METHODS FOR TRAJECTORY OUTLIER DETECTION IN SURVEILLANCE VIDEO

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Abstract: Outlier detection in trajectory data extracted from surveillance video is a useful data analysis task, which can reveal anomalous or suspicious behaviour of moving objects. This paper deals with the description, evaluation and comparision of two methods for the trajectory outlier detection. Firstly, TOP-EYE algorithm, which gradually computes and accumulates outlying score of a trajectory. Secondly, a model-based method which uses the Gaussian mixture model (GMM) and identifies trajectories not following the learned model as outliers.

Keywords: data mining, outlier detection, moving objects data, trajectory, surveillance video, TOP-EYE, GMM

1 INTRODUCTION

Recent advances in localization and surveillance systems have caused rapid increase in volume of stored data about moving objects, mostly in the form of trajectories that are sequences of spatio-temporal positions of moving objects. There are several trajectory data mining tasks including frequent or periodic pattern mining, trajectory clustering, trajectory classification and trajectory outlier detection.

Automatic detection of unusual or suspicious behaviour of moving objects is a useful spatio-temporal data analysis task. Usually, it is focused on finding outlying trajectories, which correspond to movements that are significantly different from most other trajectories.

Trajectory outlier detection can be used as a descriptive task, when the objective is to identify outliers in the whole trajectory data set, or as a predictive task, when the objective is to decide if a trajectory is outlier or not. In the case of the trajectory outlier detection as the descriptive task, it can be used some of distance-based or density-based methods, for example, algorithm called TRAOD [6]. In the case of the trajectory outlier detection as the predictive task, it can be convenient to use some classification-based method, for example, framework ROAM [7].

Usually, it is required to choose a method that is able to be used as the predictive task for the trajectory outlier detection in surveillance video. Trajectories extracted from surveillance video are usually unlabeled, therefore classification-based methods can be inappropriate to use. A more convenient candidate seems to be an approach based on evolving outlying score computation or an approach based on a statistical model. This paper deals with the description and the comparision of these appoaches and it is organized as follows. At first, we describe the method called TOP-EYE [3], which can be able to identify outlying trajectories at the early stage with a relatively low false alarm rate. Secondly, we describe a model-based method which employs the Gaussian mixture model (GMM) and detects as outliers trajectories that do not follow the learned model. Finally, we evaluate and compare these two methods and we outline our plans in this area of research.

2 TOP-EYE METHOD

An evolving trajectory outlier detection algorithm, named **TOP-EYE**, was introduced by Ge et al. in [3]. The main objective of this method is to identify outlying trajectories at the early stage with a relatively low false positive rate.

The monitored area is considered as a regular grid of small cells. Each cell is partitioned into eight direction sectors, each sector with an angle range of $\pi/4$. The goal of this partitioning is to summarize the direction information of the trajectories within each cell and to represent this summarization by a vector of eight values. Each of these values represents the probability of a move of an object in one of eight different directions. Thus cell c can be represented by a direction vector $\mathbf{c} = (p_1, p_2, p_3, p_4, p_5, p_6, p_7, p_8)$, where p_i is the frequency of trajectories which have moved within cell c along the direction sector i. After the monitored area is partitioned, the direction vector and the density of each cell are computed by analyzing each trajectory in a data set.

The algorithm continuously computes an *instant outlying score* for each new trajectory. The outlying score can be based either on the direction information of trajectories or on the density of trajectories. Assume that a new trajectory has k directions within a cell. Then the directions of this new trajectory can be represented by a direction vector, for example, $(q_1, \ldots, q_k)$, where each $q_j = 1/k$. The direction-based outlying score is given by the distance between the summarized direction vector of a cell and the direction vector of the trajectory:

$$OScoreDir = 1 - \sum_{j=1}^{k} q_j \sum_{i=1}^{8} p_i \cdot \cos\angle(v_j, v_i) \tag{1}$$

where $\cos\angle(v_j, v_i)$ is the cosine value of the angle between the j-th direction of the trajectory and the representative direction of the i-th direction sector.

Assume that each cell is represented by the summarized density information d. Then the density-based outlying score is defined as

$$OScoreDen = \begin{cases} s & \text{if } d < \tau \\ 0 & \text{otherwise} \end{cases} \tag{2}$$

where s is a density score representing the penalty for the density that is lower than a specified density threshold τ.

