EAI Endorsed Transactions
on Security and Safety
Research Article EAI.EU

Re-identification of Vehicular Location-Based Metadata

Zheng Tan[1,*], Cheng Wang[1], Weili Han[2], Xiaoling Fu[1], Jipeng Cui[1], Changjun Jiang[1]

[1]Tongji University, Shanghai 201804, China
[2]Software School, Fudan University, Shanghai 201203, China

Abstract

Amid the flourish of various data services, the privacy problems on metadata have received sufficient attention. Generally, the identity is the most sensitive attribute in metadata as identity is the key linking all attributes together. Thus, quite a few methods, such as dummy and k-anonymity, have been applied to actual applications to protect the identity . However, we still argue that the identity is very likely to be disclosed. In this paper, we study the re-identification problem in the *seemingly* privacy-preserving VLBS (Vehicular Location-Based Service). We find that the trajectories of vehicles are highly unique after studying 131 millions mobility traces of taxis. More specifically, the experiments demonstrate that only four spatio-temporal points are sufficient to uniquely re-identify the vehicle, achieving an accuracy of 95.35%. This indicates that there exists a high risk of re-identification in VLBS even identity has been protected by traditional methods.

Keywords: Privacy, VLBS, Re-identification, Uniqueness, Trajectories

Received on 1 December 2017, accepted on 01 December 2017, published on 7 December 2017

doi:10.4108/XX.X.X.XX

1. Introduction

Benefiting from yielding implicit information about individuals, large-scale data sets of human behavior play an important role in various network services, such as Location-Based Services (LBS)[1, 2], Recommending System and Authentication System. Accompanied with the convenience, privacy concerns also deserve attention as the captured data always contain large amounts of personal private attributes, including location, identity, age, etc. Note that the identity is the most sensitive information among various personal attributes because of two reasons: (1) Based on the identity, other attributes can associate with each other objectively. The identity disclosure always gives rise to leaking a series of personal attributes. (2) To trace to its source, privacy is an subjective concept. The identity is the most intuitive sensitive information for ordinary people. Thus, in this paper we aim at revealing the identity disclosure, namely, the re-identification problem. Moreover, we carry out our work in the background of LBS[3–6], which is widely used but tortured by re-identification problem.

In an LBS system, LBS providers/servers are often regarded as non-trustworthy components that perhaps leak users' information to the third party deliberately or unintentionally. To improve their reliability, the servers usually anonymize the data to protect users' privacy, [7–9]. Under such anonymous protection, if an adversary hacks into an LBS server to get its trajectory metadata, he/she usually can only obtain an anonymous trajectory dataset, and cannot infer an individual's trace from the anonymous data. As a result, a completely anonymous dataset is often presumed to be *slightly sensitive* when only several non-anonymous records of a specific user could be exposed to adversaries, [10]. The objective of our work is to probe the possibly "hidden" privacy leakage problem of user's re-identification in LBS.

More specifically, we intently investigate the user's re-identification problem for a special type of LBS, *Vehicular Location-Based Service* (VLBS). The reasons why we focus on VLBS are two-fold: Firstly, VLBS is becoming a promising type of location-based services, since more and more vehicles are able to access the Internet as mobile terminals, and then many LBS-related applications are devised to serve vehicles. For example, a transportation monitor application

★This paper's earlier version was presented at 2016 International Conference on Security and Privacy in Communication Networks, Guangzhou, Oct. 10-12, 2016.
*Corresponding author. Email: 102456@tongji.edu.cn

[11] collects real-time vehicle location information to predict road condition and generate suggestions to drivers. Secondly, a significant feature of VLBS, i.e., the mobility traces of vehicles are usually constrained by roads, draws us to figure out whether road information could improve the risk of user's re-identification. To the best of our knowledge, few researches distinguished the privacy issue of VLBS as an independent problem from the LBS privacy problem, [12–14].

In this paper, we utilize non-sensitive datasets to evaluate whether they can still cause privacy leakage problems (user's re-identification) in VLBS. To be specific, we extract a few non-anonymous trajectories from two datasets of taxi trajectory metadata, 131 millions mobility traces of taxis in Shenzhen and 1.1 billions of taxis in Shanghai, and compute the uniqueness of taxi trajectories. Surprisingly, we find that four spatio-temporal points are sufficient to identify vehicles even when anonymous protection strategies are adopted, achieving an accuracy of 95.35% for Shenzhen dataset and 96.75% for Shanghai dataset respectively. Experiment results show that vehicles trajectory privacy is inclined to be risky. We provide an intuitive explanation for this observation as follows: Compared with diverse human trajectories, vehicle traces are mostly binded by roads. The road information is possibly the underlying reason for user's re-identification only by four record points.

The rest of this paper is organized as follows: Section 2 introduces related work in LBSs and VLBSs privacy fields. Section 3 gives the main results of this work. In Section 4, we provide the analyzing procedure based on two real-life datasets. Section 5 makes a discussion on what insights can be obtained from the experimental results. Section 6 draws a conclusion and discusses about the future work.

2. Related Work

One of the classic privacy protection mechanisms is the k-anonymous algorithm [15–21]. In the model, a dataset must have k undistinguishable items on a specific property, where k infers the least risks that we can suffer when information is leaked. At the beginning, the algorithm was designed for databases like hospital and school for user privacy protection. Later, researchers found that k-anonymity can also work effectively in the LBS privacy protection.

