Trajectory Analysis of Moving Objects at Intersection Based on Laser-Data

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Abstract— **The study of traffic behavior at intersections is an important research direction in the field of intelligent transportation system (ITS). It is considered very practical to reduce accident, solve traffic jam and improve its accessibility. This paper proposed a trajectory analysis method for vehicles passing an intersection. The motion trajectories of vehicles were obtained by a traffic data collecting system using a network of single-row laser scanners. The intersection could be described by a group of route models which are built based on trajectory clustering, so large amount of trajectories could be classified to different routes and abnormal ones could also be detected. Experimental results based on real trajectories obtained from an intersection in Beijing show the validity of our proposed method.**

I. INTRODUCTION

Analyzing or monitoring traffic behavior at an intersection, such as collecting the traffic speed data, motion trajectory and counts for different kinds of traffic objects (i.e., car, bicycle and pedestrian), is very important in order to reduce accidents, solve traffic jams, and improve accessibility. There have been many researches on moving object detection and tracking of traffic scenes. Most of them study visual-based methods to acquire the motion trajectories of cars and pedestrians[1][2][3][4]. Latest research developments appear using laser scanners or fusion of multi-modal sensors for the purpose[18][19][20][21]. It has been demonstrated that large amount of motion trajectories can be obtained automatically, fostering researches on trajectory analysis to study traffic behaviors of the scene, such as collecting traffic statistics, predicting for future status, extracting scene semantics, detecting normal/abnormal motion patterns, etc.

Trajectory analysis seeks to provide a higher-level situational awareness by understanding and characterizing the behavior of every object in the scene owe to the rich information contained in objects motion. Junejo et al. [16] proposed a method for detecting nonconforming trajectories of objects which used Hausdorff distance as the pair-wise similarities between trajectories. Suzuki et al. [5], proposed a method to learn motion patterns and detect anomalies by human trajectory analysis which applied HMM to modeling of trajectories. Stefan Atev et al. [9], used spectral clustering to learn traffic patterns at intersections from trajectories of vehicles obtained by a vision tracking system. Wang et al.

[6], used nonparametric Bayesian model, Dual-HDP, for trajectory analysis and semantic region modeling in surveillance settings, in an unsupervised way. Zhang et al. [10], proposed a framework to learn semantic scene models by trajectory clustering which could be applied at intersections. Johnson et al. [17] presented a vector quantization based approach for learning typical trajectories of pedestrians in the scene, but they require entry/exit points to be marked manually. D. Makris and T. Ellis proposed a scene model that labels regions according to an identifiable activity in each region, such as entry/exit zones, junctions, paths and stop zones by trajectory learning in [14]. Hu et al. [7], presented a system for learning object motion patterns which are then used to detect anomalies and predict behaviors. B.T. Morris et al. [15] proposed a general framework for live video analysis which build a topographical scene description where nodes are points of interest (POI) learned as a mixture of Gaussians and the edges correspond to activity paths (AP) by clustering trajectories. They also summarized the techniques used in trajectory-based activity analysis for visual surveillance in [8] .

This research is based on a previous development[11] of a system for monitoring an intersection using a network of single-row laser scanners, which are set on road side to profile an intersection horizontally from different viewpoints. Different laser scanners data are integrated into a common spatial-temporal coordinate system and processed. Thus, the moving objects entered intersection are detected and tracked, for more, their trajectories are also extracted, which contains location, size, speed, direction, etc. dynamic/static parameters at each time instance. Compared to vision-based systems, laser-based system has long range and smaller data size which could collect trajectories in a long term and a large area. Based on such featured trajectories obtained by laser-tracking system, this research studies vehicle behavior at an intersection. Considering that normal vehicle motions at an intersection commonness, which can be modeled by extracting their spatial-temporal statistical characteristics, while abnormal behaviors do not obey any explicit rule, a method of route model generation on normal behaviors as well as a motion pattern classification to discriminate normal and abnormal behaviors is developed. Three subsequent procedures exist in our framework. They are trajectory clustering, route modeling and motion patterns classification. Given a set of trajectories, the trajectory clustering step is to cluster them into a number of groups on a certain distance measure, so that statistics of commonness are then extracted from each group of trajectories to generate an abstract representation,

i.e. route model.

