Suspicious Vehicle Tracking with Sparse Video Surveillance Cameras and Mobile Taxicabs

Abstract—**Due to the sparse distribution of road video surveillance cameras, tracking a precise trajectory of suspicious vehicles is a challenging task. Previous research on vehicle trajectory recovery mostly focuses on recovering trajectory with low-sampling-rate GPS coordinates by retrieving road traffic flow patterns from collected GPS information. However, to the best of our knowledge, none of them considered using on-road taxicabs as mobile video surveillance cameras as well as the time-varying characteristics of vehicle traveling and road traffic flow patterns, therefore not suitable for recovering trajectories of suspicious vehicles. With this insight, we model the travel time-cost of a road segment during various time periods precisely with LNDs (Logarithmic Normal Distributions), then use LSNDs (Log Skew Normal Distributions) to approximate the time-cost of an urban trip during different time periods. Then we propose a novel approach to calculate possible location and time distributions of the suspicious vehicle, select the optimal taxicab to verify the distributions by uploading and checking the video of this taxicab, and refine the restoring trajectory in a recursive manner. We evaluate our solution on real-world taxicab and road surveillance system datasets. Experimental results demonstrate that our approach outperforms alternative solutions in terms of accuracy ratio of vehicle tracking.**

I. Introduction

In recent years, a dramatic increases of public security surveillance systems on roads such as intelligent toll-gate system [8], road traffic video camera system [2], [15] and induction coil systems [8] have enabled the collection of large amount of vehicle monitoring information. This newly available data then contributes to improve our understanding of intelligent urban traffic system, and in turn, promotes the emergence of novel and convenient services for both road traffic administrative departments and motor vehicle drivers. Existing applications of using these data include vehicle route planning [5], [8], [14], road traffic flow analysis [2], [10], [15] and intelligent transportation [4], [16], [22], but it is insufficient for trajectory tracking of suspicious vehicles due to the sparse distribution of video surveillance cameras.

Recent advances in dashboard-mounted wireless sensors and networking technologies in mobile vehicles such as 3G/4G, Wi-Fi, GPS-embedded navigation system and vehicle traveling video recorders have allowed the acquisition of huge amount of taxicab trajectory and road traffic video information, then enhanced the intellectualize degree of urban computing [13], [18]–[21], [23]. Furthermore, a newly published intelligent taxicab monitoring system [1] captures and uploads video evidence to police so as to report traffic violations. This emerging function offers a new way to tackle the problem of suspicious vehicle trajectory tracking by using taxicabs with video recorder as mobile video surveillance cameras, since taxicabs in most cities are equipped witha GPS navigation system, 3G/4G network and video recorder nowadays.

To date, investigation on recovering vehicle trajectories with video surveillance cameras is rare. For example, [3] proposes an algorithm to analyze the microcosmic potential action of a vehicle with the snapped photo of a single camera, then estimates its one-step potential moving direction. However, this algorithm cannot recover the entire trajectory of a vehicle during a specific time period. In addition, there are some similar studies [11], [12] which mainly focus on recovering the trajectory of a vehicle with low-sampling-rate GPS coordinates, and all these algorithms rely on retrieving road traffic flow patterns from collected GPS information, then calculate the possible vehicle trajectory. The accuracy of these algorithms is insufficient because of the lack of sampling points, and pervious studies do not consider enhancing the sampling-rate of video surveillance by using the on-road taxicabs as mobile video surveillance cameras. Furthermore, all these algorithms do not consider the time-vary characteristics of road traffic flow patterns, and they are not suitable for recovering the driving trajectory of a suspicious vehicle which would like to avoid surveillance cameras by selecting an abnormal driving route.

To the best of our knowledge, there is no existing suspicious vehicle tracking system which aims to solve the above mentioned problems systematically. The main research challenges of such a system include: i) recovering trajectory of a suspicious vehicle with both fixed video surveillance cameras and moving taxicabs with video recorders; ii) extracting and utilizing time-varying characteristics of road traffic flow patterns for more realistic computation; and iii) calculating a strategy of data retrieval from moving taxicabs with video recorders to minimize the total retrieving time.

To address these challenges, we propose in this paper a self-adapting suspicious vehicle tracking algorithm with sparse video surveillance cameras and mobile taxicabs, leveraging time-varying characteristics of road traffic flow patterns. Specifically, by mining the massive trajectory dataset of 4,303 taxicabs running in the main urban area of Suzhou Industrial Park (SIP) from May 1, 2015 to April 30, 2016 and all video information of 103 intersections with fixed video surveillance system in the same region during April 1 to April 30, 2016, our experiments reveal that the patterns of road traffic flow have obvious time-varying characteristics, and this pattern for a specific road segment is strongly correlated with its position and time. With these preliminary results, we model the travel time-cost of a road segment during different time periods precisely with LNDs (Logarithmic Normal Distributions), then use Log Skew Normal Distributions to approximate the time-cost of an urban trip during different time periods. Finally, we propose a novel approach to calculate the possible location and time distributions of the suspicious vehicle, then select the optimal taxicab to verify the distributions by uploading and checking the video of this taxicab, and then refine the trajectory of the suspicious vehicle gradually and recursively. Worth noting is that additional networking resources and costs are required while asking a taxicab to upload a video file, thus the online taxicab video querying should be network efficient which means its network-cost should be minimum.

To evaluate our VTCT (Suspicious Vehicle Tracking with Sparse Video Surveillance Cameras and Mobile Taxicabs) algorithm, we compare it with the Shortest Driving Distance, Minimum Driving Time, Minimum Turning Times and Most Likely Route strategies via a real world 4,303-taxicab dataset and a 103-intersection video surveillance information dataset, the results show that our proposed algorithm increases the average *AR* value by 120.88%, 109.11%, 113.56% and 77.44% respectively. Moreover, our solution only needs to query mobile taxicabs for no more than 7 times to recover the trajectory of a trip with 10 road segments, i.e., the average number of querying times per road segment of our solution is no more than 0.7 among various kinds of premises which means our solution is very efficient in querying mobile taxicabs.

