iTV: Inferring Traffic Violation-Prone Locations with Vehicle Trajectory and Road Environment Data

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Abstract—Traffic violations like illegal parking, illegal turning, and speeding have become one of the greatest challenges in urban transportation systems, bringing potential risks of traffic congestions, vehicle accidents, and parking difficulties. To maximize the utility and effectiveness of the traffic enforcement strategies aiming at reducing traffic violations, it is essential for urban authorities to infer the traffic violation-prone locations in the city. Therefore, we propose a low-cost, comprehensive, and dynamic framework to infer traffic violation-prone locations in cities based on the large-scale vehicle trajectory data and road environment data. Firstly, we normalize the trajectory data by map-matching algorithms and extract turning behaviors, parking behaviors, and average speeds of vehicles. Second, we restore spatiotemporal contexts of driving behaviors to get corresponding traffic restrictions such as no parking, no turning, and speed restrictions. After matching the traffic restrictions with driving behaviors, we get the traffic violation distribution. Finally, we extract the spatiotemporal patterns of traffic violations to infer traffic violation-prone locations in cities and build an inference system. To evaluate the proposed framework, we conduct extensive studies on large-scale, real-world vehicle GPS trajectories collected from two cities located in the east and west of China, respectively. Evaluation results confirm that the proposed framework can infer traffic violation-prone locations in cities effectively and efficiently.

Index Terms—traffic violation, vehicle trajectory data, traffic sign detection, map-matching.

I. INTRODUCTION

Traffic violations, such as speeding and illegal parking, have become one of the greatest challenges in urban transportation systems, bringing potential risks of traffic congestions, vehicle accidents, and parking difficulties, etc. [1], [2], [3]. For example, in 2018, New York City witnessed 54,469 traffic violations and 44,508 traffic injuries across the city [4]. To reduce traffic violations, urban authorities have implemented various traffic enforcement strategies, such as deploying field enforcement officers in rush hours and installing automated monitoring cameras in road intersections [5]. Given the expensive human resource allocation and infrastructure investment, it is essential for urban authorities to identify the traffic violation-prone locations in the city so that they can maximize the utility and effectiveness of the traffic enforcement strategies.

Fortunately, with the popularization of GPS devices and map services like street view service, we can get large-scale vehicle trajectory data in cities, real panoramic street view pictures on roads, and related traffic restrictions such as speed restrictions. These rich trajectory data and road environment data provide us an unprecedented opportunity to explore traffic violation-prone locations.

In this work, we propose a low-cost, comprehensive and dynamic framework for inferring the traffic violation-prone locations in cities based on the large-scale vehicle trajectory data and road environment data fusion, so that we can provide some insights for the traffic management department about traffic violation-prone locations to help optimize the utility and effectiveness of the traffic enforcement strategies.

Firstly, we normalize the trajectory data by mapping the vehicle trajectories onto the road network and get the driving behaviors. Secondly, we model driver perspectives to match driving behaviors to corresponding road segments and get the spatiotemporal contexts of driving behaviors. Using the spatiotemporal context, we detect traffic signs to identify no-turning road intersections and no-parking road segments. We can also get speed restrictions on roads from real-time navigation service providers. After matching the traffic restriction information with driving behaviors, we extract three types of traffic violations, i.e., illegal turning, illegal parking and speeding, and extract the spatiotemporal patterns of traffic violations to infer the traffic violation-prone locations. Finally, we build a traffic violation-prone locations inference system and evaluate our framework using large-scale, real-world datasets from two cities in China, Chengdu and Xiamen.

In designing the framework, there are several research issues to be addressed:

1) It is not trivial to extract turning behaviors from vehicle

![Fig. 1: Some misunderstanding examples of turning behaviors. (a) A vehicle trajectory. (b) A sparse trajectory. (c) A dense trajectory.](image-url)


GPS trace data. When only trajectory data is used, it is easy to misunderstand some driving behaviors. For example, as shown in Fig. [1a] if we observe the trajectory separately, we may consider that it is a turning behavior in an intersection. However, if we locate the trajectory into the corresponding road network, we can find that it is not a turning behavior since it is caused by the curvy road rather than the driver’s decision in the intersection. Moreover, some sparse GPS points will also mislead us. As shown in Fig. [1b] the trajectory $P_1 \rightarrow P_2 \rightarrow P_3$ implies us a straight line, while it should be $S_1 \rightarrow S_2 \rightarrow S_3$ actually when combined with the road network. Here, two turning behaviors can be extracted. Besides, if the GPS points are dense and the driver prefers changing lanes while driving, there will be several curves on the trajectory, as shown in the circled parts in Fig. [1c] Then those curves will be mistaken for turning behaviors. Therefore, to extract turning behaviors accurately, we should take both GPS trajectories and road networks into consideration.

2) It is difficult to restore the spatiotemporal contexts of driving behaviors. To identify whether a driving behavior is illegal or not, we need to restore the spatiotemporal context of driving behavior. For example, a driver makes an impermissible left turn in the intersection with a no-left-turn sign located in the driver’s previous perspective; thus, this behavior can be identified as a traffic violation. However, with only vehicle GPS trajectories, it is difficult to get traffic restriction information for road segments where the trajectories are. Fortunately, the development of various map services enables us to get panoramic pictures of the surrounding environment of almost all streets in the city and real-time navigation service can offer us speed restriction information while driving. Those services enable us to restore spatiotemporal contexts of driving behaviors.

