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TRASMIL: A local anomaly detection framework based on trajectory segmentation and multi-instance learning

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ABSTRACT

Local anomaly detection refers to detecting small anomalies or outliers that exist in some subsegments of events or behaviors. Such local anomalies are easily overlooked by most of the existing approaches since they are designed for detecting global or large anomalies. In this paper, an accurate and flexible three-phase framework TRASMIL is proposed for local anomaly detection based on TRAjectory Segmentation and Multi-Instance Learning. Firstly, every motion trajectory is segmented into independent sub-trajectories, and a metric with *Diversity* and *Granularity* is proposed to measure the quality of segmentation. Secondly, the segmented sub-trajectories are modeled by a sequence learning model. Finally, multi-instance learning is applied to detect abnormal trajectories and sub-trajectories which are viewed as bags and instances, respectively. We validate the TRASMIL framework in terms of 16 different algorithms built on the three-phase framework. Substantial experiments show that algorithms based on the TRASMIL framework outperform existing methods in effectively detecting the trajectories with local anomalies in terms of the whole trajectory. In particular, the MDL-C algorithm (the combination of HDP-HMM with MDL segmentation and Citation *k*NN) achieves the highest accuracy and recall rates. We further show that TRASMIL is generic enough to adopt other algorithms for identifying local anomalies.

1. Introduction

Abnormal event detection is a critical research topic in visual surveillance. Basically, the abnormal events are defined as the events which are largely deviated from normal ones. So the goal of the abnormal event detection is to automatically discover the potential abnormal events from observations. Due to the unpredictability and diversity of abnormal events, it is usually difficult and infeasible to build a particular classifier for abnormal events. The remaining core problem of abnormal event detection is how to train a good classifier for detecting anomalies, by fully using the large amount of available normal events and possibly few available abnormal events.

These years, many efforts have been expended on the abnormal event detection. Existing work on abnormal event detection can be roughly classified into two categories: motion-based approaches and trajectory-based approaches. The former ones usually extract low-level motion features, e.g. optical flow [1] and motion history image [2], from fixed spatial–temporal cubic, and then apply machine learning techniques for classification to discover possible abnormal events. The latter ones usually first extract the trajectory for moving objects in the scene, and then build temporal classifiers, e.g. HMM, HDP-HMM, for trajectory classification to find potential abnormal events. The limitation of the motion-based approaches is that simple features are usually adopted, which only reflect the relatively coarse motion information and may not be suitable for the detection in more complex scenes. Our proposed method belongs to the trajectory-based approaches. With the development of the object tracking, trajectory-based approaches are widely applied in traffic surveillance for detecting abnormal vehicle trajectory. They are also used in crowded scenes for identifying complex motion patterns.

Although many trajectory-based approaches achieve many successes in detecting abnormal events, most of them are usually developed for detecting global or large anomalies, and may ignore the local anomalies that exist in some subsegments of events or behaviors. To this end, we propose in this paper a novel framework for local anomaly detection based on TRAjectory Segmentation and Multi-Instance Learning, called TRASMIL, which consists of three phases: trajectory segmentation, trajectory representation and multi-instance learning (MIL).

In trajectory segmentation phase, we consider partitioning each trajectory into several sub-trajectories, to avoid ignoring local anomalies. The criterion for the segmentation usually includes two folds: for each trajectories, (i) every segmented sub-trajectories are encouraged to be independent from others with

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the goal to find simple motions from complex trajectory, and (ii) the number of sub-trajectories is encouraged to be small with avoiding over-segmentation. In this paper, four types of different segmentation algorithms are investigated, which includes: Maximum Acceleration (MA) [3], Minimum Description Length (MDL) [4,5], Log-likelihood of Regression Function (LRF) [6], and Heterogeneous Curvature Distribution (HCD) [7]. To evaluate the quality of trajectory segmentation, we propose a metric, namely *QMeasure*, considering *Diversity* and *Granularity* of sub-trajectories, which are corresponding to the two folds of above mentioned criterion respectively. In our experiments, we found that *QMeasure* can help determine the optimal parameter of segmentation algorithms as well as choose appropriate segmentation algorithms, which will be validated in the experiments of Section 5.5.

In trajectory representation phase, the goal is to measure the similarity of any given two sub-trajectories. We first model any two sub-trajectories by sequential probabilistic models, and then calculate the distance by using the KL-divergency method [8] on the obtained two corresponding models. In our work, two sequential probabilistic models: Hidden Markov Model (HMM) and Hierarchical Dirichlet Process Hidden Markov Model (HDP-HMM) are selected due to their effectiveness in modeling time-series data. The results of the HMM and HDP-HMM are listed and compared in experiments of Section 5.3.