This paper is organized as follows. In section 2, we described our method for trajectory analysis. Experiment and results are discussed in section 3, followed by conclusions and future topics in section 4.

II. METHODS

A motion trajectory is represented as a sequence of dynamic measurements

$$T_k = \{f_k^1, f_k^2, ..., f_k^{L_k}\} \tag{1}$$

where

$$f_k^t = [x_k^t, y_k^t, v_{x,k}^t, v_{y,k}^t]^T \tag{2}$$

is a measurement of the moving object k at time t, (x_k^t, y_k^t) and $(v_{x,k}^t, v_{y,k}^t)$ are its location and velocity. Given a set of trajectories $\{T_k\}$, this research is to learn a set of route models $\{\Gamma_j\}$ that representing the major motion patterns of the dynamic scene, and to generate a classifier that recognizing normal and abnormal behaviors.

A preprocessing step is needed for two purposes. Firstly, remove fragments from original tracks by setting appropriate thresholds on time-space domain. Secondly, smooth trajectories which have short-lived skewing due to the occlusion between multiple targets.

A. Trajectory Clustering

Given a set of trajectories $\{T_k\}$, the trajectory clustering step is to cluster them into a number of groups on a certain distance measure. Trajectories in each group have a same motion pattern owing to their spatial statistical characteristics.

It is common that the lengths of trajectories are different because of their time-varying feature, so steps must be taken to ensure a appropriate comparison between differing sized inputs. Considering the area of the intersection, all trajectories are resampled at larger time intervals(once Δt frames) and each trajectory is linearly interpolated with points to ensure that all trajectories have the same number L of points. Then we take a distance measure (similar with [12]) that does not depend on having the entire trajectory for computation. Assuming trajectories T_a and T_b, have equal number L of points,

$$d(T_a, T_b) = \frac{1}{L} \sum_{i=1}^{L} d_E(f_a^i, T_b) \tag{3}$$

where

$$d_E(f_a^i, T_b) = \min_j (d_E(f_a^i, f_b^j))$$
$$j \in \{\lfloor (1-\delta)i \rfloor ... \lceil (1+\delta)i \rceil\} \tag{4}$$

$d_E(f_a^i, f_b^j)$ is the Euclidean distance to compare two equal length frame vectors and f_b^j is the best match frame to f_a^i in a sliding temporal windows of length 2δ centered on i, as shown in Fig.1. This defines a distance measure that is the mean of normalized distances from every point to its best match point.
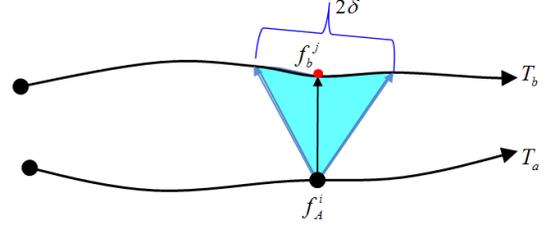
Fig. 1.   an illustration of distance between two matched frames

Once trajectories have been properly preprocessed, they can be clustered into several groups by iteration steps as follows:

1) choose the longest trajectory from unlabeled trajectories, as a new initial cluster center C_j. If all of them are labeled, end the clustering;
2) calculate the distance between C_j and every unlabeled trajectory T_i. If the distance is smaller than threshold, label T_i with j;
3) calculate the average of all trajectories labeled with j to update cluster center C_j;
4) return to (2) to recalculate, if no new trajectory added, return to (1).

B. Route Modeling

After the spatial-based clustering, all trajectories are clustered into N groups:

$$cls = \{\{T_{1,1}, ..., T_{1,M_1}\}, ...,$$
$$\{T_{j,1}, ..., T_{j,M_j}\}, ..., \{T_{N,1}, ..., T_{N,M_N}\}\}, \tag{5}$$

where M_j denotes the number of trajectories in the jth cluster. The route modeling step is to learn a set of route models $\{\Gamma_j\}$ as an abstract representation of the statistics of commonness extracted from each group of trajectories.