In summary, the main contributions of this paper include:

1) To the best of our knowledge, this is the first work using vehicle trajectory and road environment data to extract traffic violations and infer traffic violation-prone locations in cities.

2) We proposed a low-cost, dynamic, comprehensive, data-driven method to identify traffic violation-prone locations. Firstly, we normalize the GPS trajectories with map-matching methods and get the driving behavior distribution. Secondly, we model driver perspectives based on regression to augment the spatiotemporal contexts of driving behaviors. Thirdly, we extract three types of traffic restrictions from those contexts, i.e., no-parking, no-turning, and speed restrictions. After matching those restrictions with driving behaviors, we get the traffic violation distribution and extract the spatiotemporal features of traffic violations. Finally, we build the traffic violation-prone location inference system.

3) We evaluate our framework using large-scale, real-world datasets from two cities in China, i.e., Chengdu and Xiamen, including vehicle GPS trajectories, street view pictures, and speed restrictions. The experimental results are visualized in a traffic violation-prone location inference system.

II. RELATED WORK

A. GPS Trajectory Mining

In the literature, there have been many studies on mining various kinds of GPS trajectories for different application scenarios. In a study on human mobility, Zheng et al. [6] proposed a framework to mine interesting locations and travel sequences from human GPS trajectories, while Alves et al. [7] proposed a model to enrich human GPS trajectories with semantic geographical meanings. On taxi operation study, Zhang et al. [8] detected anomalous passenger delivery trips from taxi GPS traces, Chen et al. [9] explored citywide night bus planning issues leveraging taxi GPS traces, and Zhang et al. [10] identified taxi refueling behaviors from GPS trajectories to estimate citywide petrol consumption and analyze gas station efficiency. Chen et al. [11] proposed a framework for container port performance measurement and comparison using ship GPS traces. As for driving violation identification, He et al. [12] proposed a framework to detect illegal parking events using shared bikes’ trajectories. Lee et al. [13] proposed a disclosed method of traffic control, which can detect and identify the vehicle speeding. In this work, the GPS trajectory data is one of the major resources, on which we can infer the traffic violation-prone locations.

B. Traffic Sign Detection

Traffic sign detection has been widely studied in the field of computer vision. Escalera et al. [15] used color thresholding and shape analysis to detect the signs in the picture and classified signs with a neural network. Bahllmann et al. [16] detected the signs using a set of Haar wavelet features obtained from AdaBoost training and classified signs using Bayesian generative modeling. Mogelmose et al. [17] provided a survey of the traffic sign detection literature, detailing detection systems for traffic sign detection for driver assistance. Houben et al. [18] introduced a real-world benchmark data set from Germany for traffic sign detection and compared several detection approaches. In recent years, deep learning methods have shown superior performance for many tasks, such as object detection. Zhu et al. [19] proposed a framework of traffic sign detection and detection based on proposals by the guidance of a fully convolutional network. Zhu et al. [20] provided 100000 pictures containing 30000 traffic-sign instances and demonstrated how a robust end-to-end convolutional neural network (CNN) could simultaneously detect and classify traffic signs. Luo et al. [21] proposed a data-driven system to detect all categories of traffic signs, which include both symbol-based and text-based signs, in video sequences captured by a camera mounted on a car. Huang et al. [22] introduced GAN into the Faster-RCNN framework and improved the performance of small object detection compared to Faster-RCNN. Yolov3 [23]
is a well-known state-of-art object detection system, which has achieved great performance both in accuracy and time. It has made great progress in small object detection and has strong generalization ability. In this work, we choose YOLOv3 as the backbone network to train the traffic sign detection model.

C. Map-Matching

Map matching is the procedure for mapping a vehicle’s trajectory onto the correct road segments, which plays an important role in in-vehicle navigation systems, routing engines, etc. [24]. Ren et al. [25] introduced the GPS-based wheelchair navigation based on a novel map-matching algorithm. Bernstein et al. [26] introduced the personal navigation assistants based on the map matching method. He et al. [12] used the map-matching method to detect illegal parking events. White et al. introduced some map-matching algorithms for personal navigation assistant [27]. Chen et al. [28] proposed an online map-matching-based trajectory compression framework running under the mobile environment. Vaughn et al. [29] described the GPS-map speed matching system for controlling the speed of the vehicle. Since the map-matching method has been applied in many fields effectively and is suitable for our issue, in this work, we normalize the trajectory data with a map-matching method.

III. PRELIMINARY AND FRAMEWORK OVERVIEW

In this section, we introduce different kinds of traffic signs, define several terms used in this paper, and present the overview of the proposed framework.

A. Preliminary

Road Network: A road network can be defined as a graph \( G = (I, R) \), where \( I = \{i_1, i_2, ..., i_n\} \) is a set of road intersections, and \( R = \{r_1, r_2, ..., r_m\} \) is a set of road segments.

