofold: a) it can accommodate well the variations in the unseen normal behavior patterns in terms of both duration and temporal ordering by generalizing from a training set of a limited number of samples. This is important because in reality, the same normal behavior can be executed in many different normal ways. These variations cannot possibly be captured in a limited training data set and need to be dealt with by a learned behavior model. b) Such a model is robust to errors in behavior representation. A mixture of DBNs can cope with errors that occurred at individual frames and is also able to distinguish an error corrupted normal behavior pattern from an abnormal one.

Maximum likelihood:

This is in order to overcome any ambiguity among different behavior classes observed online due to insufficient visual evidence at a given time instance. By doing so, robust behavior recognition and anomaly detection are ensured at the shortest possible time, as opposed to previous work such as, which requires completed behavior patterns to be observed. Our online LRT-based behavior recognition approach is also advantageous over previous ones based on the Maximum Likelihood (ML) method .An ML-based approach makes a forced decision on behavior recognition at each time instance without considering the reliability and sufficiency of the accumulated visual evidence. Consequently, it can be error prone.

COCNLUSION

In this paper, we introduced a method to detect abnormal behaviors in a crowd scene using an integrated multiple behavior model. We showed how our method captured the dynamics of crowd behavior based on the multiple behavior models which consisted of the personal and social model of individuals without individual object tracking or segmentation. The result of our proposed method showed that our method was effective in the detection of abnormal behaviors in a crowd scene. It would be interesting to extend our behavior model by using an explicit model of pedestrian behavior that considers more personal and social property. Furthermore, in our future work, we will take into consideration not only pedestrian behavior but also static scene objects such as benches

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