DETECTING ANOMALOUS TRAJECTORIES FROM HIGHWAY TRAFFIC DATA

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ABSTRACT

In this paper we modify our unsupervised anomaly detection algorithm [1,2] and apply it to highway traffic anomaly analysis. We propose a method to identify anomalies under a probabilistic framework. Instead of determining anomalies based on the size of each cluster, they are determined in a probabilistic framework. Moreover, we present our findings on using different features when analyzing real highway vehicle trajectory data. Based on real highway traffic video data we demonstrate that the inclusion of certain features, brings us closer to identifying events that are both anomalous and abnormal (based on driving rules).

Index Terms— Object trajectory, anomaly detection, clustering

1. INTRODUCTION

A system that can automatically detect anomalous events in highway traffic video, such as accidents, reckless driving, slow-driving, sudden braking, swerving and speeding, is very useful for traffic congestion alerting, management and resolution [3]. Therefore there has been an increased interest in vehicle tracking and trajectory-based analysis.

Towards this task, one possible direction is the explicit event recognition approach [4, 5]. The system has a priori knowledge of the normal patterns of traffic events. Models are trained based on labeled trajectories of each pattern. A new trajectory is labeled/classified to one of these normal patterns, or identified as anomaly if it does not fit in any model. The main drawback of this approach is the need for prior modeling of each possible pattern.

Alternatively, event models could be built by the system itself in an unsupervised manner, as the data are acquired. A commonly used approach in this case is based on the clustering of the trajectories; the obtained clusters are then used as a normality model for anomaly detection. Typically, trajectories are represented by a hidden Markov model (HMM) [6,7] or resampled to a fixed-dimension vector [8,9]. The clustering methods used include k-means [7,8], mixtures of Gaussians (MoGs) [10], spectral clustering [6], sequential grouping [11], and Support Vector Machines (SVM) [9].

However, since the clustering-based approach is performed on all trajectories -normal and anomalous- a proper procedure of outlier removal and anomaly identification is necessary. Some address this concern by removing clusters with few trajectories [8] or of large covariance [10]. In [7], only those trajectories that fit the route well were retained for normality modeling. Geometric considerations in the SVM feature space were utilized to automatically detect and remove outliers in [9].

Another concern is the choice of trajectory features used in the modeling. For example, some used only 2-D position information [9, 11], while others also included instantaneous speed within one feature vector [6, 10]. On the other hand, spatial and dynamic information could be handled separately as was done in [7, 8].

In this paper we apply our unsupervised anomaly detection algorithm [1, 2] that has distinct advantages in addressing the above concerns, to highway traffic data. Our unsupervised algorithm uses an information-based similarity measure to model and cluster vehicle trajectories. Specifically, a probabilistic framework, instead of cluster size thresholding, is used to identify normal/anomalous trajectory clusters, which is described in Sec. 2. Our algorithm also allows for the straightforward inclusion of various positional and dynamic features. Sec. 3 presents our experimental findings. Based on real highway traffic video data we demonstrate that the inclusion of certain features, brings us closer to identifying events that are both anomalous and abnormal (based on driving rules). We conclude our paper in Sec. 4.

2. CLUSTERING-BASED ANOMALY DETECTION

The proposed unsupervised anomaly detection approach consists mainly of two steps. First, all trajectories extracted from the video are clustered into groups. Second, the normal trajectory groups are identified using a probabilistic framework.

In our system, a trajectory which is a time sequence is modeled by an HMM with Gaussian emission probability. At

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the clustering step, we measure the distance between trajectories based on the similarity between their corresponding models. Specifically, the distance between two trajectories or trajectory groups i, j is defined as

$$d(i,j) = \log L_i + \log L_j - \log L_{ij} - \frac{1}{2} K_0 \log N, \quad (1)$$

where L_i and L_j denote the likelihoods of i and j being generated by their own models, L_{ij} is the likelihood of i, j being generated by a model trained on themselves, N the number of all trajectories, and K the number of model parameters.