GPS Point Trajectory: A GPS point can be denoted as 4-tuples, \( p = (id, t, lat, lng) \), where \( id \), \( t \), \( lat \), \( lng \) are the unique trajectory ID, time stamp, latitude, and longitude from GPS transmitters, respectively. A GPS point trajectory \( traj_p \) can be defined as a time-ordered sequence \( P_n = \{p_1 \rightarrow p_2 \rightarrow ... \rightarrow p_n\} \), where \( n \) is the number of GPS points in the trajectory.

Road Segment Trajectory: A road segment trajectory \( traj_g \) can be denoted by 2-tuples, \( traj_g = (id, R_s) \), where \( id \) is the unique trajectory ID, and \( R_s \) is defined as a time-ordered sequence of road segments, \( R_s = \{r_1 \rightarrow r_2 \rightarrow ... \rightarrow r_m\} \), where \( r_i \in R, 1 \leq i \leq m \) and \( m \) is the number of road segments in the trajectory.

Turning Behavior: The turning behavior can be defined as 8-tuples, \( tn_i = (type, id, lat, lng, t, bb, ba, conf) \), where \( id \), \( lat \), \( lng \), \( t \), \( bb \), \( ba \), \( conf \) are the unique trajectory ID, latitude, longitude, time of the turning behavior, \( bb \) and \( ba \) are the direction of the vehicle before and after the turning behavior, respectively, which are the clockwise angles from the North, \( conf \) is the confidence value of the turning behavior and \( type \) is the type of the turning behavior, \( type \in \{left - turn, right - turn, u - turn\} \), as shown in Fig. 2, which is consistent with the three traffic signs shown in Fig. 3. A set of turning behaviors is denoted by \( TN = \{tn_1, tn_2, ..., tn_m\} \), where \( m \) is the number of turning behaviors.

Parking Behavior: The parking behavior can be defined as 5-tuples, \( pk_i = (id, lat, lng, st, et) \), where \( id \), \( lat \), \( lng \), \( st \), \( et \) are the unique trajectory ID, latitude, longitude, start time and end time of the parking behavior, which is consistent with the no-parking sign shown in Fig. 3 (d). A set of parking behaviors is denoted by \( PK = \{pk_1, pk_2, ..., pk_m\} \), where \( m \) is the number of parking behaviors.

We also introduce the four most frequently used traffic signs in our study, i.e., no-left-turn, no-right-turn, no-u-turn, and no-parking, as shown in Fig. 3.

B. System Framework Overview

As shown in Fig. 4 the framework consists of three phases, i.e., driving behavior extraction, driving behavior context augmentation and traffic violation-prone location inference system. We briefly elaborate on the whole process as follows.

In the driving behavior extraction phase, we normalize the trajectory data based on the road network using map-matching methods. Then we extract parking behaviors from the normalized data by static points and extract turning behaviors from the road segment trajectory. In the driving behavior context augmentation phase, we model driver perspectives based on regression and retrieve corresponding street view pictures and other traffic restriction information. Then we train a traffic sign detection model to detect traffic signs in street view pictures and obtain speed restrictions from real-time navigation service providers. In the traffic violation-prone location inference system phase, we first match driving behaviors with those restrictions to get the traffic violation distribution. Then we extract the spatiotemporal patterns of traffic violations to infer the traffic violation-prone locations and build a traffic violation-prone location inference system.
IV. DRIVING BEHAVIOR EXTRACTION

In this section, our goal is to extract average velocities and driving behaviors, i.e., parking, left turn, right turn, and u-turn from vehicle GPS trajectories. First, we employ map-matching methods to normalize trajectory data into road segment trajectories. We then extract the average velocity and driving behaviors, i.e., parking, left turn, right turn, and u-turn from the normalized trajectories.

A. Map-Matching Based Trajectory Normalization

The map-matching method used in this paper is based on the Hidden Markov Model (HMM) algorithm [24], which described a novel, principled map-matching algorithm that uses a Hidden Markov Model (HMM) to find the most likely road route represented by a timestamped sequence of latitude/longitude pairs. We first preprocess the raw vehicle trajectories by removing duplicate and abnormal points and reconstructing trajectories. In this algorithm, the states of the HMM are the individual road segments, denoted as \( r_i \), \( i = 1, \ldots, m \), and the state measurements are the noisy vehicle location measurements. The goal is to match each latitude/longitude location measurement \( z_t \) with the proper road segment.

The emission probability for each road segment \( r_i \) and each location measurement \( z_t \) is

\[
p(z_t|r_i) = \frac{1}{\sqrt{2\pi}\sigma_z} e^{-0.5\left(\frac{\|z_t - x_{t,i}\|_d}{\sigma_z}\right)^2}
\]

where \( \sigma_z \) is the standard deviation of GPS measurements, and the points within \( 2\sigma_z \) of the previously included point are removed. \( \sigma_z \) is estimated by the median absolute deviation, i.e.,

\[
\sigma_z = 1.4826 \times \text{median}_t(\|z_t - x_{t,i}\|_d)
\]

The initial state probabilities is started at the first measurement, \( \pi_i = p(z_1|r_i), i = 1, \ldots, m \). Also, we do not consider matching to road segments that are quite distant from the measurement. The measurement probability from a road segment that is more than 200 meters away from \( z_t \) is set to zero, which helps reduce the number of candidate matches.