The main contributions of this paper are as follows:

- To the best of our knowledge, this is the first paper targeting suspicious vehicle tracking with both fixed video surveillance cameras and mobile taxicabs with video recorders, meanwhile considering the time-varying characteristics of the patterns of road traffic flow.
- By mining the massive trajectory dataset of taxicabs and video dataset of surveillance cameras, we model the travel time-cost of a road segment during a specific time period with a Logarithmic Normal Distribution, then for the first time calculate the time-cost of an urban trip during a specific time period with a Log Skew Normal Distribution approximatively.
- To solve the challenge of self-adapting suspicious vehicle tracking, we propose a novel method to calculate the possible location and time distribution of a specific suspicious vehicle, thus give the optimal taxicab with a video recorder to verify, then refine the trajectory of a suspicious vehicle with the minimum networking-cost. The frequency of querying mobile taxicabs is no more than 0.7 times per road segment.
- To evaluate our solution, we conducted a series of experiments by driving a car in SIP for a whole month to simulate the behavior of a suspicious vehicle. Together with a real world 4,303-taxicab dataset and a 103-intersection video surveillance information dataset, experimantal results demonstrate that our proposed algorithm outperforms alternative approaches.

The rest of this paper is organized as follows: After reviewing related literatures in Section II, we formulate the problem in Section III. In Section IV, we analyze and model the travel time of road segments and total time-costs of urban trips with considering their time-varying characteristics. Section V describes the suspicious vehicle tracking algorithm with sparse video surveillance cameras and mobile taxicabs. Numerical studies are presented in Section VI and Section VII concludes.

II. Literature Review

Great effort has been expended in understanding intelligent urban computing with public security surveillance systems, including planning optimized driving routes for vechiles [5], [8], [14], analyzing traffic flows of road networks [2], [10], [15] and realizing intelligent transportation systems [4], [16], [22]. In this paper, we consider the suspicious vehicle tracking problem. The investigations on recovering vehicle trajectories with video surveillance cameras are few, but include [3], [11] and [12] .

[3] first proposes a boosting light and pyramid sampling histogram of oriented gradients feature extraction method to detect vehicles by combining with a support vector machine, then devise a spatio-temporal appearance-related similarity measure to analyze the motion of the detected vehicles. It tries to analyze the microcosmic potential action of a vehicle with the snapped photo of a single camera, then to estimate the one-step potential moving direction of this vehicle. This work has not considered cooperative computing with multiple video cameras, since the deployments of fixed video cameras are still sparse and cannot support the seamless monitoring of suspicious vehicles in nature.

With the emergence of vehicle-mounted GPS navigation systems and vehicular networks, a collection of a series of GPS coordinates became a reality. Based on these, [11] and [12] mainly focus on recovering detailed trajectory of a vehicle with a series of sparse GPS coordinates and timestamps. [11] proposes a novel global map-matching algorithm with considering the spatial geometric/topological structures of the road network as well as the temporal/speed constrains of the trajectories. In this paper, the basic rule that true paths of vehicles tend to be direct rather than roundabout is utilized to enhance the accuracy of computing actual vehicle trajectories. But for suspicious vehicles, they'd like to choose abnormal paths to avoid fixed video surveillance cameras to increase the difficulty of trajectory recovery. Further on recovering detailed trajectories with GPS information, [12] proposes a Hidden Markov Model based map-matching algorithm to find the most likely road route, at the same time, it can be robust to location data which is both geometrically noisy and temporally sparse. In summary, previous research on recovering detailed trajectories of vehicles have never taken information from mobile taxicabs with video record as well as time-vary characteristics of road traffic flow patterns into account to improve the algorithm precision.

Specific to the raised problem in this paper, existing studies on recovering detailed trajectories of vehicles with GPS coordinates are designed for normal vehicles which should basically obey the principle that drivers always tend to select most convenient paths, in another words, they are not appropriate for suspicious vehicles which may have obvious evading and zigzaging behaviors. Moreover, we cannot even obtain any GPS information of suspicious vehicles in practice, and the information from public security surveillance system and taxicabs with video recorders is the only thing we can leverage.

III. Background and System Model

A. Basic Settings

Given the road network in the urban area of SIP, this paper aims to find a method to track suspicious vehicles by combining the information from fixed video surveillance cameras and mobile taxicabs with video recorders, thereby helping governments recover trajectories of suspicious vehicles as precise as possible. The basic settings of this paper is outlined as follows:

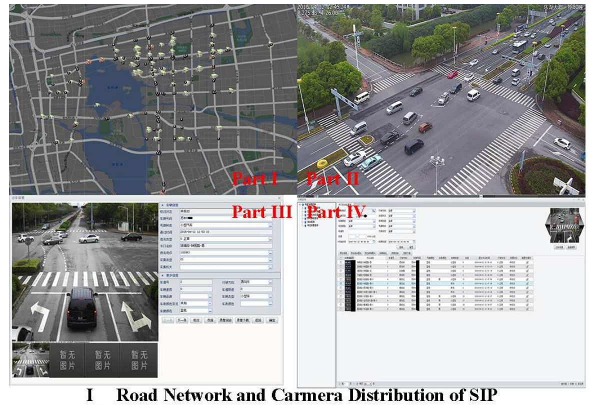
- **Road Network of SIP:** The main urban area of SIP covers 288 square kilometers. A road network with 518 intersections and 1,560 road segments exists in the urban area of SIP.
- **Road Video Surveillance System:** So far, there are 103 key intersections in the road network of SIP which are equipped with video surveillance system. As illustrated in Figure 1, each vehicle passing a intersection with video surveillance system is detected, the corresponding video is captured, uploaded and scanned, thereby the vehicle license information will be identified and stored into a database automatically.
- **Intelligent Taxicab System:** There are 4,303 taxicabs running independently in the road network. As shown in Figure 2, all taxicabs are equipped with a GPS-based navigation system, 3G/4G network and 4 video recorders. A taxicab cannot analyze and identify the captured video information independently, it uploads its vehicle ID, real-time position, speed, direction, occupancy status once every 2 minutes, and also uploads captured videos to a remote server. Policeman can check the real-time position, running status and captured videos via a taxicab monitoring system. Note here that since uploading video information consumes significant network resources taxicabs usually store video files locally and only attempt to upload upon request.