To disclose the risk of user's re-identification in anonymous dataset, Montjoye et al.[22] studied the uniqueness of shopping mall metadata. The shopping mall metadata has four fields: anonymous ID, time, location and money spent by that customer. In their experiments, they applied different resolutions to all fields except ID to simulate basic privacy protection methods. The conclusion is that four purchase records are enough to uniquely re-identify 90% individuals. This result is achieved with metadata that has three dimensions (purchase time, shop, price). If an individual is re-identified, his/her mobility traces corresponding to purchase behaviors can be inferred by adversaries. To explain this result, an underlying reason is that the *relatively high dimension of metadata* could expose individuals' privacy with a high accuracy. Another similar work [23] studied the uniqueness of human traces associated with phone activities. They use anonymous mobile phone dataset for their experiments. When people use their phones (to make a call or send a message), the phone will communicate with the nearest antenna and the whole activity is recorded by telecommunication company. There are three fields in their dataset: anonymous ID, the beginning time and antenna used (location, one antenna covers a specific area). Similarly, they applied different resolutions to the time and location fields. The result shows that four phone activities are enough to uniquely identify 95% individuals. If an individual is re-identified using the dataset, his/her mobility traces corresponding to phone activities are exposed to adversaries. Compared to the shopping mall metadata which has three dimensions, this work just use a two-dimension metadata. We notice that the location information of user is indeed represented by the coverage area of corresponding antenna. In other words, adversaries are just aware of which antenna the individual has communicated with. An antenna covers a large area, so privacy problem in this two-dimension metadata seems not that critical.

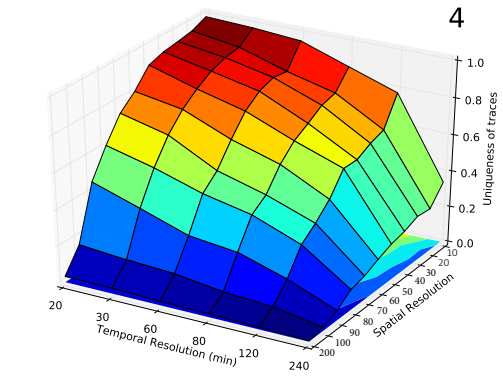
In our problem, the taxi trajectory metadata has two dimensions: LBS query time and position. Such a low data dimension makes the privacy problem seem less serious.

3. Main Results

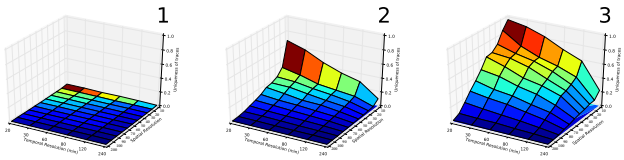
3.1. Four Points for Re-Identification

In LBS, application server stores records of users, including ID, time and location information. We cannot infer one's real identity by ID, since ID is anonymously stored in the server. For example, when we use Google Maps [24] for navigation, Google just uses our Google account as ID, so the application will never know our identities or the plates of our cars. Although this basic mechanism protects our privacy to some extent, the LBS servers are still considered unreliable.

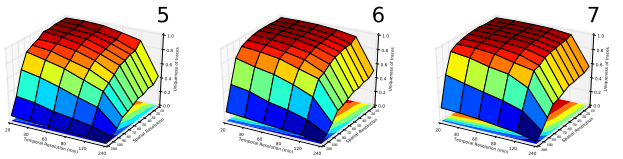
In our attacker model, we assume that adversaries have full access to LBS servers, and that adversaries conduct attacks by collecting several spatio-temporal points of a user's car,[22, 23]. When these spatio-temporal points are collected, adversaries use them to match with the database on servers. If an unique match is found, adversaries can decide the identity of the user in the database, and know the precise position



(a) N=4

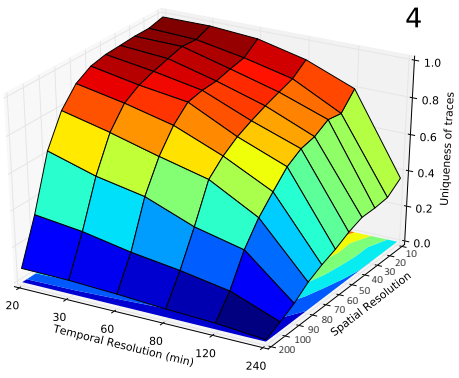


(b) N=1 (c) N=2 (d) N=3

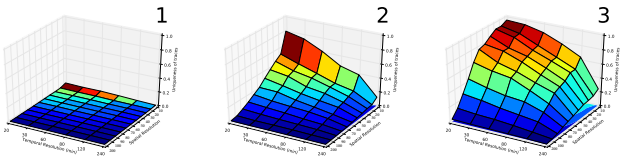


(e) N=5 (f) N=6 (g) N=7

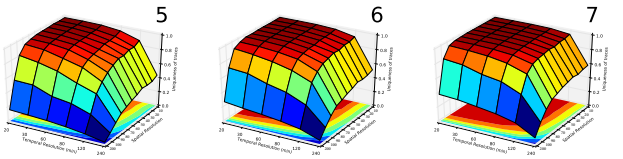
Figure 1. The Result of Shanghai's Taxis.



(a) N=4



(b) N=1 (c) N=2 (d) N=3



(e) N=5 (f) N=6 (g) N=7

Figure 2. The Result of Shenzhen's Taxis.

of the car at any moment. Generally, one spatio-temporal point is enough for re-identifying a target if its trajectory is without an anonymous protection. In our experiments, we attempt to figure out the risk of being re-identified with basic generalization protection methods. Generalization also helps to eliminate spatial and temporal error because the adversaries cannot record spatio-temporal points without any error. It is achieved by spatial and temporal resolution. The details will be explained in Section 4 later.