Not relying on lane structure or geometry, the model we propose is depicted in Fig.2(a). Given a route model Γ_j, it consists of a sequence of equidistant nodes $\{\phi_j^i\}$, where each node ϕ_j^i is characterized by:

- centroid: a 2-D position point $\mu_j^i = [x_j^i, y_j^i]$, which is part of the main axis;
- normal vector: $\vec{\nu}_j^i = [nx_j^i, ny_j^i]$ defined as the unit vector perpendicular to the local route direction, as defined by the sequence of the nodes;
- envelope range: σ_j^i defined as the width of route around the node position.

Therefore, the route model Γ_j can be represented by a group of nodes

$$\{\phi_j^i = (\mu_j^i, \vec{\nu}_j^i, \sigma_j^i) | i = 1, 2, ..., n_j\}, \tag{6}$$

where n_j is the number of nodes in Γ_j. It's easy to see that the spatial distribution density of trajectories in a route looks like a ridge shape in most cases, so there could be further assumption that trajectories position obey Gaussian distribution around every cross-section of the route, as shown

(a) The route model description

(b) The Gaussian distribution assumption
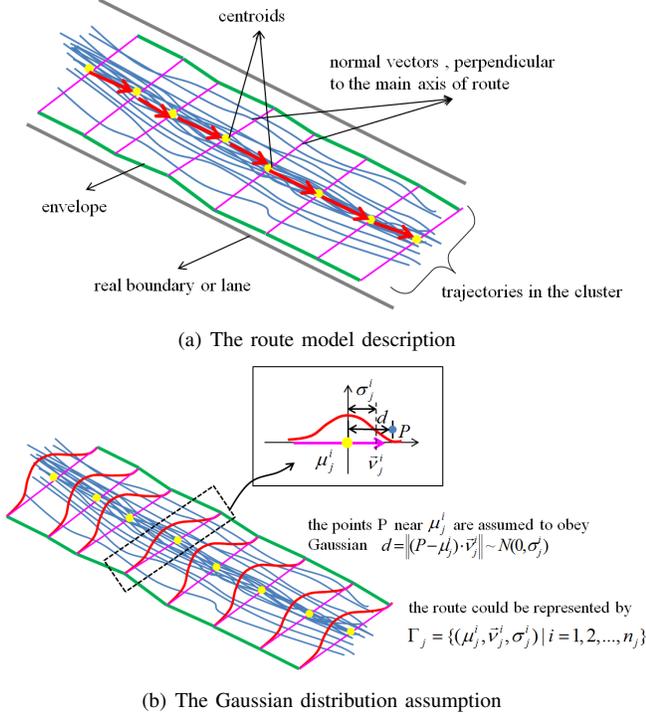
Fig. 2. Definition of the route model

Fig. 3. The procedure of route modeling

in Fig.2 (b). Given a cluster center C_j and corresponding group of trajectories

$$cls_j = \{T_{j,1}, ..., T_{j,M_j}\}, \qquad (7)$$

we propose the route modeling algorithm summarized as follows:

1) centroids $\{\mu_j^i | i = 1, 2, ..., n_j\}$
   Resample the cluster center C_j at spatial distance r_j to get n_j nodes, as shown in Fig.3(a). Then compute the average of all trajectories points in a neighbourhood zone of each node to get n_j new points as the centroids $\{\mu_j^i | i = 1, 2, ..., n_j\}$, as shown in Fig.3(b).

2) normal vectors $\{\vec{\nu}_j^i | i = 1, 2, ..., n_j\}$
   Compute the tangent line of each centroid μ_j^i by curve fitting the entire sequence, and then get the normal vector $\vec{\nu}_j^i$, as shown in Fig.3(c).