In MIL detection phase, trajectories and segmented sub-trajectories are viewed as bags and instances in multi-instance learning, respectively. To solve the MIL problem, we use two conventional MIL methods, Diversity Density [9] and Citation *k*NN [10] in the phase. Their detection results are compared and analyzed in the experiment section. Finally, to validate the superiority of the proposed TRASMIL framework, all the combination methods in three phases are experimented and compared with two whole-trajectory-based methods.

The main contribution of the proposed TRASMIL is that it can successfully incorporates trajectory segmentation, modeling-based representation and multi-instance learning, which is able to effectively detect the trajectories with local anomalies that cannot be identified by existing methods. We combine this TRASMIL framework with 16 algorithms for different phases and test the performance. Substantial experiments show that the TRASMIL-based algorithms are effective in local anomaly detection, in which the combination of HDP-HMM with MDL segmentation and Citation *k*NN, MDL-C algorithm, performs the best.

1.1. Organization

The remainder of the paper is organized as follows. Section 2 gives a brief overview of related work. Problem statement and framework structure are described in Section 3. The working mechanism of TRASMIL and its combination with 16 algorithms are introduced in Section 4. Section 5 presents experimental results, which are compared to two whole-trajectory detection algorithms. Discussions are presented in Section 6, followed by conclusions in Section 7.

2. Related work

Recent years, many works have been proposed for abnormal event detection. The related works can be roughly classified into two categories: motion-based approaches and trajectory-based approaches. Our proposed method belongs to the trajectory-based approaches, so we will pay more attention to the previous works about trajectory-based abnormal event detection.

For motion-based approaches, low-level features, e.g. optical flow, gradient, are first extracted from local spatial–temporal patches, then the extracted features of the normal events will be learned as normal model by using certain classifier, e.g. Gaussian Mixture Model [11,12], Markov Random Field [13,14] and Social Force Model [15]. After obtaining the normal model, for the new coming frames, the abnormal events will be detected for the events, which are largely deviated from normal model by computing the likelihood. Although motion-based approaches can achieve satisfactory results in some datasets, most of them are only suitable for simple motion patterns since they usually model the variation of speed and direction at pixel/patch-level. The results for detecting complex abnormal events are undesirable.

For trajectory-based approaches, most of them rely on trajectories obtained from object detection and tracking. Much previous research works have been developed for trajectory-based approaches. The trajectory-based approaches mainly focus on trajectory representation and trajectory classification.

In terms of trajectory representation, related algorithms are listed in Table 1. As can be seen from the table, trajectory representation methods can be classified into three types: sequence of flow vectors, sequence of other features, and modeling-based representation. Firstly, flow vectors are usually represented as four-dimensional vectors (x, y, dx, dy) that contain spatial coordinates and velocities such as that claimed in literature [16]. Since abnormal behaviors are triggered by motion objects, Wang et al. [17] add some features of objects, such as the size, into the flow vectors. Secondly, there are other sequences of features which differ from the above flow vectors. For example, semantic spatial primitives are proposed by Chan et al. [18] to encode trajectories with binarized distance relations among objects. Pelekis et al. [19] propose a local trajectory descriptor by computing local density and trajectory similarity to represent line segments. Lastly, modeling-based representation is becoming popular for representation due to its statistical description of trajectory distribution. Hidden Markov Model (HMM), a method of sequence modeling is adopted by Lester et al. [20] for activity modeling. Since HDP-HMM can automatically adjust the state number of sequences, unlike HMM, which cannot, it is also widely applied for trajectory modeling by Hu et al. [21] and Zhang et al. [22].

In terms of trajectory classification, the related work is usually based on two metrics, e.g., similarity-based and model-based metrics. The similarity-based methods [24,25,21] compute the similarity between trajectories in terms of Euclidean distance, Hausdorff distance or Dynamic Time Warping. Zhou et al. [24] propose a supervised algorithm of trajectory edit-distance for learning trajectory similarity function. Those trajectories having a distance to normal ones larger than a given threshold are detected as abnormal. Fu et al. [25] use hierarchical clustering to find dominant paths and lanes. Test trajectories are predicted to a cluster where the spatial constraints and velocity constraints are checked to detect anomalies. Different from Fu's work, Hu et al. [21] use Fuzzy Self-Organizing Neural Network to learn activity patterns. Then, the Euclidean distance between test trajectories and the best matching neuron is calculated. Model-based methods [16,23,26] model the observations of normal trajectories with no temporal order. Johnson et al. develop a model of the probability density functions (pdfs) for object trajectories. Neural network based vector quantisation is used to learn the pdfs of flow vectors. Hu et al. use HDP-HMM and One-class SVM to learn the model of normal trajectories. Anomalies can be detected via fitting the normal activity models. Different from Hu's work, sequential patterns are mined in feature selection phase by Lee et al. [26], and then a classifier model is built for trajectory classification.

In our previous work, HDP-HMM and ensemble learning were used in [22] to generate a normal activity model for detecting anomalies. Abnormal activity models, which are derived from normal activity models, are applied to correct misclassified normal