In our experiments, we have 6 levels (20, 30, 60, 80, 120, 240 minutes) of temporal resolutions and 11 levels (10×10, 20×20, ..., 100×100 and 200×200 blocks) of spatial resolutions. Besides, $1\sim7$ spatio-temporal points are randomly sampled for our matching experiment respectively. The three mentioned parameters have 462 ($6\times11\times7$) combinations in all. For each combination, we obtain 150,000 samples and for each sample we test its uniqueness. By this procedure, we can compute the proportion that a taxi can be uniquely identified. Figure 3 illustrates the uniqueness of traces when we set the temporal resolution to 20 minutes and spatial resolution to 100×100 square blocks. We can observe that the uniqueness grows rapidly as the number of known spatio-temporal points increases, and its value approximates 100% rapidly when the number is larger than 4. What's more, the uniqueness of Shanghai's grows slightly faster than that of Shenzhen's. By now, we can state that 4 spatio-temporal points are sufficient to re-identify a taxi's trajectory.

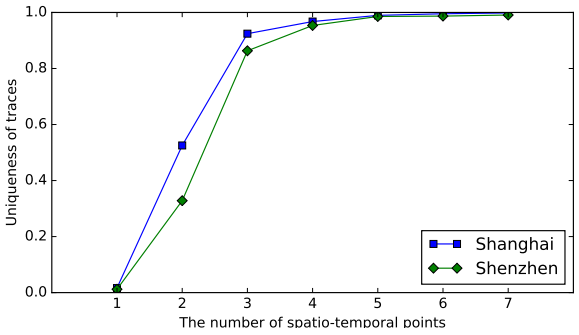


Figure 3. The Uniqueness of Traces with A Specific Number of Known Non-anonymous Spatial-Temporal Points. Given a 100×100 spatial resolution and 20 minutes temporal resolution, the uniqueness is up to 95.35% for Shenzhen taxis and 96.75% for Shanghai's, when the number comes to 4.