B. System Model

In this subsection, we define the road network, taxicab fleet and vehicle trajectory used in our model.

*Definition 1 (**ROAD NETWORK**): Given the intersections and road segments between intersections, the road network of the main urban area of SIP can be modeled as a directed graph $G(V, E)$ where the vertex set V denotes all 518 intersections and the edge set E corresponds to all 1560 road segments. $\forall i, j \in [1, |V|]$, intersection $I_i \in V$ and $r_{ij} \in E$ illustrates the road segment from intersection I_i to I_j.*

*Definition 2 (**VEHICLE AND TAXICAB FLEET**): The vehicle fleet running in the urban area of SIP is denoted as $VF = \{v_1, v_2, \cdots, v_{|TF|}\}$, and v_i represents the i_th vehicle in the fleet. Further, the entire intelligent taxicab fleet of SIP is*



I Road Network and Carmera Distribution of SIP
II Image From High Altitude Panorama Carmera
II Video and Identification Information of a Vehicle
VI Stored Monitoring Information of a Vehicle

Fig. 1: Road Network of SIP and Existing Road Video Surveillance System

I Vehicle-mounted intelligent taxicab system
II Intelligent taxicab monitoring platform

Fig. 2: Intelligent Taxicab Monitoring System

denoted as $TF = \{n_1, n_2, \cdots, n_{|TF|}\}$, and n_j represents the j_th taxicab.

*Definition 3 (**TAXI TRAJECTORY**): Regarding taxicab n_i, its trajectory in one specific day d can be formulated by $TR_{n_i}(d) = \{start = r_{k_1k_2}(t_1, t_2), r_{k_2k_3}(t_2, t_3), \cdots, r_{k_{e-1}k_e}(t_{e-1}, t_e) = end\}$ which means taxicab n_i starts its journey at road segment $r_{k_1k_2}$ and time t_1, then ends at road segment $r_{k_{e-1}k_e}$ and time t_e. For one element $r_{k_{j-1}k_j}(t_{j-1}t_j)$ $(2 \le j \le e)$ in this trajectory, t_{j-1} is the time that vehicle n_i enters road segment $r_{k_{j-1}k_j}$ and time t_j corresponds to the time it leaves this road segment.*

*Definition 4 (**VEHICLE TRIP AND CAPTURED INFORMATION**): Regarding vehicle v_i, the j_th urban trip in day d can be denote as $UT_{v_i}^{j}(d) = \{r_{k_1k_2}(t_1, t_2), r_{k_2k_3}(t_2, t_3), \cdots, r_{k_{h-1}k_h}(t_{h-1}, t_h)\}$ which means vehicle v_i starts its j_th urban trip in day d at road segment $r_{k_1k_2}$ and time t_1, then ends at road segment $r_{k_{h-1}k_h}$ and time t_h.*

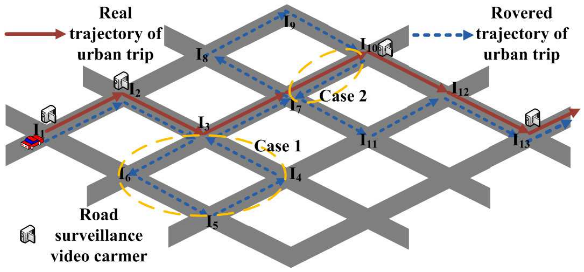


Fig. 3: An example of vehicle tracking

In practice, Road video surveillance system can only capture fragmental monitoring information during a trip of a vehicle. For an urban trip $UT_{v_i}^{j}(d)$, the corresponding captured information can be wrote as $FI_{v_i}^{j}(d) = \{I_{x_1}(t_1), I_{x_2}(t_2)\cdots, I_{x_g}(t_g)\}$.

Note that in above mentioned four definitions, road segment r_{ij} and r_{ji} represent two different road segments between intersection I_i and I_j with opposite directions, and there must have $VF \supset TF$.

C. Problem Description

As illustrated in Figure 3, a vehicle v_s has a real trip $UT_{v_s} = \{r_{12}, r_{23}, r_{37}, r_{7(10)}, r_{(10)(12)}, r_{(12)(13)}\}$. Note that in the following descriptions, we omit the parameters of day d and trip number j because the discussion is limited to the current j_th trip in day d. Since there are fixed video surveillance cameras on intersection I_1, I_2, I_{10} and I_{13}, the captured information should be $FI_{v_s} = \{I_1(t_1), I_2(t_2), I_{10}(t_{10}), I_{13}(t_{13})\}$. Assuming the recovered trajectory is $R(FI_{v_s}) = \{r_{12}, r_{23}, r_{34}, r_{45}, r_{56}, r_{63}, r_{37}, r_{78}, r_{89}, r_{9(10)}, r_{(10)7}, r_{7(11)}, r_{(11)(12)}, r_{(12)(13)}\}$. For the sub-trip from I_2 to I_7, compared with its corresponding recovered trajectory of the blue dotted line, the round of **Case 1** is totally redundant. Thereby, in evaluating the performance of a trajectory recovery algorithm, the redundant ratio as a necessary indicator should be considered. In this paper, our solution aims to increase the overlapped road segments as much as possible between a real trajectory and the corresponding recovered one, and at the same time decrease the redundant road segments in the recovered trajectory. Note that since road segment $r_{ij} \neq r_{ji}$, as illustrated in **Case 2** of Figure 3, the real trajectory ($I_7 \rightarrow I_{10}$) and the recovered trajectory ($I_{10} \rightarrow I_7$) are not overlapped, and in another words, this road segment is failed to be recovered. So far, based on the basic settings and system model, the goal of suspicious vehicle tracking problem can be denoted as:

Definition 5: ***SUSPICIOUS VEHICLE TRACKING PROBLEM*** *For a suspicious vehicle v_s, given the trip UT_{v_s} and the corresponding captured information FI_{v_s}, we aim to design a method to recover trajectory of v_s as $R(FI_{v_s})$ with the minimum online mobile taxicab video querying and uploading times, and at the same time have the minimum accuracy ratio AR value:*

$$\max\left\{AR = \frac{\left|R(FI_{v_s}) \cap UT_{v_s}\right|}{\left|UT_{v_s}\right|} \times \frac{\left|R(FI_{v_s}) \cap UT_{v_s}\right|}{\left|R(FI_{v_s})\right|}\right\} \quad (1)$$

In this formulation, the first part gives the the successful rate of trajectory recovery, the second part means the effective rate of recovered trajectory, and we here intend to maximize the successful rate as well as the effective rate at the same time.

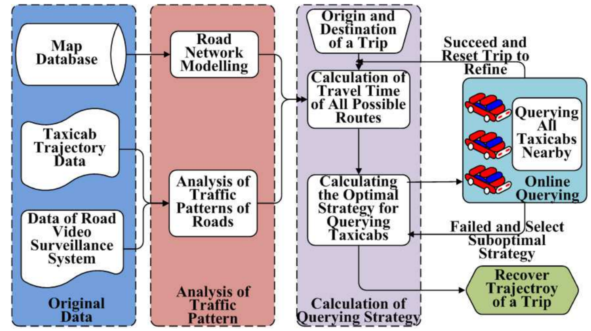


Fig. 4: Solution overview

IV. Vehicle Tracking System with Sparse Video Cameras and Mobile taxicabs

A. System Description

Figure 4 illustrates the architecture of our method, which consists of four major components: 1) original data; 2) analysis of time-varying traffic patterns; 3) calculation of an optimal querying strategy and 4) online querying with mobile taxicabs. Our solution first analyzes the time-varying traffic patterns of all road segments, and this part only needs to be executed once. Based on these preliminary results, given an urban trip, our solution calculates the optimal querying strategy of this urban trip, then queries information from mobile taxicabs until the information of the suspicious vehicle is confirmed exactly. According to this newly confirmed information, the original trip is divided into two sub-trips. Our solution then calls the vehicle trajectory recovery algorithm for these two sub-trips recursively and independently. This calculation terminates when we recover the vehicle trajectory uniquely. We detail each step in the following sections.

B. Analysis of Travel Time-costs of Urban Trips

In this subsection, we first reveal the time-varying characteristics of road traffic patterns, and fit the travel time-cost of a specific road segment during a specific time period with a LND, then devise a method to calculate the total travel time-cost of a specific urban trip approximatively.

1) Analysis of travel time-costs of road segments: Previous studies including [23] and [17] have revealed that the existence of the time-varying road traffic patterns, which is strongly correlated with the urban layout. Also as described in [7], the travel time-cost of a specific road segment during a specific time period should follow a LND. We first divide the traffic busy period (7:00a.m. to 8:00p.m.) in one day into time slots of 6 minutes, and for each time slot, we calculate the average speeds of all road segments, then use Kolmogorov-Smirnov test(K-S test) [9] to check whether the travel time of a road segment follows a LND. All calculations are based on our real world taxicab trajectory dataset, and the results are demonstrated in Figure 5. The red line demonstrates the percentage of road segments with the travel time-costs follow

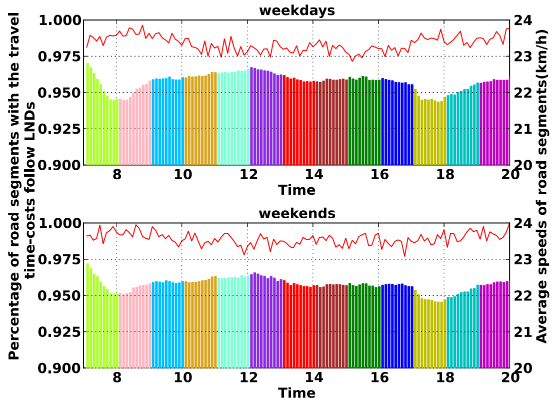


Fig. 5: Analysis of travel time-costs of road segments

LNDs which are always more than 97% both on weekdays and weekends, the color bar shows the average driving speeds of road segments during different time periods, and one color corresponds to one hour. We discover that the percentage indicator is totally independent of the average driving speed of road segment which means the travel time-costs of road segments follow LNDs, and is rarely influenced by traffic conditions.

By checking the trajectory dataset of taxicabs over the year, we generate the passing by set $PB_{r_{ij}}^{TP} = \{pb_1(r_{ij}, TP), pb_2(r_{ij}, TP), \cdots\}$ of road segment r_{ij} and time period TP in which $pb_k(r_{ij}, TP), (1 \le k \le |PB(r_{ij}, TP)|)$ means a taxicab runs through road segment r_{ij} during time slot TP in one day of the period from May 1, 2015 to April 30, 2016 and $ts[pb_k(r_{ij}, TP)]$ means its corresponding time-cost. So far, we write the LND of the time-cost t for a taxicab to travel road segment r_{ij} during time period TP as:

$$f_{r_{ij}}^{TP}(t) = \frac{1}{\sqrt{2\pi} t \sigma_{r_{ij}}^{TP}} \exp\left(-\frac{[\ln(t) - \mu_{r_{ij}}^{TP}]^2}{2(\sigma_{r_{ij}}^{TP})^2}\right) \tag{2}$$

where

$$\mu_{r_{ij}}^{TP} = \frac{1}{\left|PB_{r_{ij}}^{TP}\right|} \sum_{k=1}^{\left|PB_{r_{ij}}^{TP}\right|} ts[pb_k(r_{ij}, TP)] \tag{3}$$

$$\sigma_{r_{ij}}^{TP} = \frac{1}{\left|PB_{r_{ij}}^{TP}\right|} \sum_{k=1}^{\left|PB_{r_{ij}}^{TP}\right|} \left(ts[pb_k(r_{ij}, TP)] - \mu_{r_{ij}}^{TP}\right)^2 \tag{4}$$