3) envelope ranges $\{\sigma_j^i | i = 1, 2, ..., n_j\}$
   To every trajectory point P in the neighbourhood zone of μ_j^i, compute the projection distance d between P and μ_j^i on axis $\vec{\nu}_j^i$. According to our assumption, the projections obey Gaussian

$$d = \left\| (P - \mu_j^i) \cdot \vec{\nu}_j^i \right\| \sim N(0, \sigma_j^i), \qquad (8)$$

so the envelope range σ_j^i could be represented by the variance, as shown in Fig.3(d).

C. Behavior Classification and Abnormal Detection

Once a route model Γ_j has been constructed, it is represented by a group of nodes

$$\{\phi_j^i = (\mu_j^i, \vec{\nu}_j^i, \sigma_j^i) | i = 1, 2, ..., n_j\}.$$

The classification step is to discriminate normal and abnormal behaviors as well as new trajectories can be placed into the appropriate route with probabilistically Bayesian inferencing.

In this research, we use joint probability distribution

$$P(T_k, \Gamma_j) = P(T_k|\Gamma_j)P(\Gamma_j) \qquad (9)$$

to describe the likelihood that a trajectory T_k belongs to the route Γ_j. The prior route distribution $P(\Gamma_j)$ can be estimated from the cluster density or frequency in the training trajectories set. Assuming the length of T_k is L_k, we define

$$P(T_k|\Gamma_j) = \prod_{p=1}^{L_k} P(f_k^p|\Gamma_j) = \prod_{p=1}^{L_k} P(f_k^p|\phi_j^{i'}) \qquad (10)$$

where f_k^p represents the Pth frame of T_k, and $\phi_j^{i'} = (\mu_j^{i'}, \vec{\nu}_j^{i'}, \sigma_j^{i'})$ is a new node estimated using linear interpolation of two nearest nodes to f_k^p. As shown in Fig.4, we can still assume that the projection distance d from $\mu_j^{i'}$ to f_k^p also obey Gaussian distribution. Therefore, Gaussian probability density is used to describe $P(f_k^p|\phi_j^{i'})$ as

$$P(f_k^p|\phi_j^{i'}) = \frac{1}{\sqrt{2\pi}\sigma_j^{i'}} e^{-d^2 / 2\sigma_j^{i'2}} \qquad (11)$$

Through the modeling procedure, we have got n normal routes $\{\Gamma_1, \Gamma_2, ..., \Gamma_n\}$, representing n kinds of typical motion patterns of vehicles at intersection. Besides, there is another motion pattern contains a few kinds of special behaviors like disobeying traffic rules, called abnormal route Γ_a. The route type of a novel trajectory is described by finding the maximum a posteriori route

$$\begin{aligned} \Gamma_* &= \arg\max_i P(\Gamma_i|T_*) \\ &= \arg\max_i P(T_*|\Gamma_i)P(\Gamma_i) \end{aligned} \qquad (12)$$
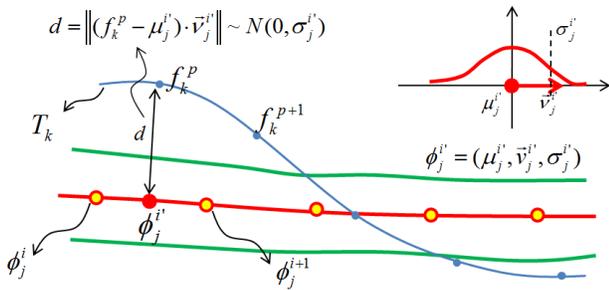
Fig. 4. An illustration of distance between a route centroid and a trajectory frame

Fig. 5. A screen copy of the tracking result

This determines which route best matches the new datum. For those normal routes, the likelihood $P(T_*|\Gamma_i)$ of route Γ_i could be calculated according our previous definition. For route Γ_a, $P(\Gamma_a)$ could be set a value manually, for example, we assume that the ratio of abnormal behaviors is less than 5%. But $P(T_*|\Gamma_a)$ could not be computed by route model parameters directly. Since normal routes denote typical motions, if a new trajectory does not belong to any normal routes, it can be considered an abnormality. According to this, we define the likelihood of route Γ_a as

$$P(T_*|\Gamma_a) = \prod_{i=1}^{n} f(P(T_*|\Gamma_i)) \qquad (13)$$
$$\{if \ x < \varepsilon, \ f(x) = 1 \ else \ f(x) = 0\}$$

The threshold $\varepsilon \in [0,1]$ controls the abnormality rate. Larger ε will cause more trajectories to be considered anomalous.