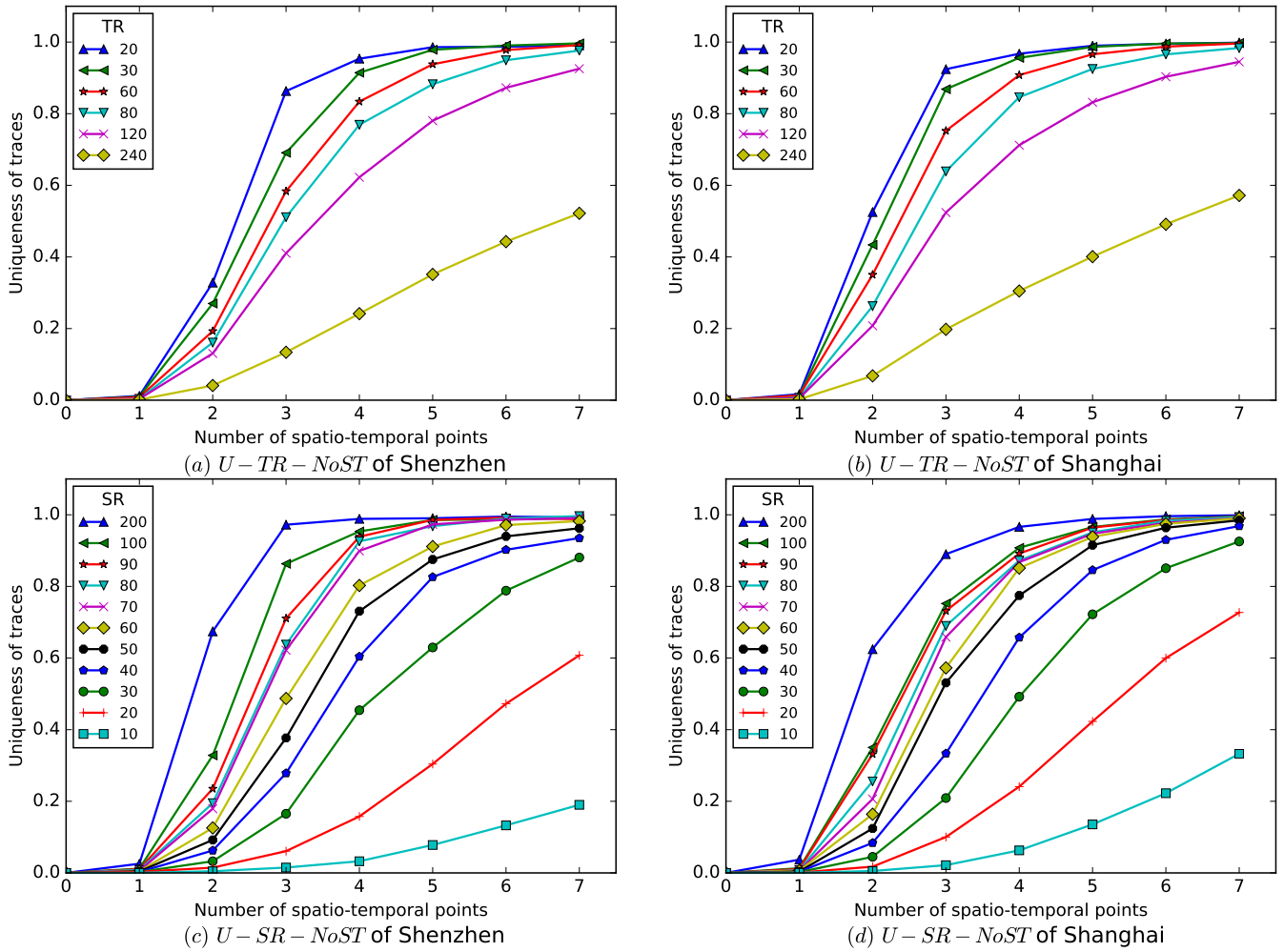
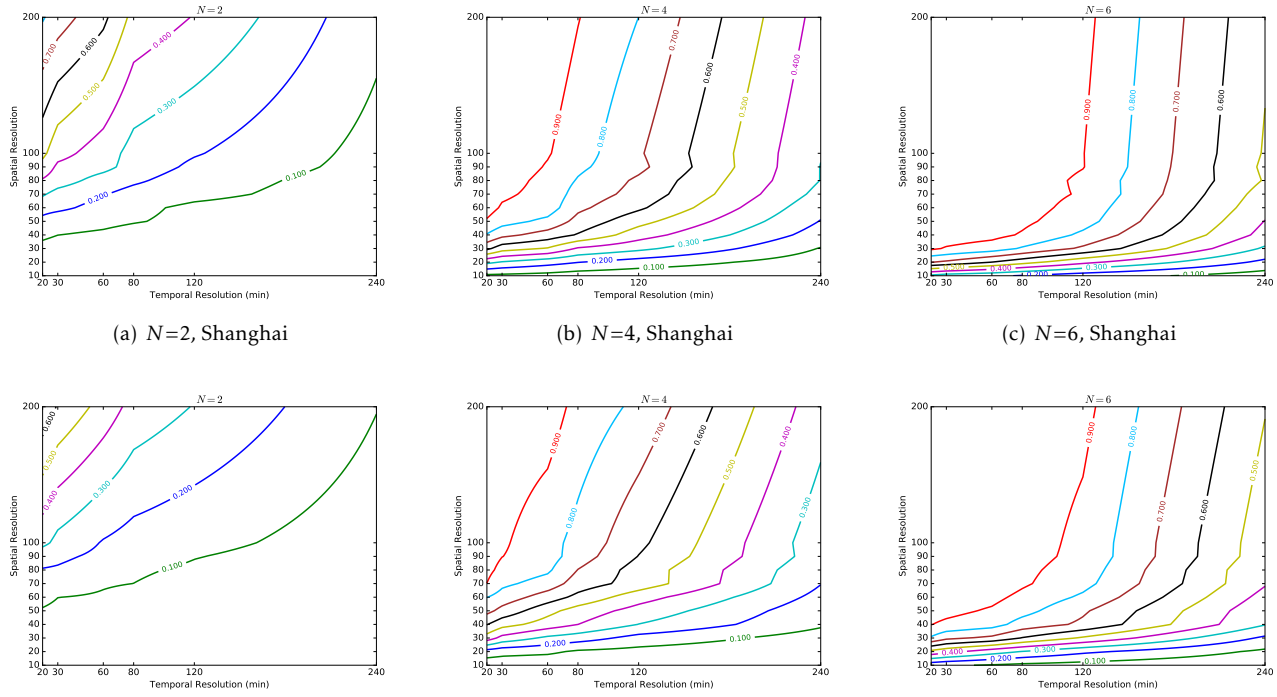


Figure 4. The Impacts of Temporal and Spatial Resolutions on The Uniqueness. Figure (a) and (b) show how different levels of temporal resolutions affect the uniqueness. Figure (c) and (d) show the effects of different spatial resolutions on the uniqueness. The notations U, TR, SR, $NoST$ stand for Uniqueness of traces, Temporal Resolution, Spatial Resolution, Number of Spatio-Temporal points, respectively.

In order to find out the effects of the temporal and spatial resolution on the uniqueness of traces, we conduct experiments with different temporal and spatial resolutions. The results are shown in Figure 4. By these, we can conclude that the uniqueness benefits from a larger number of spatio-temporal points, a shorter temporal resolution, and a bigger spatial resolution (i.e., a smaller block size). Furthermore, in Figure 5, we plot the contour map according to the uniqueness of traces extracted from two cities with the given known points 2, 4 and 6.

For each given number of spatio-temporal points, we plot the uniqueness of two datasets in Figure 1 and Figure 2, corresponding to changing temporal and spatial resolutions. When the number of spatio-temporal points equals to 1 ($N = 1$, Figure 1(b), 2(b)), the surface is nearly flat, which means that a single point is insufficient to re-identify a taxi, whatever the temporal and spatial resolutions are given. With the growing of N, the re-identified accuracy (uniqueness) is increasing rapidly. When N equals to 4 ($N = 4$, Figure 1(a), 1(a)), moderate temporal and spatial resolutions can lead to a uniqueness over 90%. And the uniqueness exceeds 90% for most temporal and spatial resolutions while N equals to 7 ($N = 7$, Figure 1(g), 2(g)).

In both datasets, the trajectories cover square areas with a side length of 200 kilometers, spreading over two degrees in longitude and latitude. If the spatial resolution is chosen to be 10×10, then we get 100 square blocks, with a 20-kilometer side length for each. Such a block is much too huge for estimation. The appropriate and practical resolution is 100×100, which means that the side length of each block becomes only 2 kilometers.