2) Calculation of travel time-costs of urban trips: After using LNDs to approximate the travel time-costs of different road segments during different time periods, we then calculate the travel time-cost ts of an urban trip during time slot TP by adding the independent LNDs of all road segments which belongs to the given urban trip. Note that the travel time between two road segments is independent. By using the way in [6], we use a LSND (Logarithmic Skew Normal Distributions) to approximate the sum of independent LNDs. For a given urban trip $UT_{v_s} = \{I_{k_1}(t_1), I_{k_2}(t_2) \cdots, I_{k_e}(t_e)\}$ in time period TP, the LSND of its travel time-cost t can be written as:

$$f_{UT_{v_s}}^{TP}(t) = \frac{2}{\omega \times t} \varphi\left(\frac{\ln(t) - \varepsilon}{\omega}\right) \phi\left(\lambda \frac{\ln(t) - \varepsilon}{\omega}\right) \tag{5}$$

where φ and ϕ denote the pdf and the cdf of a standard Gaussian distribution, respectively, and λ, ε and ω is calculated as follows. In calculating parameter λ, we take solution $\lambda_{UT_{v_s}}^{TP}$ of the following nonlinear equation as the result.

$$\frac{\sum_{i=1}^{e-1} e^{2\mu_{r_{i(i+1)}}^{TP}} e^{\left(\sigma_{r_{i(i+1)}}^{TP}\right)^2} \left(e^{\left(\sigma_{r_{i(i+1)}}^{TP}\right)^2} - 1\right)}{\left(\sum_{i=1}^{e-1} e^{\mu_{r_{i(i+1)}}^{TP}} e^{\frac{\left(\sigma_{r_{i(i+1)}}^{TP}\right)^2}{2}}\right)^2} = e^{\frac{1+\lambda^2}{\sum_{i=1}^{e-1}\left(\sigma_{r_{i(i+1)}}^{TP}\right)^{-2}}} \frac{\phi\left(2\frac{\lambda}{\sqrt{\sum_{i=1}^{e-1}\left(\sigma_{r_{i(i+1)}}^{TP}\right)^{-2}}}\right)}{\phi^2\left(\frac{\lambda}{\sqrt{\sum_{i=1}^{e-1}\left(\sigma_{r_{i(i+1)}}^{TP}\right)^{-2}}}\right)} - 1 \tag{6}$$

This nonlinear equation can be solved by using mathematical utilities such as ”fsolve” in Python. Such a type of nonlinear equation needs a starting solution guess to converge rapidly; we take the solution λ_s of the next equation as the starting guess:

$$\lambda_o = \sqrt{\max_i \left(\sigma_{r_{i(i+1)}}^{TP}\right)^2 \sum_{i=1}^{e-1} \left(\sigma_{r_{i(i+1)}}^{TP}\right)^{-2} - 1} \tag{7}$$

and parameter $\omega_{UT_{v_s}}^{TP}$ and $\varepsilon_{UT_{v_s}}^{TP}$ can be derived from $\lambda_{UT_{v_s}}^{TP}$ by:

$$\begin{cases} \omega_{UT_{v_s}}^{TP} = \sqrt{\dfrac{1+\left(\lambda_{UT_{v_s}}^{TP}\right)^2}{\sum_{i=1}^{e-1}\left(\sigma_{r_{i(i+1)}}^{TP}\right)^{-2}}} \\ \varepsilon_{UT_{v_s}}^{TP} = \ln\left(e^{\mu_{r_{i(i+1)}}^{TP}} e^{\frac{\left(\sigma_{r_{i(i+1)}}^{TP}\right)^2}{2}}\right) - \dfrac{\left(\omega_{UT_{v_s}}^{TP}\right)^2}{2} - \ln\left(\phi\left(\dfrac{\lambda_{UT_{v_s}}^{TP}}{\sqrt{\sum_{i=1}^{e-1}\left(\sigma_{r_{i(i+1)}}^{TP}\right)^{-2}}}\right)\right) \end{cases} \tag{8}$$

C. Vehicle Trajectory Recovery with Mobile Taxicabs

In the previous subsection, we focused on how to calculate the distribution models of the travel time-costs of road segments and urban trips. Based on the preliminary results, in this subsection, we first focus on calculating the optimal time and road segment to query information from taxicabs while given a set of potential trajectories determined by two fixed surveillance cameras, then describe the recursive algorithm to recover vehicle trajectories with mobile taxicabs.

1) Calculation of the optimal querying strategy: We here denote the set of potential paths by $_{v_s} = \{UT_{v_s}^1, UT_{v_s}^2, \cdots, UT_{v_s}^g\}$ and the time period TP, the travel time-cost of trip $UT_{v_s}^i$ is $ts_{UT_{v_s}^i}^{TP}$ which follows the distribution in equation (5). If we denote the prior probability that vehicle v_s followed trajectory $UT_{v_s}^i$ is p_i, thus we calculate the probability that vehicle v_s followed trajectory $UT_{v_s}^i$ while the time-cost of the trip is T by:

$$P(UT_{v_s}^i | T) = \frac{p_i * f(ts_{UT_{v_s}^i}^{TP} = T)}{\sum_{j=1}^{g} p_j * f(ts_{UT_{v_s}^j}^{TP} = T)} \tag{9}$$