In our algorithm, agglomerative hierarchical clustering is performed, i.e., the two trajectories or trajectory groups i, j with smallest $d(i,j)$ as defined in (1) are continuously merged until there is no $d(i,j) < 0$. In addition, in order to prevent model overfitting given few training samples, we update the clustering results at each merging step. In other words, once a new HMM is trained after trajectory merging, all the trajectories in the database are reclassified. It is possible that some incorrectly clustered trajectories of previous steps are associated to the new HMM. All the HMMs are then retrained based on the updated trajectory clusters. We refer to this process as dynamic hierarchical clustering (DHC), which is summarized below:

1. *Initialization:* each trajectory in the dataset forms a group and is fitted with an HMM. There are N groups with N HMMs;
2. *Dissimilarity Measurement:* calculate the dissimilarity $d(i,j)$ for every two groups i and j in the dataset by the measure in (1);
3. *Merging:* the two groups $\hat{i}$ and $\hat{j}$ with smallest $d(\hat{i},\hat{j})$ ($d(\hat{i},\hat{j}) < 0$) are merged; if there is no $d(i,j) < 0$, the clustering terminates;
4. *Reclassification:* a new HMM $\theta_{\hat{i}\hat{j}}$ is trained, replacing $\theta_{\hat{i}}$ and $\theta_{\hat{j}}$; then based on the $(N-1)$ HMMs, all trajectories are reclassified into $(N-1)$ groups by the maximum likelihood (ML) criterion;
5. *Retraining:* $(N-1)$ HMMs are retrained based on the updated $(N-1)$ data groups, respectively;
6. *Update:* $N = N - 1$; go back to step 2.

In the following we briefly describe the process for identifying anomalous trajectories, which is thoroughly presented in [2]. Let us suppose that all trajectories are clustered into C groups with C corresponding HMMs. As mentioned in Sec. 1, some methods utilize the number of trajectories in each group to identify normal from anomalous groups. In contrast, we propose a method to identify anomalies under a probabilistic framework, which utilizes the prior probability of each group to categorize it.

At the reclassfication step in the DHC algorithm (step 3), the likelihood of each trajectory being generated from every HMM, i.e., $L_c^i = P(i \,|\, \theta_c)$, is calculated, where $i = 1, 2, \cdots, N$ denotes any trajectory in the dataset and θ_c ($c = 1, 2, \cdots, C$) the trained HMMs. In other words, each trajectory i has probability L_c^i of being generated by model θ_c. Hence, we may consider each trajectory as being generated by a mixture model, with each component being one of the C HMMs, i.e.,

$$P(i) = \sum_{c=1}^{C} \Big[\pi(c) \cdot L_c^i \Big], \quad (2)$$

where $\pi(c)$ is the prior probability of the HMM component c, which can be estimated by the EM iteration. Initially, we assume equal prior probabilities, i.e., $\pi(c) = 1/C$. In the E-step, the posterior probability of component c given trajectory i is estimated by Bayes' rule,

$$P(c \,|\, i) = \frac{\pi(c) \cdot L_c^i}{\sum_{r=1}^{C} \Big[\pi(r) \cdot L_r^i \Big]}. \quad (3)$$

In the M-step, the prior probability of each component can be computed by averaging $P(c \,|\, i)$ for all trajectories, i.e.,

$$\pi(c) = \frac{1}{N} \sum_{i=1}^{N} P(c \,|\, i). \quad (4)$$

These updated $\pi(c)$ are substituted into (3) for another round of iterations. The iteration continues until $\pi(c)$ converges.

Based on the mixture model calculated above, groups of normal events can be determined as those with high $\pi(c)$ (e.g., above average). Other groups are determined as anomalies.