(a) N=2, Shanghai (b) N=4, Shanghai (c) N=6, Shanghai

(d) N=2, Shenzhen (e) N=4, Shenzhen (f) N=6, Shenzhen

Figure 5. Contour Map of Uniqueness of Traces of Two Cities.

3.2. Time Closeness

Based on the above conclusions, we further investigate on the temporal correlation between the four observation points. As all users are restricted to the road network in VLBS, one vehicle's moving trace is most likely to be analogous to his adjacent vehicles for some time, especially during the rush hours. Intuitively, if the observing time of the four points is too close, obtaining four points are not enough to distinguish one vehicle from others. To validate this supposition, we carry out the following experiments.

Firstly, we extract the feature to characterize the closeness degree of the four points To formulate, we assume that the time stamps of the four points is denoted by $T = \{T_1, T_2, T_3, T_4\}$. Without loss of generality, we regard that the four time stamps are in chronological order. Then we define the average time difference between two adjacent time stamps as the closeness degree, shown as

$$C = \frac{T_4 - T_1}{3} \tag{1}$$

Specially, in the above setting, we choose n points randomly as the observing points. We can regard their time stamps as the dots sampled from a Uniform Distribution $U(0, \theta)$. Then the difference between two adjacent time stamps, $D = \{d_{ij} = T_i - T_j \mid i - j = 1\}$, is subject to the following probability density function,

$$f(d) = \frac{n!}{\theta^n (j-i-1)!(n-j+i)!} d^{j-i-1} (\theta - d)^{n-j+i} \tag{2}$$

And the expectation of D is shown as follow,

$$E(D) = \frac{\theta(j-i)}{n+1} \tag{3}$$

Actually, the expectation can be regarded as the closeness degree of the random selection C_R. In our experiments, the four points can re-identify one vehicle in one day's traces randomly. Thus we can obtain $C_R = 4.8h$ as $\theta = 24h$ and $n = 4$.

Next we carry out a series of experiments, illustrated by Fig. 6 and 7. Taking Fig. 6 as an instance, we calculate the uniqueness with $C = \{0.5, 1, 2, 4.8, 6\}$ while N takes 4. Apparently, the uniqueness increases along the closeness degree grows and reveals convergent tendency when $C \geq 2$. Moreover, the figure of uniqueness in $C = 4.8$ is similar to the that of the random selection(shown in fig. 1(a)). Our experiments validate that the time closeness of observation points can indeed influence the uniqueness.

4. Investigating Procedure

In the experiments, we generalize the spatial and temporal dimensions to simulate the basic privacy protection methods. Our experiments can be divided into four

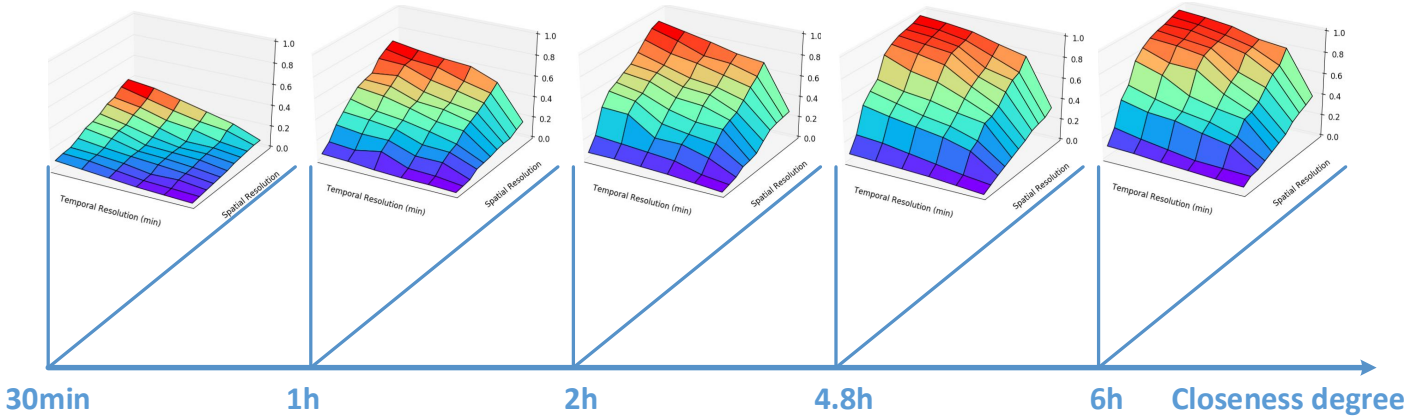


Figure 6. The Uniqueness of Traces with different closeness degree in Shanghai. Note that the observation points count N takes 4.