To determine the prior probability p_i, we choose to use the same value for p_i's. Further, the probability that vehicle v_s travelled through any road segment r, denoted by q_r, is:

$$q_r = \sum_{r \in UT_{v_s}^i, i=1}^{g} P(UT_{v_s}^i | T) \tag{10}$$

After calculating the probabilities of all road segments, we then rank them by the value of q_r and query the one with largest values first. If vehicle v_s is not identified in the road segment with the largest q_r value, we then query the segment with the next largest value of q_r. Once a road segment is identified, the whole path can be recovered recursively. After determining the road segment, we then have to determine the time interval for the queries of segment r. For a potential path $UT_{v_s}^i = \{ST_a, r, ST_b\}$ with road segment r at time t, the likelihood that the vehicle is at road segment r is:

$$P\left(t, r, UT_{v_s}^i | T\right) = \frac{\int_0^t dx_1 \int_{t-a_1}^{T-a_1} dx_2 f_{ST_a}^{TP}(x_1) f_r^{TP}(x_2) f_{ST_b}^{TP}(T - x_1 - x_2)}{f_{UT_{v_s}^i}^{TP}(T)} \tag{11}$$

Note here r is a road segment, and ST_a and ST_b are both urban trips, and this equation can be solved using mathematical utilities such as "SciPy" in Python. After calculating this value, we calculate the likelihood that vehicle v_s is at road segment r at time t by:

$$P(t, r|T) = \sum_{UT_{v_s}^i : r \in UT_{v_s}^i} P\left(t, r, UT_{v_s}^i | T\right) * P\left(UT_{v_s}^i | T\right) \tag{12}$$

For each possible time point, we compute such probabilities and we query road segment r at a small interval around t with largest $P(t, r|T)$ values. Further, in the final solution, the potential path sets can be determined ahead to save time by reducing repetitive computation.

2) The RVTR algorithm: The overall suspicious vehicle tracking algorithm consists of two parts. The first part is an algorithm to extract the time-varying traffic patterns of road segments by mining the historical trajectory taxicab dataset from May 1, 2015 to April 30, 2016. This part only needs to be executed once and the results are recorded for urban vehicle trajectory recovery. The second part is the **RVTR (recursive vehicle trajectory recovery)** algorithm to recover the detailed trajectories of suspicious vehicles. This part should be executed recursively while given two captured information of a suspicious vehicle, and is terminated when the detailed trajectory is determined or no further information can be queried from mobile taxicabs. More precisely, given an urban trip, we first calculate the optimal querying strategy of this urban trip, then query information from mobile taxicabs until the information of the suspicious vehicle is confirmed exactly. According to this newly confirmed information, the original trip is divided into two sub-trips. We then call the vehicle trajectory recovery algorithm for these two sub-trips recursively and independently. This kind of calculation is terminated when we recover the vehicle trajectory uniquely.

V. Numerical Studies

Since this is the first piece of work that uses the information from mobile vehicles to enhance the precision of trajectory recovery, we evaluate the performance of our recursive vehicle trajectory recovery algorithm by comparing with the **SDD (Shortest Driving Distance)** strategy, the **MDT (Minimum Driving Time)** strategy, the **MTT (Minimum Turning Times)** strategy and the **MLR (Most Likely Route)** strategy. In the SSD strategy, we assume that a suspicious vehicle always selects the shortest path in distance between two fixed video cameras. In the MDT strategy, the suspicious vehicle always selects the path with minimal time-cost. In the MTT strategy, we assume that the suspicious vehicle will try its best to select a direct path and avoid turning in driving, and in MLR strategy, we calculate the most likely driving path based on the fact that the driving travel time-costs of all road segments follow LNDs.

The metrics for evaluating the performance of our **RVTR** algorithm include: i) the average *AR* value (Accuracy Ratio, defined in Definition 5, Equation 1) of suspicious vehicle trajectory recovery; and ii) the average online query times per road segment. We investigate i) the impact of weekdays and weekends, ii) the impact of time periods; iii) the impact of density of fixed video cameras and iv) the impact of vehicle driving actions.

we conducted a series of experiments by driving a car in SIP for a whole month to simulate the behavior of a suspicious vehicle. We use a real world 4,303-taxicab dataset and a 103-intersection video surveillance information dataset in this evaluation. We use the dataset of taxicabs from May 1, 2015 to March 31, 2016 to estimate the LNDs of all road segments. Afterwards, we drive a vehicle running abnormally in the road network during April 1 to April 30, 2016, then collect captured video information of all fixed video surveillance cameras and mobile taxicabs during this month. Next, we filter and select 2,600 trips, each of which contains 20-30 road segments, to run our simulations. Unless otherwise specified, the default values are set according to Table 1.

Parameters	Description
Road network	518 intersections 1560 road segments
Intelligent taxicab system	$4,303$ taxicabs in SIP
Road surveillance system	103 intersections with fixed cameras
Number of trips for simulation	2600 trips
Number of road segments per trip	$20 \sim 30$ road segments
Length of time slot in calculating the LNDs of road travel time-costs	6 minutes

TABLE I: Evaluation Setup

A. Impact of day type

In this subsection, we compare our solution with the SDD strategy, the MDT strategy, the MTT strategy and the MLR strategy. Ten random days, including five weekdays and five weekends, are selected to run our experiments , and the results are shown in Figure 6. In this figure, the dark blue dotted line with small pentagons indicates the result of our RVTR solution, the light blue line with small diamonds corresponds

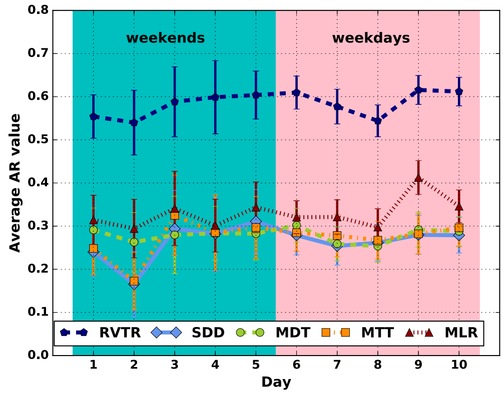


Fig. 6: Average AR values in different day types

to the performance of the SDD strategy, the green dotted line with small dots indicates the result of the MDT strategy, the orange dotted line with small squares gives the result of the MTT strategy, the red dotted line with small triangle indicates the performance of the MLR strategy. The left blue part corresponds to five weekends, and the right red part demonstrates the five weekdays. From this figure, we observe that the performance of our RVTR solution is significantly better than other alternative solutions. Furthermore, we discover that different traffic patterns of different day types can rarely influence the performance of our RVTR solution, and our solution increases the average *AR* value by 120.88%, 109.11%, 113.56% and 77.44% compared with the SDD, MDT, MTT and MLR strategies, respectively. Note here in this simulation, all trips are of suspicious vehicles.