III. EXPERIMENTAL RESULTS

To test the validity of the proposed approach, an experiment was conducted to collect moving objects trajectories at an intersection near Peking University, as shown in Fig.5. We choose vehicle trajectories in twenty minutes for training and then 1295 complete trajectories are picked out by pre-processing to remove outliers. The clustering result base on trajectory position and moving direction is shown in Fig.6. According to their motion patterns, these trajectories are divided into 9 groups, including 4 straight, 2 left turn, 2 right turn and 1 U-turn.

As mentioned in Section 2.2, each trajectory cluster represents a typical route through which vehicles pass the intersection. The route model is shown in Fig.7, different color represents different route. The color's change (deeper to lighter) of each route denotes the moving direction of vehicle in the route which looks like a ridge and its cross-section obey Gaussian distribution.

Based on the route model, novel trajectories could be classified to different routes. We set the prior abnormal route distribution $P(\Gamma_a)$ to 0.05 and normal likelihood threshold ε to 0.003. Fig.8 shows 4 different trajectories classification results, in Example 1, the trajectory to be classified (white color) is a normal one which has a probability of 0.9948 to
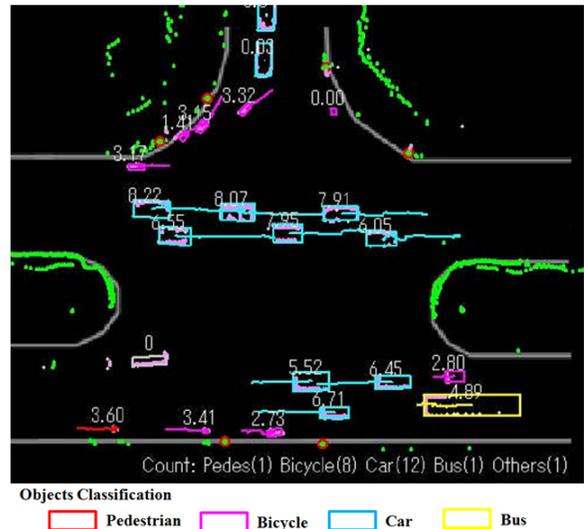
belong to a deeper blue route, the red route is 0.0052, and the other normal routes and abnormal behavior are both 0 (the color of number is corresponding to the route's color, white number means the probability of abnormal behavior). In the other 3 examples, the white trajectories are all detected as abnormal behaviors because they don't belong to any normal routes. To prove the detection results is correct or not, we could check the entire tracking procedure of a vehicle passing the intersection through playback of the raw laser data.

As shown in Fig.9, during the playback of Example 2, a vehicle appeared in the entrance of a left-turn route (deeper blue) in frame 11241. Only a part of body was detected due to the occlusion so it seemed to be a small car waiting to turn left. But indeed the vehicle kept moving straightly as well as we know it was a bus in frame 11392 and then it passed the intersection. Therefore, this trajectory is real abnormal behavior because of driving in wrong lane. Similarly, as shown in Fig.10, in Example 3, a car was running in the bicycle lane when it entered the intersection (frame 12765), then it tended to turn left to enter the motor way in frame 13215 and succeeded in frame 13965. This is also real abnormal behavior as the same reason. However, in Example 4, shown in Fig.11, the moving object was an electric bicycle actually and entered the intersection from a bicycle lane, but there was another electric bicycle which runs parallel with the first one. Then they were merged to be one target in frame 3704 which was classified to be a vehicle when the trajectory was output by the system. This is an error occurred during the tracking procedure, so it is false abnormal detection in our results.