The transition probabilities give the probability of a vehicle moving between the candidate road matches at \( t \) and \( t+1 \). Specifically, for the next measurement \( x_{t+1} \) and candidate road segment \( r_j \), the corresponding point is \( x_{t+1,i} \). We compute the direct distance between \( z_t \) and \( x_{t+1} \), \( \|z_t - x_{t+1}\|_d \) and the route distance (the shortest length of road segments between two GPS points on the road) between \( x_t \) and \( x_{t+1} \), \( \|x_{t,i} - x_{t+1,j}\|_r \). With the intuition that these two distances will be
After map-matching, the GPS point trajectory $\text{traj}_p = (id, P_s)$ is normalized into road segment trajectory $\text{traj}_g = (id, R_s)$. For example, as shown in Fig. 5(b) there is a GPS point trajectory $\text{traj}_p = (i, P_s)$, where $P_s = \{p_1 \rightarrow p_2 \rightarrow p_3 \rightarrow p_4 \rightarrow p_5 \rightarrow p_6 \rightarrow p_7 \rightarrow p_8 \rightarrow p_9\}$. After map-matching, we get the corresponding locations of each GPS points on the road segment, as shown in Fig. 5(a). The mapped point $p_i'$ is on road segment $r_1$, $p_2'$ and $p_3'$ are on road segment $r_2$, $p_4'$ to $p_6'$ are on road segment $r_3$, $p_7'$ to $p_{10}'$ are on $r_4$, $p_{11}'$ is on $r_5$. Thus we can get the corresponding road segment trajectory $\text{traj}_g = (i, R_s)$, where $R_s = \{r_1 \rightarrow r_2 \rightarrow r_3 \rightarrow r_4 \rightarrow r_5\}$, as shown in Fig. 5(c).

B. Driving Behavior Extraction

Based on the normalized trajectories, we further extract vehicles’ average velocities on roads, the turning behaviors in road intersections, and the parking behaviors on road segments from the normalized trajectories.

1) Turning Behavior Extraction: From the normalized road segment trajectories, we extract the turning behaviors. $bb$ and $ba$ are the directions of the vehicle before and after the turning behavior, which are the clockwise angles from the North. If $ba - bb = 0^\circ$, it is a straight behavior, which is not considered in this paper; if $0^\circ < ba - bb < 160^\circ$, it is a right-turn behavior; if $160^\circ \leq ba - bb \leq 200^\circ$, it is a u-turn behavior; if $200^\circ < ba - bb < 360^\circ$, it is a left-turn behavior. As shown in Fig. 5(b) from $r_1$ to $r_2$, there is a left-turn behavior; from $r_2$ to $r_3$, there is a left-turn behavior; from $r_3$ to $r_4$, there is a left-turn behavior; from $r_4$ to $r_5$, there is a u-turn behavior; from $r_4$ to $r_5$, it is a straight behavior. Therefore we can get a turning behavior trajectory, $\{\text{left-turn} \rightarrow \text{left-turn} \rightarrow \text{left-turn} \rightarrow \text{u-turn}\}$, as shown in Fig. 5(d).

2) Parking Behaviors Extraction: We extract the parking behaviors in the normalized GPS point trajectories with a sliding-window-based method. More specifically, for a normalized GPS point trajectory $\text{traj}_p = (i, P_s)$, where $P_s = \{p_1' \rightarrow p_2' \rightarrow \ldots \rightarrow p_n'\}$, we extract every parking sequence $p_m' \rightarrow p_{m+1}' \rightarrow \ldots \rightarrow p_{m+k}' (1 \leq m < n, 1 \leq k \leq n-m)$ in which the average speed between the first point and any other points is less than a small threshold $\delta$, i.e.,

$$\forall m \leq i < m + k, \frac{\text{dist}(p_i', p_{i+1}')}{\Delta t} < \delta$$

where $\text{dist}(p_i', p_{i+1}')$ is the route distance between $p_i'$ and $p_{i+1}'$ and $\Delta t = |p_i', t - p_{i+1}', t|$ is the time difference of $p_i'$ and $p_{i+1}'$. We use a sliding-window with adaptive size along the trajectory to find such parking behaviors. In particular, we dynamically extend the window size by adding new points until the newly-formed sequence violates requirement [5]. For example, as shown in Fig. 6 for the trajectory $p_1' \rightarrow p_2' \rightarrow p_3' \rightarrow p_4' \rightarrow p_5' \rightarrow p_6'$, we start by creating a window consisting of the first two points ($p_1', p_2'$ in this case), and check whether the average speed between $p_1'$ and $p_2'$ is less than $\delta$. Since $\frac{\text{dist}(p_1', p_2')}{|p_1', t - p_2', t|} > \delta$, we discard this window, and slide the window to start over from the end point($p_2'$), and create a new window.
(p’2, p’3). We keep this window for \(\text{dist}(p’2, p’3) < \delta\) and repeat the procedure for the next adjacent points until the speed constraint is violated. Finally, we obtain a sequence containing a set of consecutive points \(p’2 \rightarrow p’3 \rightarrow p’4 \rightarrow p’5\).