3. EXPERIMENTAL RESULTS

The proposed method was tested with vehicle trajectories extracted from a real highway traffic video scene. The videos are from a large database of traffic videos from NGSIM (http://ngsim.camsys.com/) recorded by cameras located on top of highways. All trajectories of vehicles are provided by this database. For our experiments we have used 1000 trajectories from the scene shown in Fig. 1. In this highway section,

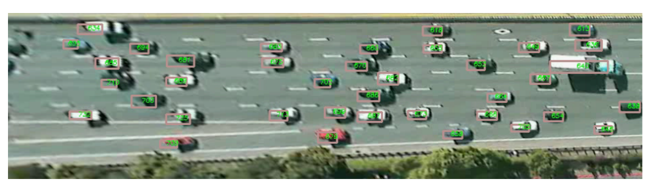


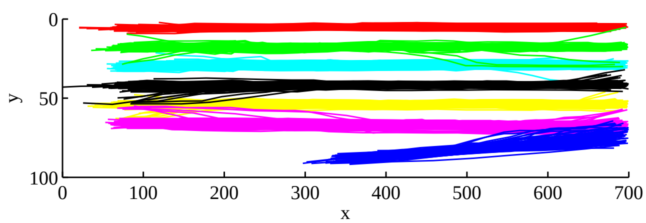
Fig. 1. Video scene of an analyzed traffic video

there are 6 traffic lanes and 1 merging lane. All vehicles travel from left to right. The objective is to analyze all trajectories and detect those that are anomalous and may cause problems to normal traffic, without any prior knowledge of the traffic pattern of this scene. The available trajectory features include 2-D position, instantaneous speed, and acceleration. We emphasize that our method can be used with feature sequences of any dimension. To that effect we present our results sequentially as we incorporate more features. Detection results were validated visually by taking into account the rules of the road.

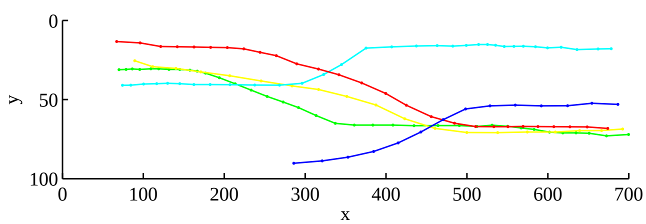
We should note that identification of disruptive events (excluding accidents) in highway video is difficult even for an experienced observer who is aware of driving regulations. It is rather cumbersome to identify a speeding car without knowing its average speed (attainable through the extraction of its trajectory). By visual inspection only, human observers actually rely on the speed of neighboring cars to identify whether one car is speeding or not. However, without proper speed measurements and knowledge of the speed limit, a decision is still impossible. It is evident that automated quantification algorithms are necessary to mine all available information and identify events that are disruptive to traffic.

3.1. Positional anomalies

When only the 2-D position features were used in trajectory clustering, we ended up with 7 clusters of normal events, corresponding to 7 lanes, respectively, as shown in Fig. 2(a) in different colors. When only spatial features are concerned,



(a) 7 clusters of normal trajectories



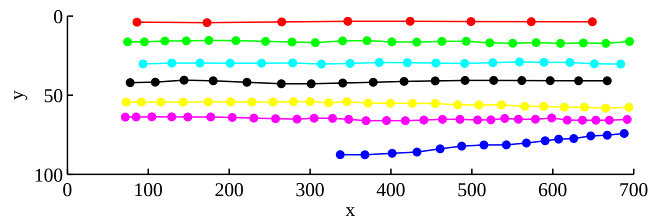
(b) Examples of abrupt lane changers

Fig. 2. Results of trajectory analysis based on 2-D positions

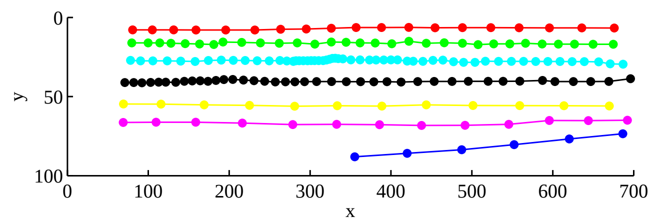
as most of the vehicles are moving along their own lanes or only change lanes slightly in the given section, the normal events are automatically detected in our method as lane followers [12]. Only a few vehicles change lanes abruptly and they are detected as anomalous events (some examples are shown in Fig. 2(b).) These anomalies may not be necessarily disruptive or in violation of the rules of the road (lane changes are allowed).