IV. CONCLUSIONS AND FUTURE WORKS

A. Conclusions

In this research, we propose a trajectory analysis method for vehicles passing an intersection. The motion trajectories of vehicles are obtained by a traffic data collecting system
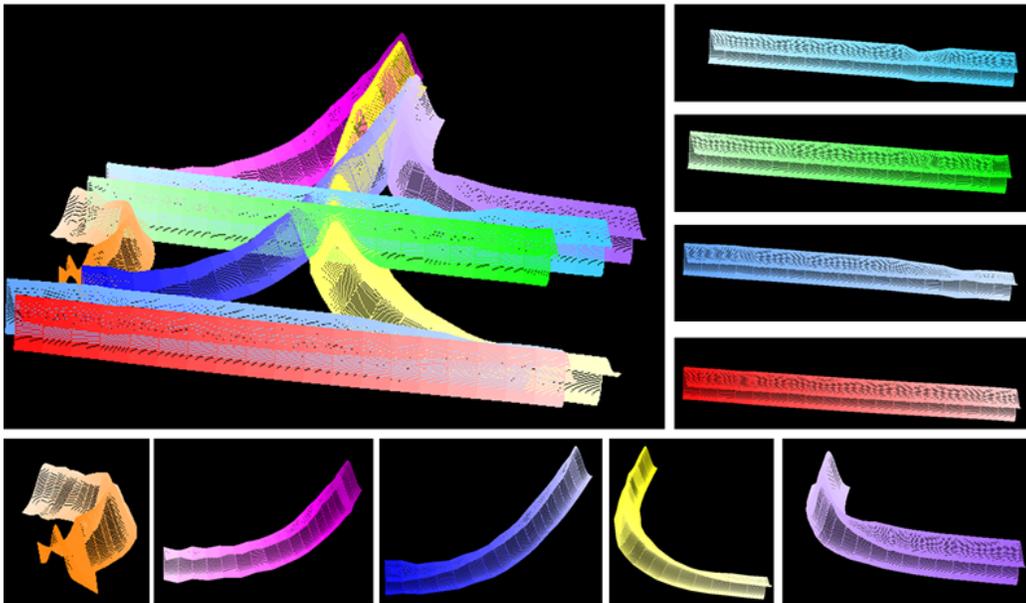
Fig. 7.   Vehicle route model at the intersection
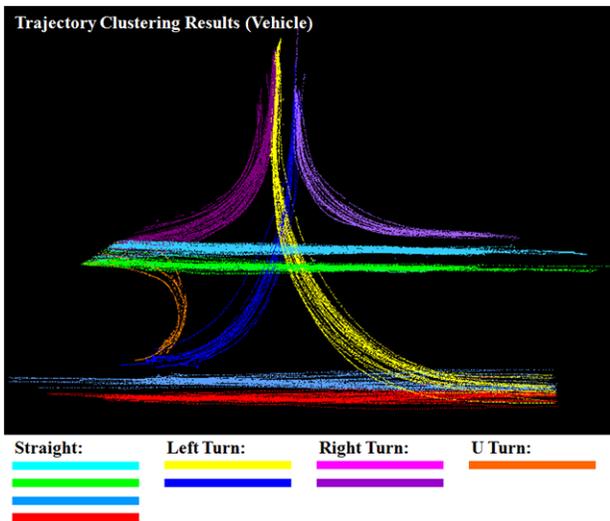
Fig. 6.   The clustering result of vehicle trajectories

(a) Ex.1: Normal Trajectory

(b) Ex.2: Abnormal Trajectory

(c) Ex.3: Abnormal Trajectory

(d) Ex.4: Abnormal Trajectory

Fig. 8.   Examples of behavior classification and abnormal detection

using a network of single-row laser scanners to detect and track moving objects at intersection. The typical motion patterns of vehicles are generated by trajectory clustering using a modified Euclidian distance as the pair-wise similarities between trajectories. Then route models based on a sequence of Gaussians are built by these motions patterns. Probabilistically Bayesian inferencing is used for behavior classification and abnormal detection. Those vehicles passing the intersection in a normal way could be classified into different routes, and a few special ones could also be detected as abnormal behaviors. In our experimental results, we have shown examples of real abnormal behavior (driving in wrong lane) detected by our system. We also analyzed a false detection result caused by tracking mistake.