We map each parking sequence \(p’m \rightarrow p’_{m+1} \rightarrow \ldots \rightarrow p’_{m+k}\) extracted from the GPS trajectories to a parking behavior \(pk = (id, lat, lng, st, et)\). The \(id\) of \(pk\) is the \(id\) of the trajectory where the parking behavior is extracted, \(lat\) is the average latitude of the points in the parking sequence, \(lat = \sum_{i=m}^{m+k} p’i\text{.latitude} / k+1\), \(lng\) is the average longitude of the points in the parking sequence, \(lng = \sum_{i=m}^{m+k} p’i\text{.longitude} / k+1\), \(st\) is start time of the parking behavior, \(st = p’m\text{.t}\), \(et\) is the end time of the parking behavior, \(et = p’_{m+k}\text{.t}\).

3) Average Velocity Extraction: After trajectory normalization, we can get sequences of road intersections, from which we extract the subsequences. The intersections from the same subsequence are of the same road. For each subsequence, we calculate the average speed through dividing the route distance between the head intersection and the rear intersection by the difference of the time. More specifically, for a road intersection sequence \(p_1 \rightarrow p_2 \rightarrow p_3 \rightarrow \ldots \rightarrow p_n\), where \(n\) is the length of the sequence. If \(p_1, p_{k+1}\), and \(p_{k+2}\) are of the same road, we extract the subsequences \(p_1 \rightarrow p_{k+1} \rightarrow p_{k+2}\), and the average speed \(v = \frac{\text{dist}(p_1, p_{k+2})}{\Delta t}\), where \(\text{dist}(p_1, p_{k+2})\) and \(\Delta t\) are the route distance and duration between \(p_1\) and \(p_{k+2}\).

V. DRIVING BEHAVIOR CONTEXT AUGMENTATION

After extracting driving behaviors, we need to know the contexts of driving behaviors to identify whether a driving behavior is illegal or not. To this end, we model the driver perspectives based on regression and get the corresponding street view pictures to detect the no-left-turn, no-right-turn, no-u-turn, and no-parking signs.

A. Driver Perspective Modeling

Since vehicle trajectory data we use in this paper are extremely large-scale, the GPS points in the trajectories can almost cover the urban road network completely. Therefore, after getting the driving behavior database \(DB = (PK, TN)\), we can detect almost all the road intersections in the city by extracting the distinct location of turning behaviors. The no-left-turn, no-right-turn, and no-u-turn traffic signs are erected near the road intersections to guide drivers. And the no-parking signs are often erected on the road intersections to inform drivers whether they can park on the following road segments.

For each intersection, there are several different kinds of turning behaviors from different directions. We define those turning behaviors at the same road intersection from the same direction as a bunch = \((lat, lng, bb)\), where \(lat, lng\) are the latitude and the longitude of the intersection, \(bb\) is the bearing before the behaviors. Thus for the turning behaviors from one bunch, their spatiotemporal contexts before the behaviors should be the same. As shown in Fig. 7, the behaviors drew in red are a bunch, denoted as bunchr, and those in blue are another bunch, denoted as bunchb.

For each bunchi = \((lati, lngi, bb)\), we select the corresponding GPS point trajectories in bunchi, and for each trajectory \(j\), the corresponding turning behavior at this road intersection is \(tn_{ij}\), and we select a segment of the trajectory \(\text{traj}_{pj} = \{pk \rightarrow pk_{k+1} \rightarrow \ldots \rightarrow pk_{m}\}\) before \(tn_{ij}\), the time span of which is limited by a threshold \(\theta\). Moreover, in order to avoid the GPS points on the branch road, the start time of the trajectory segment should be no earlier than the former turning behavior \(tn’_{ij}\) of \(tn_{ij}\), i.e.,

\[tn_{ij}.t - pk.t < \theta, pk_{k+m} \leq tn_{ij}.t, tn’_{ij}.t \leq pk.t \leq tn_{ij}.t\]  

For example, as shown in Fig. 8 suppose that there are two GPS trajectories in the bunch at this road intersection, according to \(6\) we select two trajectory segments, \(\text{traj}_{j1} = \{q_1 \rightarrow q_2 \rightarrow q_3 \rightarrow q_4 \rightarrow q_5 \rightarrow q_6 \rightarrow q_7 \rightarrow q_8 \rightarrow q_9 \rightarrow q_{10}\}\) and \(\text{traj}_{j2} = \{p_1 \rightarrow p_2 \rightarrow p_3 \rightarrow p_4 \rightarrow p_5 \rightarrow p_6 \rightarrow p_7 \rightarrow p_8\}\), where \(tn_{i1}.t - q_1.t \leq \theta, q_{10} \leq tn_{i1}.t, tn_{i1}.t - p_{1}.t < \theta\) and \(p_8 \leq tn_{i1}.t\). However, for traj_{j2}, there is a right-turn behavior \(tn’_{ij}\) before \(tn_{i1}\), \(p_1.t < tn’_{ij}.t\) and \(p_2.t < tn’_{ij}.t\), so we drop points \(p_1\) and \(p_2\). Finally, the trajectory segments selected are \(q_1 \rightarrow q_2 \rightarrow q_3 \rightarrow q_4 \rightarrow q_5 \rightarrow q_6 \rightarrow q_7 \rightarrow q_8 \rightarrow q_9 \rightarrow q_{10}\) and \(p_3 \rightarrow p_4 \rightarrow p_5 \rightarrow p_6 \rightarrow p_7 \rightarrow p_8\), respectively.