The main idea of TOP-EYE algorithm is to gradually accumulate instant outlying scores and thus combine the instant outlierness with the historical outlierness of a moving object. The influence of the historical outlierness is decayed with time by an exponential decay function $\exp(-\lambda\Delta t)$, where λ is a user-specified parameter that determines the decay rate. Assume that S_{t_i} is the instant outlying score obtained by equation (1) or equation (2). Then the *evolving outlying score* at time instant t_i is defined as

$$S_{t_i}^{\Sigma} = S_{t_i} + S_{t_{i-1}} \cdot \exp(-\lambda\Delta t_{i-1}) + S_{t_{i-2}} \cdot \exp(-\lambda\Delta t_{i-2}) + \cdots + S_{t_0} \cdot \exp(-\lambda\Delta t_0) \tag{3}$$

where Δt_{i-k} is a time interval between time t_i and time t_{i-k}. The trajectory is identify as outlier once the evolving outlying score is above a user-specified threshold.

3 GMM-BASED METHOD

Statistical, also known as model-based, methods for outlier detection usually assume that normal objects in a data set are generated by some stochastic process. The main idea of these methods is to learn a generative model fitting the given data set and then to identify the objects in regions with a low probability as outliers [4].

We transform each trajectory into a feature vector consisting of four components. These components represent trajectory beginning, ending and average with its standard deviation. Each of these components comprises a location of trajectory, a size of moving object and information about direction and speed.

Gaussian mixture model (GMM) [1] is a linear combination of Gaussian distributions defined as

$$p(\mathbf{x}) = \sum_{k=1}^{K} \pi_k \mathcal{N}(\mathbf{x}|\mu_k, \Sigma_k) \tag{4}$$

where each π_k is called a *mixing coefficient*, $0 \leq \pi_k \leq 1$ and $\sum_{k=1}^{K} \pi_k = 1$. Each Gaussian density function $\mathcal{N}(\mathbf{x}|\mu_k, \Sigma_k)$ with its mean μ_k and covariance Σ_k is called a *component* of the mixture model. The component of GMM corresponds to a cluster in modeled data set. $\mathbf{x}$ is an object in a data set, for example, the feature vector representing a trajectory in our case.

Expectation-maximization algorithm (EM) [1, 2] is usually used for learning GMM by iterative estimating the model parameters (the means and covariances of the components and the mixing coefficents). The goal of EM algorithm is to maximize the likelihood function with respect to these parameters. The number of mixture components K has to be specified in advance. Therefore, it is convenient to repeatedly train the model with different numbers of components and to choose the model which fits the data best. We use a criterion called *Bayesian Information Criterion* (BIC) [1] for this purpose. BIC is based on the likelihood function and it penalizes model complexity.

After the model is selected and trained by the EM algorithm, it can be used for outlier detection. The outlierness of a trajectory should be detected either if the trajectory is in a low probability region of GMM or if the trajectory is classified to be generated by multiple GMM components but none of them with a sufficient probability. Assume that each trajectory is represented by the feature vector described above. Our method for trajectory outlier detection using GMM involves the following steps:

1. For each trajectory $\mathbf{x}$ and each GMM component k, it is calculated the *Mahalanobis distance MD* from $\mathbf{x}$ to μ_k as follows [4]:

$$MD(\mathbf{x}, \mu_k) = (\mathbf{x} - \mu_k)^T \Sigma_k^{-1} (\mathbf{x} - \mu_k) \tag{5}$$

2. The *Grubbs' test* [4] is used to detect outliers. Trajectory $\mathbf{x}$ is an outlier if

$$MD(\mathbf{x}, \mu_k) \geq \frac{N-1}{\sqrt{N}} \sqrt{\frac{t^2_{\alpha/(2N),N-2}}{N-2+t^2_{\alpha/(2N),N-2}}} \tag{6}$$

   for at least one GMM component k. N is the number of trajectories in the data set and $t_{\alpha/(2N),N-2}$ is the value taken by a t-distribution with $N-2$ degrees of freedom at a significance level of $\alpha/(2N)$.

3. The trajectory that has not yet been detected as outlying is an outlier if

$$P_{max} \leq \frac{1}{K} c \tag{7}$$

   where P_{max} is the maximum probability that the trajectory is generated by any of GMM components, K is the number of GMM components and c is a parameter that determines the degree of tolerance to outlierness, $1 < c < K$. The greater the value of c, the more trajectories are detected as outliers.