B. Impact of time period

In this subsection, we evaluate the performance of our RVTR solution and the SDD, MDT, MTT, MLR strategies during different time periods and traffic periods, and the results

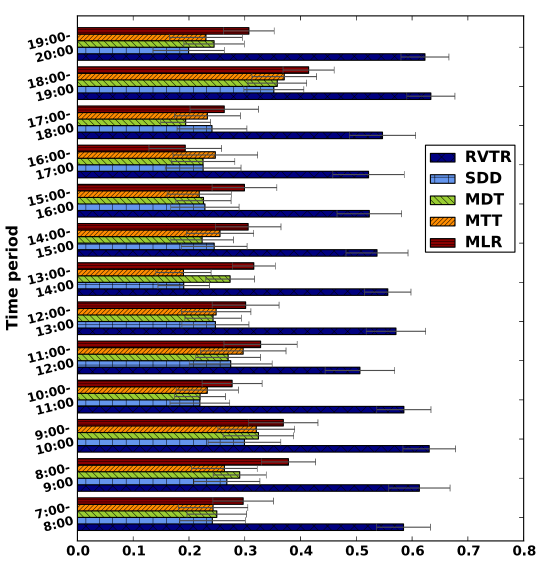


Fig. 7: Average AR values during different time periods

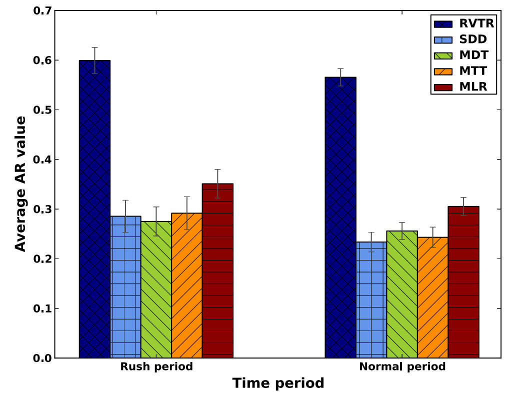


Fig. 8: Average AR values during different traffic periods

are illustrated in Figures 7 and 8. In these two figures, the dark blue bar with skew lattices indicates the performance of our RVTR solution, the light blue bar with square lattices corresponds to the result of the SDD strategy, the green bar with right-hand twills gives the result of the MDT strategy, the orange bar with left-hand twills demonstrates the performance of the MTT strategy, and the red bar with horizontal stripes indicates the performance of the MLR strategy. And in Figure 8, rush periods include 7:30a.m.-9:30a.m. and 17:00p.m.-18:30p.m. and normal periods include the rest hours. From these two figures, it is clear that our RVTR solution outperforms other alternative approaches. Moreover, we discover that the performance of our solution increases a little bit with the increase of road congestions. This is because with the increase of road congestions, the travel speeds of suspicious vehicles decease, thus their information are easier to be captured by mobile taxicabs. Note that in Figure 7, the performance of our solution during 11:00a.m.-12:00a.m. is obviously poor, the reason is that during this period most taxicab drivers stop driving to have lunch, thus the information of suspicious vehicles is difficult to obtain by mobile taxicabs. However, this kind of phenomenon does not occur during dinner time for most taxicab drivers postpone their dinner to get more business during dinner rush hours.

C. Impact of video surveillance camera density

We investigate the impact on the performance of different strategies while the density of fixed road video surveillance

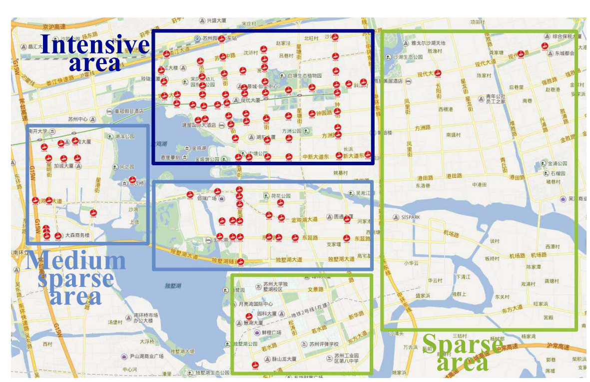


Fig. 9: Distribution of fixed video surveillance cameras in SIP

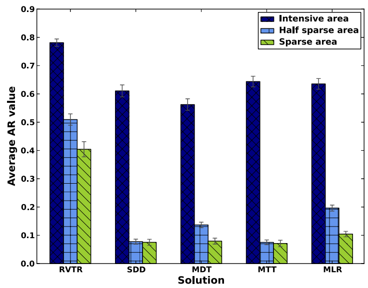


Fig. 10: Average AR values of trips in different areas

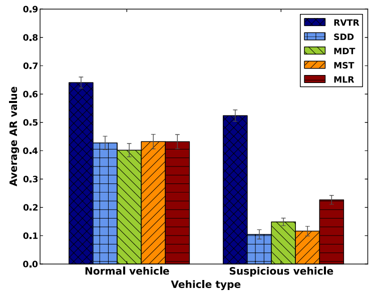


Fig. 11: Average AR values with different vehicle types

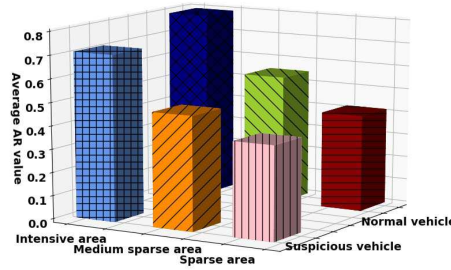


Fig. 12: Average AR values of RVTR with both different vehicle types and different video camera densities