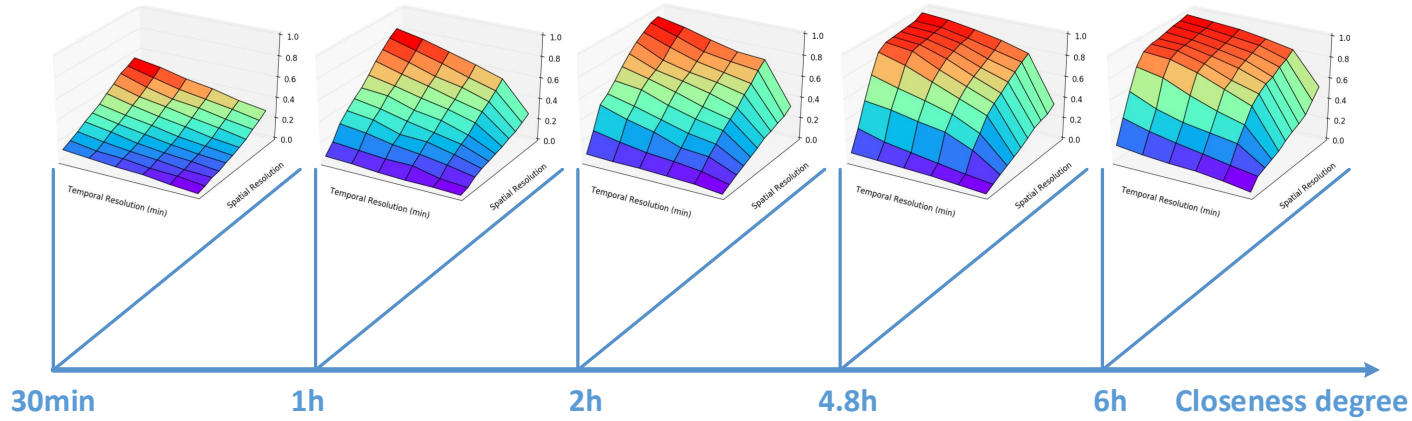


Figure 7. The Uniqueness of Traces with different closeness degree in ShenZhen. Note that the observation points count N takes 4.

steps: pre-processing, temporal generalization, spatial generalization and uniqueness calculation. During pre-processing, datasets are processed to satisfy the requirements of experiments. Temporal generalization applies a specific resolution to the time field. For adversaries, points within a resolution cannot be distinguished. Similarly, spatial generalization applies a resolution to the location field. After temporal and spatial generalization, the last step is to find out the possibilities that one taxi can be re-identified uniquely by adversaries given specific number of spatio-temporal points. When carrying out the experiment, we test different temporal and spatial resolutions with different number of spatio-temporal points.

The details of each step are shown in the following sections. We will give an overview of our datasets at the end.

4.1. Dataset Pre-processing

The two adopted datasets take about 60 Gigabytes disk storage in all. The data get a lot of redundances and mistakes when taxi companies record and store them. Before implementing the experiments, we have to do some pre-precessing work to clean the datasets.

In the first step of pre-processing, redundant fields are removed. Besides redundant data, logs can also have minor mistakes. The data contains broken records, such as those with temporal disorder and spatial misplace.

Records in datasets are expected to be temporally well organized, but some of them are chronological disordered. When such a temporal disorder takes place, uncorrelated points may occur in the chronological sequences (as is shown in Figure 8(a)). All of the temporal uncorrelated points in the logs should be removed in this stage. Another temporal disorder case is that all the point sequences are correlated with each other, but some of them are shifted (as Figure 8(b) shows). In general, GPS-measured time has a difference from GPS-received time, and the records on logs may shift over one or two records. By scanning the sequences, one point temporal disorder can be fixed easily. Given that one point temporal disorder is already a low possibility event, we do not concern the high-order points temporal disorder cases.

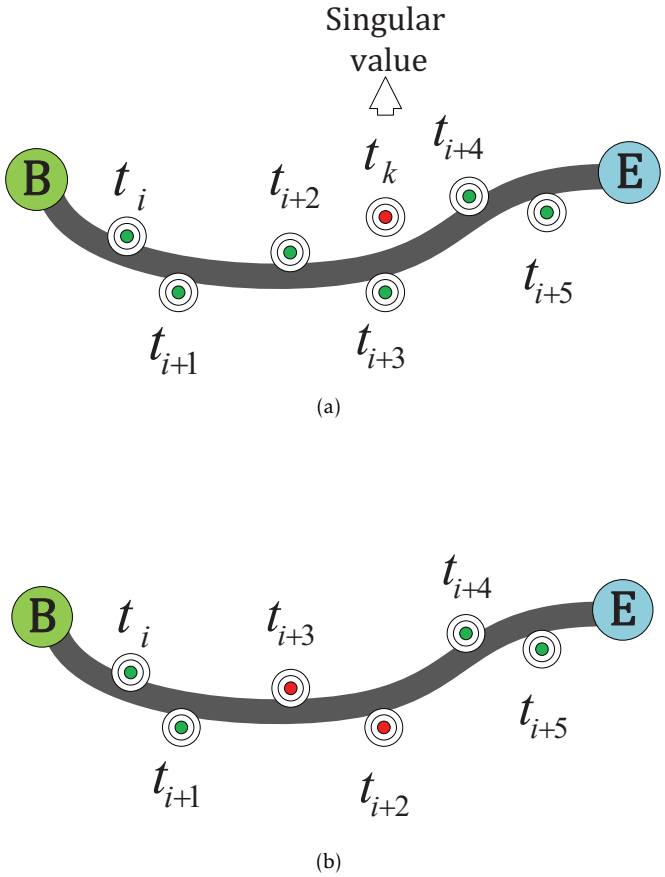


Figure 8. Illustration of Temporal Disorder. In Figure 8(a), on the road segment from B to E, there are several points among t_i and t_{i+5}, and t_k's temporal tag doesn't match the surrounding points' tags, which makes it a broken point. So t_k should be removed in the pre-precessing stage. In Figure 8(b), t_3 shifts ahead t_2 (or t_2 shifts behind t_3). Two solutions are used for solving this temporal error. One is removing t_2 or t_3, the other is correcting t_2's or t_3's temporal tag. Both solutions need the average speed parameter as a reference.