Since the trajectory data are extremely massive, we select a large number of trajectory segments that can describe contexts before turning behaviors at the road intersections. For each turning behaviors \(tn_{i1}\), we denote the GPS points in the corresponding trajectory segments as a set \(P_i = \{(x_1, y_1), (x_2, y_2), \ldots, (x_m, y_m)\}\), where \(m\) is the number of the points, we model the shape of the lane segment by regression. We select five typical road segments and try three kinds of regression, linear regression, spline regression, and cubic polynomial regression. The result shows that cubic polynomial regression achieves the best performance, as shown in Fig. 9.
Therefore for \((x_i, y_i)\)\((i = 1, ..., m)\), we can get a curve 
\[ h(x) = \theta_0 + \theta_1 x + \theta_2 x^2 + \theta_3 x^3 \]
satisfied that,
\[
\theta_0, \theta_1, \theta_2, \theta_3 = \arg \min_{\theta_0, \theta_1, \theta_2, \theta_3} J(\theta)
\]
where
\[
J(\theta) = \frac{1}{2m} \sum_{i=1}^{m} (h(x_i) - y_i)^2
\]

The regression curve segment can be regarded as a virtual driver’s route before the driving behavior, representing all the drivers of selected trajectories.

B. Driving Behavior Context Augmentation

We pick several points as a point sequence on the regression curve segment uniformly and normalized them by map-matching, regard the tangent of the curve at those points as the direction of the vehicle at these locations. Therefore we can get the corresponding street view picture sequence, through which we can restore what drivers have seen before those road intersections. For example, Fig. 10 shows a sequence of street view pictures. In addition, we also collect the speed restrictions of each road from real-time navigation service providers.

VI. TRAFFIC VIOLATION-PRONE LOCATIONS INFERENCE SYSTEM

In this section, our goal is to infer the traffic violation-prone locations in cities. Firstly, we detect the traffic sign in street view pictures to identify traffic violations. Then we extract the spatiotemporal patterns of traffic violations to infer traffic violation-prone locations.

A. Traffic Sign Detection

From driver perspectives, we can find no-left-turn signs, no-right-turn signs, no-u-turn signs, and no-parking signs erected at the side of or above the roads to give instructions to drivers. After modeling driver perspectives, we then detect these four categories of traffic signs in the spatiotemporal context around the road intersections to help infer the illegal turning behaviors.

The state-of-art object detection system YOLOv3 [23] has achieved great performance both in accuracy and time. It has a few incremental improvements on YOLOv2 [33], such as using independent logistic classifiers instead of softmax, adding shortcut connections, and concatenating feature maps with upsampled features, which helps it make great progress in small object detection and has strong generalization ability. Thus we choose YOLOv3 as the backbone network to train the traffic sign detection model.

We first use the Chinese traffic-sign benchmark created by Zhu et al. [20] to train a traffic sign detection model. Fig. 11
shows the types of traffic signs selected from the benchmark, in which some signs shown are representative of a family, such as speed restriction signs for different speeds (‘pl*’). ‘*’ can be replaced by a specific value, e.g. ‘pl40’ for a 40 km/h speed restriction sign [20]. Then we fine-tune the model based on a small dataset consisting of four categories of traffic signs, i.e., no-turn-left, no-turn-right, no-u-turn, and no-parking. The small dataset is consistent with the street view picture dataset, as shown in Fig. 12.

B. Traffic Violation Identification

1) Illegal Turning: If there exists the corresponding traffic sign in the street view picture sequence before the turning behavior, such as a no-left-turn sign for a left-turn behavior, this behavior can be identified as an illegal turning behavior. We denote the no-turning road intersections in the city as \( L = \{l_1, l_2, ..., l_m\} \), where \( l_i (i = 1, ..., m) \) is the distribution of illegal turning behaviors on each unique intersection.

2) Illegal Parking: From the traffic sign database constructed above, we can get the locations of the no-parking traffic signs. After mapping these locations to the nearest road segments, we get the list of no-parking road segments. If the corresponding road segment of a parking behavior is in the no-parking road segment list and the direct distance between the no-parking sign and the parking behavior is less than a threshold \( \zeta \), the parking behavior can be identified as an illegal parking behavior. We denote the no-parking segments in the city as a set \( B = \{b_1, b_2, ..., b_n\} \), where \( b_i (i = 1, ..., n) \) is the distribution of illegal parking behaviors on each unique road segment.

3) Speeding: As for speeding, we first collect road speed restrictions from Gaode Map Open Platform [1] and get the list of speed restrictions on the roads. Then we compare the average speed with the speed restrictions of the corresponding roads. If the average speed exceeds the speed restriction on the road, it can be identified as a speeding behavior. We denote the roads with speed restrictions in the city as \( S = \{s_1, s_2, ..., s_l\} \), where \( l \) is the number of roads, \( s_i (i = 1, ..., l) \) is the distribution of speeding behaviors on each unique road.

C. Traffic Violation-Prone Location Inference

After identifying traffic violations, we extract the spatiotemporal patterns of traffic violation to infer the traffic violation-prone locations.