3.2. Speed anomalies

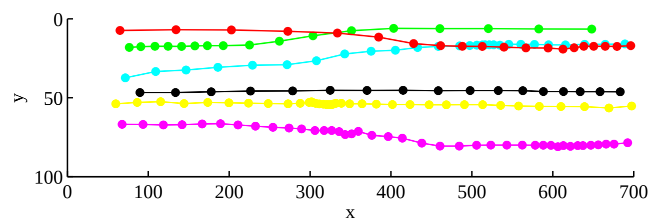
Speed is an important parameter of safe driving. Thus in the second experiment, we have incorporated instantaneous speed in the feature vector. Based on clustering of the 3-D feature sequences, more anomalous trajectories are detected. In addition to the lane changers detected before, we have detected many speed-related anomalies. These are trajectories with different speed than most of the trajectories in the same lane. Fig. 3(a) shows examples of normal velocities. For each lane,



(a) Examples of normal velocities for each lane



(b) Examples of speed anomalies



(c) Examples of acceleration anomalies

Fig. 3. Results of trajectory analysis incorporating dynamics

one trajectory that has the most similar speed to the average speed of the normal cluster is shown. By observing the spacing between the markers, we can see that the lanes close to the left side of the highway have higher speed (few points), while the lanes on the right have lower speed (more points).

Fig. 3(b) shows examples of speed anomalies that are detected in this experiment. It was expected that trajectories on the left with lower speed and trajectories on the right with higher speed were determined as anomalies. This is very useful because those traveling with different speed compared to the normal lane speed are possible causes of traffic congestion and accidents [13].

3.3. Acceleration anomalies

Speed fluctuation of vehicles is also an important concern of highway traffic. According to [3], abrupt speed changes can cause shock waves to form in the traffic stream, rippling backwards and causing more vehicles to slow down. Therefore, we have performed experiments by adding the instantaneous acceleration of a vehicle as part of our feature vector. A different type of anomalous trajectories is detected based on clustering of the 4-D feature sequences. These correspond to acceleration anomalies, examples of which are shown in Fig. 3(c). These trajectories have obvious speed changes during the length of the observation.

4. CONCLUSION

The goal of this work is to process trajectory data offline, with the scope of identifying anomalous events. We adopt our dynamic hierarchical clustering (DHC) method [1, 2] to the scenario of highway traffic anomaly detection. In our framework anomalies are determined by their prior probabilities, instead of checking group size (as was previously done). We have shown that both instantaneous speed and acceleration increase our capability of discerning abnormal driver behavior. Overall, speed and positional fluctuations detected by our algorithm, form a pattern of lane-change maneuvers that may cause disruptions to traffic flow (for example wave propagations [13]) and may increase the occurrence of accidents and cause congestion.

However, it remains unanswered as to whether an anomaly was caused as a reaction to an anomaly that occurred in the vicinity of the vehicle. Therefore, we plan to include vehicle interaction into the problem formulation. In doing so, the feature vector needs to be augmented with elements determining the interaction with other vehicles (e.g., the distance from and the relative speed with respect to neighboring vehicles). We will also consider some contextual features, e.g., the average speed and density of vehicles in a given time window. By detecting anomalous trajectories we can now analyze the data and determine the correlation of anomalies in different time windows. We will be able to infer if the occurrence of an anomaly creates a disruption in subsequent traffic, e.g., the reduction of the average speed of subsequent vehicles, the increase of occurrence of abnormal events, and congestion build up.

5. REFERENCES

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