B. Future Works

Under the current research, only the spatial information of trajectories is used for analysis. Actually, the intersection is a highly time-share traffic scene for multiple kinds of moving objects. Therefore, we plan to use the temporal information of trajectories to further extend our framework which would be able to distinguish not only between objects traversing spatially dissimilar but also objects traversing spatially proximal paths but having different spatio-temporal characteristics.

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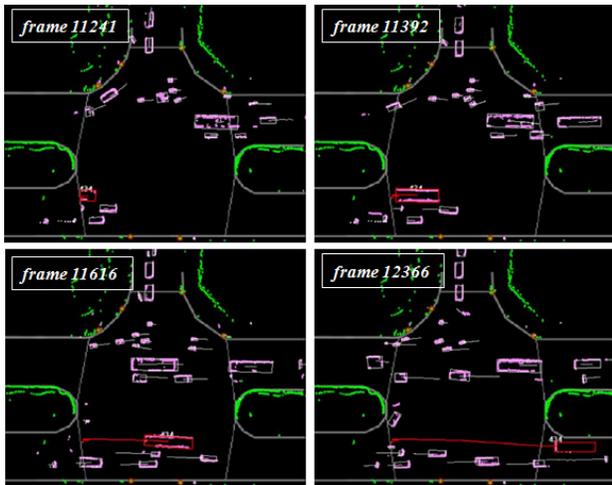
(a) Example 2: real abnormal behavior
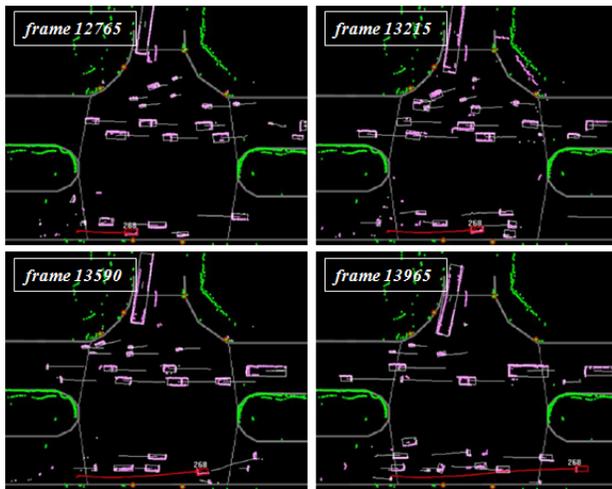
(b) Example 3: real abnormal behavior
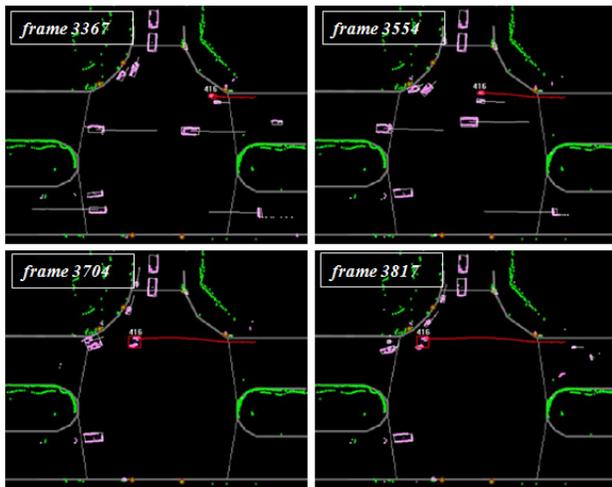
(c) Example 4: false abnormal behavior

Fig. 9. Playback of three abnormal trajectories

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