For each traffic violation-prone location candidate, we aggregate the traffic violations related to this location. More specifically, We aggregate different illegal turning behaviors on the same intersection, parking behaviors on the same road segment and speeding behaviors on the same road.

For each traffic violation-prone location candidate \( r_i (r_i \in L \cup B \cup S) \), we aggregate its hourly traffic violations to build the temporal profile, i.e.,

\[
\Phi(r_i) = [tv_1, tv_2, ..., tv_n]
\]

where \( tv_j (i = 1, ..., n) \) is the number of traffic violations of the \( i^{th} \) hour and \( n \) is the number of hours. Then for each traffic violation-prone location candidate, we aggregate and average hourly traffic violations in the dataset over a typical day to determine the threshold of each hour in a day to infer traffic violation-prone locations, i.e.,

\[
\Phi(r_i) = [tv_1, tv_2, ..., tv_24]
\]

where \( tv_j (i = 1, 2, ..., 24) \) is the average number of aggregated traffic violations of the \( i^{th} \) hour in a day.

For each hour \( j (j = 1, 2, ..., 24) \), we set the threshold of this hour as the average number of the traffic violations plus the double standard deviation of the traffic violations in the city, i.e.,

\[
\text{thre}_j = \frac{\sum_{i=1}^{N} r_{ij}}{N} + 2 \sqrt{\frac{\sum_{i=1}^{N} (r_{ij} - \frac{\sum_{i=1}^{N} r_{ij}}{N})^2}{N}}
\]

where \( N \) is the number of traffic violation-prone location candidates, \( r_{ij} \) is the typical traffic violation of \( r_i \) at hour \( j \). Therefore, we can get the traffic violation-prone locations for each hour.

VII. Evaluation

In this section, we evaluate the performance of our framework based on two large-scale, real-word trajectory datasets from two cities in China, Xiamen and Chengdu, respectively. Firstly, we describe the datasets we use. Then we show the evaluation results on traffic sign detection and traffic violation-prone location inference. Finally, we present a traffic violation-prone location inference system and give several case studies.

A. Dataset Description

1) Taxi Trajectory Data in Xiamen: This dataset is provided by Xiamen Traffic Management Department. After a data cleansing process that removes invalid records. We obtain the taxi trajectories of 5,486 vehicles in Xiamen, Fujian Province, in China. The detailed summary of the dataset is shown in TABLE. The GPS trajectories in Xiamen are shown in Fig. 13(a) and (b).

![GPS trajectories in Xiamen and Chengdu. (a) GPS trajectories in Xiamen. (b) GPS trajectories in Chengdu.](image-url)
2) Car-Hailing Trajectory Data in Chengdu: This dataset is provided by GAIA Open Dataset \(^2\) from DiDi Chuxing, the largest online car-hailing service provider in China, which handles around 11 million orders per day all over China. After a data cleansing process that removes invalid records, we obtain the vehicle trajectories of 6,096,022 orders. The detailed summary of the dataset is shown in TABLE I, and the GPS trajectories in Chengdu are shown in Fig. 13b.

3) Speed Restriction Information: We collect the speed restrictions on 150 roads in Xiamen and 281 roads in Chengdu from Gaode Map Open Platform, as shown in TABLE II.

4) Street View Pictures: We drop the traffic signs the numbers of which are less than 100 and select 23923 traffic signs (45 categories) of 10267 pictures from the Chinese traffic-sign benchmark \(^2\). We denote this dataset as DS\(_1\). Moreover, we prepare the street view pictures consistent with the street view pictures to be detected containing 162 no-left-turn signs, 127 no-right-turn signs, 108 no-u-turn signs, 106 no-parking signs and 149 negative samples, denoted as DS\(_2\). DS\(_1\) and DS\(_2\) are used to train the traffic sign detection model.

TABLE I: Vehicle Trajectory Dataset Description

| City   | Duration | Record 352,300,768 (5378 vehicles) |
|--------|----------|----------------------------------|
| Latitude (WGS84) | 24.369406°N - 24.619351°N |
| Longitude (WGS84) | 117.990364°E - 118.265022°E |

TABLE II: The number of different speed restrictions on roads in Xiamen and Chengdu.

| Speed Limit (km/h) | Xiamen | Chengdu |
|-------------------|--------|---------|
| 5                 | 2      | 17      |
| 30                | 89     | 220     |
| 40                | 25     | 8       |
| 50                | 25     | 28      |
| 60                | 3      | 1       |
| 70                | 1      |         |
| 80                | 1      |         |

B. Results on Traffic Sign Detection

After driver perspective modeling, we collected 79,855 and 47,088 street view pictures in Xiamen and Chengdu, respectively from Baidu Map \(^3\) and DiDi Chuxing, the largest online car-hailing service provider in China, which handles around 11 million orders per day all over China. Specifically, according to the basic design criteria for state highway from the New Zealand Transport Agency, when the driving speed is 0 km/h, the driver's horizontal angle of field is 180°. When the speed increases to 60 km/h, the angle decreases to 74°, and when the speed increases to 80 km/h and 100 km/h, the angle decreases to 60° and 40°, respectively. Generally, the speed of the vehicle on the urban road is lower than 60 km/h. Thus, we set field of view FOV = 74°.