The last case is spatial displace. When taxis report their locations to the server, they upload their longitude and latitude information, and the server receives and stores this information into database. The whole process can not be done perfectly. The bits representing the longitude and latitude may be changed when the location information is being transmitted and stored, which leads to spatial displace. Spatial displace makes one point from the sequences shift away from others, as is shown in Figure 9. After calculating the speed between points, a point spatial displace can be distinguished if its speed to adjacent points is extremely large. Spatial displaced points will be removed from the records.

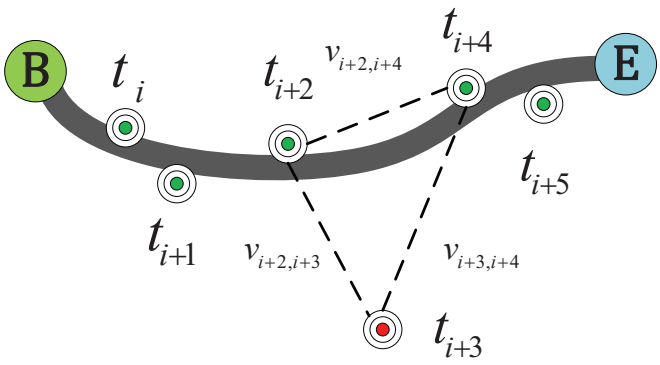


Figure 9. Illustration of Spatial Misplace. t_{i+3} has a deflection from the main road, which can be tested by communication error between GPS devices and GPS servers. The average speed is calculated for finding the deflection points. In the figure, $v_{i+2,i+3}$ is the average speed between t_{i+2} and t_{i+3}, and so are $v_{i+3,i+4}$ and $v_{i+2,i+4}$. By comparison, $v_{i+2,i+3}$ and $v_{i+3,i+4}$ are much more larger than $v_{i+2,i+4}$. Frequently their values exceeds taxis' maximum speed. So we can consider t_{i+3} as an invalid point and remove it from logs.

In the end, some taxis have only a small number of records, so they are not suitable for the experiments. These cars are simply removed from logs.

4.2. Temporal Generalization

Take Shenzhen taxis data as an example, whose timeline covers 9 days. In temporal generalization step, different levels of temporal resolutions are tested in our experiments. A specific temporal resolution tr will divide the whole timeline (9 days, 12, 960 minutes) into $12,960/tr$ periods. In Figure 10, the spatio-temporal points are mapped to each interval according to their temporal tags. By doing so, points nearby are classified to the same period. Thus, the adversaries can not tell the temporal differences among the points within the same period.

Actually, two time-related concepts are involved in our attacker model, say, the Adversary spying time (AST) and the Server recording time (SRT). AST is the time that adversaries record when following a car, while SRT is the time that the server records when a car starts a query to server. In fact, the adversary can not obtain the query start time (QST) easily and the QST also has a numerical difference from the AST. These two reasons make a unstable numerical difference between AST and SRT. In our experiments, we set temporal resolutions to simulate the situations that AST has a shift from SRT.

In the experiments, we try 6 levels of temporal resolutions: 20, 30, 60, 80, 120, and 240 (minutes).

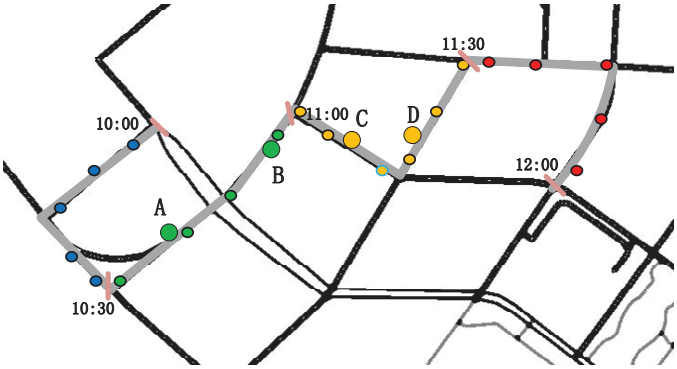


Figure 10. Illustration of Temporal Generalization. The gray line is the trajectory of a car in timeline from 10:00 to 12:00. In temporal generalization process, we set the temporal resolution to half an hour, and the path is divided into 4 periods marked by different colors. Points in the same period are considered undistinguishable. For example, A and B, C and D are undistinguishable, while A and C, B and D are distinguishable.

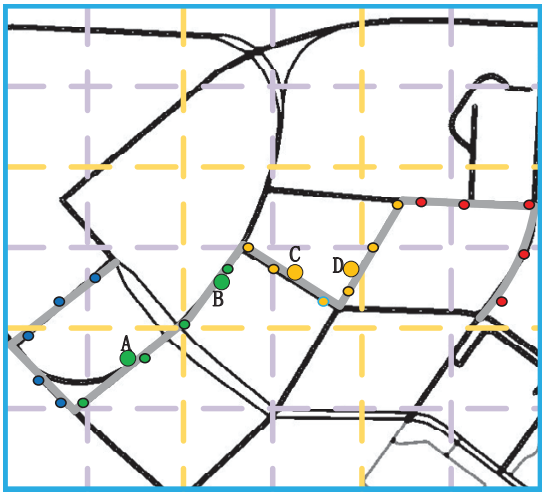


Figure 11. Illustration of Spatial Generalization. The entire area is divided into 6×6 blocks bounded by yellow and gray dotted lines. After the spatial generalization, A and B are in different blocks, while C and D are in same block. So A and B are distinguishable, C and D are undistinguishable. We say that the 6×6 spatial resolution cannot tell C from D. When spatial resolution level is reduced to 3×3 (divided by yellow dotted line), B is mingled with C and D.