cameras is changing. The distribution of road video surveillance cameras is illustrated in Figure 9. As shown in this figure, we divide the whole road network in three type of areas: intensive area (in the dark blue frame), medium sparse area (in the light blue frames) and sparse area (in the green frames). In accordance with where a trip is located, we distinguish all trips into three classes, then evaluate the performances of all possible solutions. The results are demonstrated in Figure 10. In this figure, the dark blue bar with skew lattices indicates the performances of all solutions while recovering trips in intensive areas, the light blue bar with square lattices corresponds to the results of recovering trips in medium sparse area and the green bar with right-hand twills gives the results of trips in sparse area. The performance of our RVTR solution is always better than other alternative solutions. More precisely, the performance of our solution are significantly better than the performances of other approaches with regard to those trips in medium sparse and sparse areas. It is because in these two areas, the captured information from fixed video surveillance cameras is not enough for recovering detailed trajectories of suspicious vehicles, and the mechanism that using the video information from mobile taxicabs to help recovering trajectories of suspicious vehicles does work.

D. Impact of vehicle type

For the evaluation describd in this subsection, we first divide all vehicles into two types: normal vehicle and suspicious vehicle. Compared to normal vehicle, suspicious vehicle tends to hide their trajectories by going around different paths and stopping frequently to avoid fixed road video surveillance cameras. Based on these preliminary facts, we then evaluate the differences of the performances of different solutions when they are used to recover trajectories of different vehicle types, and illustrate the results in Figure 11. In this figure, the dark blue bar with skew lattices indicates the performance of our RVTR solution, the light blue bar with square lattices corresponds to the result of the SDD strategy, the green bar with right-hand twills gives the result of the MDT strategy, the orange bar with left-hand twills demonstrates the performance of the MTT strategy, and the red bar with horizontal stripes indicates the performance of the MLR strategy. From this figure, we discover that our RVTR solution outperforms other alternative strategies with both normal vehicles and suspicious vehicles. Furthermore, the performance of our solution is rarely influenced by the type of vehicle, but other alternative approaches are not suitable for suspicious vehicles. In other words, our solution is significantly better than other solutions in tracking urban suspicious vehicles.

Next, we investigate the impact on the performance of our RVTR solution with both different vehicle types and different video camera densities. The results are shown in Figure 12. In this figure, the dark blue bar with skew lattices, the green bar with right-hand twills and the red bar with horizontal stripes indicate the results for normal vehicles in intensive area, medium sparse area and sparse area respectively, and the light blue bar with square lattices, the orange bar with left-hand twills and the pink bar with vertical stripes correspond to the performance for suspicious vehicles in intensive area, medium sparse area, and sparse area separately. It is clear that the factor of vehicle type can rarely impact the performance of our algorithm, since our recursive algorithm is appropriate for trajectories with frequent off route paths and stops. On the other hand, the performance of our solution is also pretty stable when the density of fixed road video cameras is changed. The decreases between sparse area, medium sparse area and intensive area are caused by the decreases of the densities of both fixed video cameras and mobile taxicabs, since the density of fixed road video cameras is identical with the density of mobile taxicabs as well as the density of traffic flows.

E. Query times of RVTR algorithm

In this subsection, we present the evaluation of the query times of our RVTR algorithm. More precisely, we investigate the average numbers of query times per road segment of our solution with different vehicle types, different fixed camera densities and different time periods, and the results are demonstrated in Figure 13. In subfigure I, the dark blue bar with skew lattices shows the result of recovering the trajectory of normal vehicles, and the light blue bar with square lattices indicates the performance while tracking suspicious vehicles. We discover that the number of query times of our solution is quiet stable in tracking both normal vehicles and suspicious vehicles. In subfigure II, the dark blue bar with

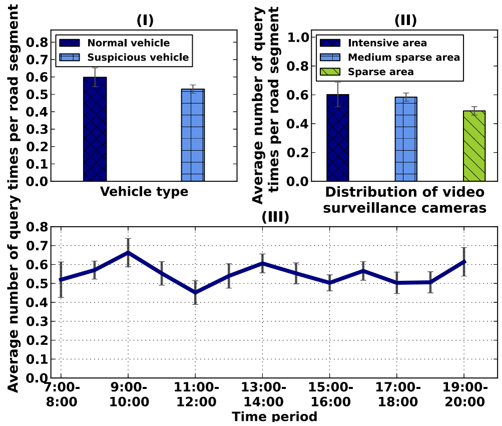


Fig. 13: Average number of query times per road segment

skew lattices demonstrates the results in tracking suspicious vehicles in intensive area, the light blue bar with square lattices corresponds to in medium sparse area, and the green bar with right-hand twills is the results in sparse area. We also discover our solution is pretty stable in querying taxicabs with different distributions of fixed video cameras. In addition, the query times while tracking suspicious vehicle in sparse area is a little lower because of the exiguity of taxicabs in the same area. We also evaluate the query times of our solution during different time periods, and the result is shown in subfigure III. It is fairly clear that it has nothing to do with the road traffic status, and is also steady during different time periods. In summary, the average number of query times per road segment is no more than 0.7 among various kinds of premises, and our solution is quiet efficient in querying mobile taxicabs.

VI. Conclusion

Recent technology advances provide new opportunities to implement a suspicious vehicle tracking system with sparse road video cameras and mobile taxicabs. In this paper, we model the travel time-cost of a road segment during various time periods precisely with LNDs, then use LSNDs to approximate the time-cost of an urban trip during different time periods and propose an approach to calculate possible location and time distributions of suspicious vehicles. Based on these preliminary results, a novel method is designed to select an optimal set of taxicabs to verify the distributions by uploading the video clips from the taxicabs, and refine the trajectory in a recursive manner. Performance evaluation from real-world taxicab and video surveillance information datasets demonstrates the effectiveness of our algorithm. With the increasing popularity of intelligent road surveillance system and intelligent taxicab system, this paper offers a new perspective to tracking suspicious vehicle with sparse video surveillance cameras and mobile taxicabs.

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