Then we detect traffic signs in these street view pictures. We first separate DS\(_1\) into training set and validation set, 80% and 20% respectively, and train a traffic sign detection model based on the YOLOv3 \(^2\) model. Then from DS\(_2\), we select 10% of each type of traffic signs as the test set and we fine turn the model with the rest of the traffic signs, which is separated into training set and validation set, 80% and 20% respectively. Finally, we evaluate the performance of the model on test set and the results are shown in TABLE III. AP = \( \sum_{k=1}^{N} p(k)(r(k-1) - r(k)) / N \) is the average precision of each category, \( p(k) \) and \( r(k) \) are the precision and recall at the \( k \)th threshold, and mAP is the mean of AP for each category.

TABLE IV: Summary of Traffic signs Detected in Xiamen and Chengdu

| Items            | Xiamen | Chengdu |
|------------------|--------|---------|
| No-left-turn     | 282    | 198     |
| No-right-turn    | 110    | 71      |
| no-u-turn        | 29     | 19      |
| No-parking       | 848    | 344     |
| Total            | 1269   | 632     |

We detect the traffic signs in street view pictures collected from Xiamen and Chengdu using the model. The summary of the traffic signs detected from the street view pictures in Xiamen and Chengdu are shown in TABLE IV and Fig. 14 shows some examples of traffic signs detected in street view pictures.

C. Results on Traffic Violation-Prone Location Inference

Fig. 15 shows the thresholds of traffic violation-prone locations in Xiamen and Chengdu, respectively, and the points marked in the figure represent the inferred traffic violation-prone points of a location in the corresponding city in a month. Fig. 16 shows the number of traffic violation-prone locations in Chengdu, November, 2016, and Xiamen, September, 2016, respectively. Specifically, there were two typhoons influenced Xiamen in this month, Meranti on September 15th and Megi on September 27th, which are corresponding to the lowest two segments on the curve of Xiamen.
D. Traffic Violation-Prone Location Inference System

We build a traffic violation-prone location inference system, as shown in Fig. 20. From this system, we can easily find the traffic violation-prone locations in a city at different time. Sample datasets and codes can be found at: https://github.com/zhihanjiang/iTV, and the system can be visited at: https://zhihanjiang.github.io/tv-infer-web/

E. Case Study

1) Illegal Turning: Illegal turning is the second most frequent traffic violation in Chengdu, and we found a lot of illegal turning behaviors happen on the intersection of Wucheng Street and Dongan South Road, as shown in Fig. 17. In this intersection, drivers are forbidden to turn left (the red arrow...
in the figure) after crossing a bridge, but there are still many people violating the traffic regulation.

2) **Illegal Parking:** According to the Xiamen Traffic Police, illegal parking is the most frequent traffic violation from 2015 to 2018. Through observing heat maps, we can find that the intersection of Chenggong Avenue and Nanshan Road had a large number of illegal parking behaviors. However, after an in-depth investigation, we found that a new subway station was being built during that time, which led to terrible traffic conditions there. Thus there were many illegal parking behaviors. Besides, Xiahe Road, Siming South Road, and many other roads near the tourist hotspots are also traffic violation-prone locations. Siming South Road is a very busy road in Xiamen, along which there are a lot of tourist hotspots, such as Xiamen University, Nanputuo Temple, Overseas Chinese Museum, and it also intersects Zhongshan Road, which is a famous tourist road. The complex environment and the large traffic volume make it become the road with maximum illegal parking behaviors in Xiamen. As shown in Fig. 18, some vehicles are parked on the road, although there is a no-parking sign erected there.

3) **Speeding:** Speeding is the sixth most frequent traffic violation in Xiamen. Fig. 19 shows a speeding behavior on Bailuzhou Road in Xiamen. Bailuzhou Road is a speeding-prone location in Xiamen, which is a 4-lane dual carriageway. The speed restriction of Bailuzhou Road is 60 km/h. Besides we found a lot of speeding behaviors on Jiahe Road and Chenggong Avenue. They are both important roads crossing over Xiamen Island.

### VIII. Conclusion

In this work, we propose a low-cost, comprehensive and dynamic method for inferring the traffic violation-prone locations in cities based on the large-scale vehicle trajectory data and road environment data fusion to provide some insights for the traffic management department about traffic dynamics in cities to help optimize the utility and effectiveness of the traffic enforcement strategies. Firstly, we normalize the trajectory data by map-matching algorithms and get the driving behavior distribution. Secondly, we model match driving behaviors to corresponding road segments and restore the spatiotemporal contexts of driving behaviors to get the traffic rule information so that we can get three types of traffic violation distributions, i.e., illegal turning, illegal parking and speeding. Then we extract the spatiotemporal patterns of traffic violations to infer the traffic violation-prone locations in cities. Finally, we build a traffic violation-prone location inference system and give some case studies. The framework is evaluated using large-scale, real-world datasets.

In the future, we plan to broaden and deepen this work in two directions. Firstly, we plan to incorporate more trajectory open data sources from other cities. Secondly, we plan to incorporate urban environment data, such as Points of Interests and traffic volumes, to explore more in-depth relationships between traffic violation-prone locations and the urban environment.
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