4 EVALUATION AND COMPARISION

We implemented the TOP-EYE algorithm in Java and we tested and evaluated it on a set of trajectories extracted from a set of videos. This set of videos is from i-LIDS dataset [5] and it comes from five cameras at the airport. A visualization of some results of the TOP-EYE method is shown in Figure 1. Left, some direction-based trajectory outliers from the first camera are depicted. Right, there is an example of some density-based trajectory outliers from the first camera.

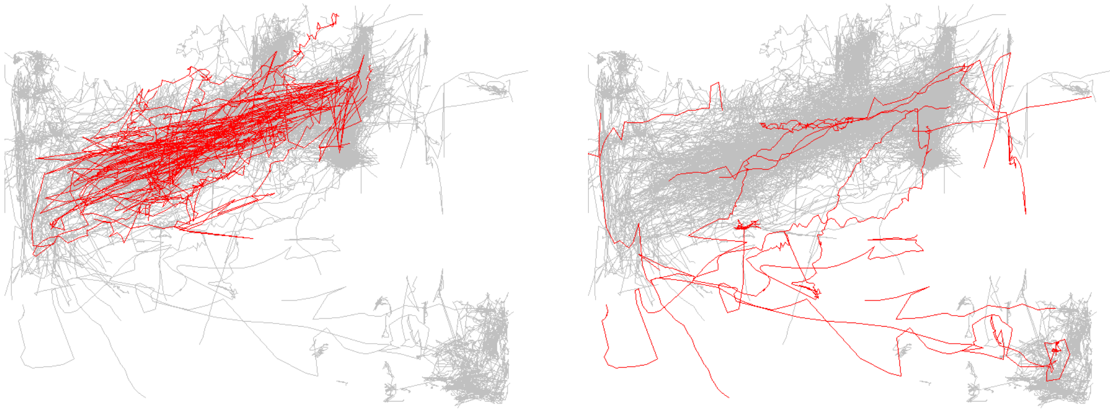

Figure 1: Examples of some results of the TOP-EYE algorithm (outlying trajectories are in red).

We implemented the GMM-based method in C++ using an implementation of the EM algorithm in the OpenCV library. We tested and evaluated the method on the trajectory dataset on which we evaluated the TOP-EYE algorithm implementation. However, it was necessary to transform the trajectories into the form of the feature vector described above. We used only location-based features in order to be able to compare this method with the TOP-EYE method. A visualization of a result of the GMM-based method is shown in Figure 2. There is an example of some outlying trajectories from the first camera.

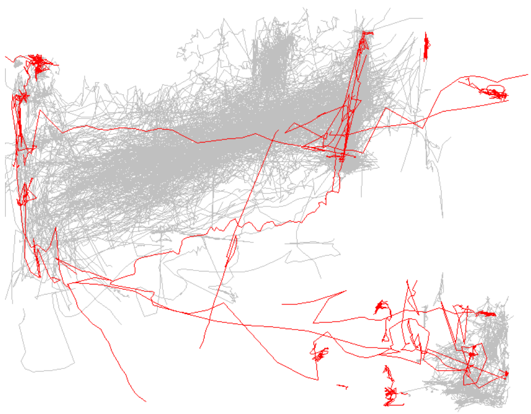

Figure 2: An example of a result of the GMM-based method (outlying trajectories are in red).

The advantages of the TOP-EYE method include the ability to capture an evolving nature of outlying trajectories and to identify outlying partitions of the trajectories. On the other hand, the TOP-EYE algorithm is not able to detect direction-based outliers in a low density region. The main disadvantage of this algorithm can be a consideration of the monitored area as a regular grid and a relatively large number of user-specified parameters.

The main advantages of the GMM-based method include the ability to detect outliers based on density and outliers based on a velocity and a size of a moving object. Another advantage is that this method does not require any user-specified parameters. Furthermore, the model obtained by the EM algorithm can be also considered as a result of a clustering of an input data set. The main disadvantage of the GMM-based method is that the trajectories are considered as a whole and it is not possible to identify outlying partitions of the trajectories.

5 CONCLUSION

This paper dealt with the trajectory outlier detection in surveillance video, which is one of useful data mining tasks. The main objective of this paper was to describe, evaluate and compare two approachs for the trajectory outlier detection, namely an evolving trajectory outlier approach and an approach based on statistical model. The former approach was represented by an algorithm called TOP-EYE. The latter approach was represented by a method based on Gaussian mixture model (GMM). The evaluation of these methods showed their advantages and disadvantages and encouraged us to a future research in this area.

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