4.3. Spatial Generalization

The Shenzhen and Shanghai taxis' trajectories both cover an approximate square area that spreads over 2° in longitude and 2° in latitude. In this stage, we use a simple and direct way to generalize the spatial area. We draw lines with different densities along the longitude and latitude lines and divide the entire mobility spatial area into different blocks.

As shown in the Figure 11, points in the same blocks are identical in their location when exposed to adversaries. This method of division can simulate k-anonymous algorithm to some extent, while pure k-anonymous division will create dynamic districts as time goes by. With the source dataset, we can not locate the precise position of all taxis at a specific time, which means that the pure k-anonymous algorithm is impractical. In our experiments, different division densities are set to replace different values of k's in k-anonymous algorithm. The more blocks are divided, the smaller each block is. We apply 11 different spatial resolutions in the experiments (10×10, 20×20,..., 100×100, and 200×200).

4.4. Uniqueness Calculation

After pre-processing, temporal generalization and spatial generalization, we can calculate the uniqueness of a taxi's trajectory. Let U_s denote the uniqueness of a trace given several known spatio-temporal points. We also define uniqueness indicator ϵ, which indicates the possibility that a trace can be identified with a specific number of spatio-temporal points.

$$U_s = \begin{cases} 1 & \text{if a sample is unique,} \\ 0 & \text{otherwise.} \end{cases}$$

In Figure 12, when the number of known spatio-temporal points is 2 (points B and C here), the value of U_s is 0 according to the above formula. If 3 points are known (either A, B, C or B, C, D), then U_s equals 1.

Now that we can calculate the value of U_s given several spatio-temporal points, the last problem to solve is how to get enough samples of several spatio-temporal points. We use statistical approaches to sample from the taxis' records repeatedly, and match it with the entire dataset to calculate U_s. With enough samples, the uniqueness indicator ϵ can be inferred as in Equation (4).

$$\epsilon = \frac{\sum_{s \in S} U_s}{|S|} \times 100\% \tag{4}$$

In our experiments, we mainly have 3 variables (the temporal resolution TR, the spatial resolution SR, and the number of known spatio-temporal points N). Please refer to the detailed results of our experiment and the relations between ϵ and the three variables can be found in Section 3.

Algorithm 1 gives the procedures of computing the uniqueness of users' traces.

4.5. Datasets Overview

We adopt two datasets, the overview of which is shown in Table 1. Table 2 gives the main fields of the datasets. *ID* corresponds to taxi's identity, which is the unique

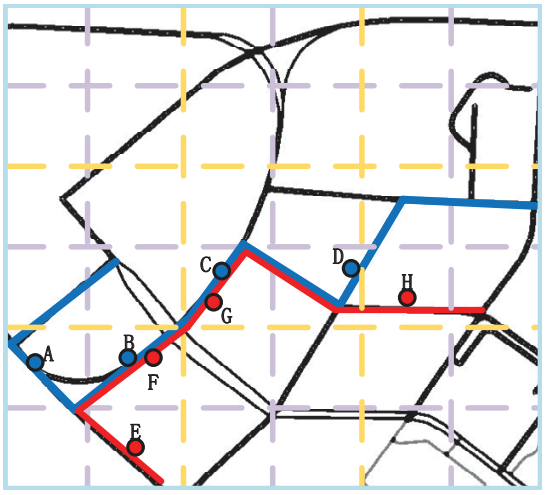


Figure 12. Illustration of Uniqueness Judgement. The blue and red lines are trajectories of two taxis with a timeline from 10:00 to 12:00, A and E turned out to be in period 10:00 to 10:30 (similarly, B and F in period from 10:30 to 11:00; C and G in period from 11:00 to 11:30; D and H in period from 11:30 to 12:00). Given 2 spatio-temporal points, B and C, we cannot identify the blue line trajectories. But if additional points, A or D or both of them, are given, this trajectory can be uniquely identified.

Table 1. Overview of Datasets

Index	*Date*	*#Taxis*	*#Records*
Shenzhen	2011 04/18~04/26	13798	130,551,644
Shanghai	2015 04/01~04/10	13899	1,141,606,183

identification of taxis. *Time* is the time when the taxi reports its location to LBS server. *Longitude* and *Latitude* denote the location of a taxi.

In our datesets, each taxi has plenty of records every day, and more records mean that a taxi has more trajectory data. Figure 13 gives the probability density distribution of the number of taxi trajectory records per day. We can see from the figure that the probability density of Shanghai dataset is increasing with the growing number of records while that of Shenzhen dataset is decreasing. Taxis in Shanghai tend to have more trajectory records per day than those in Shenzhen.

Actually, a larger number of records do not mean more trajectory information. For example, given the same number of trajectory records, those with larger time-span may contain more information. Figure 14 gives the interval length distribution of two adjoined records. As we use taxi trajectory data from taxi companies instead of private cars, and taxi companies often collect their taxis' location diligently, more than 95% interval length is within one hour. The rest of

Algorithm 1 Computing Uniqueness of Traces

Require:
The entire original datasets, DS_o.
Ensure:
A list with result tuples which contain parameters and the value of uniqueness, R.
1: Clean the original dataset DS_o with methods in pre-preprocess stage, get DS_c.
2: Initialize R with an empty list.
3: Initialize *Count* with 150,000.
4: **for** each $TR \in [20, 30, 60, 80, 120, 240]$ **do**
5: **for** each $SR \in [10, 20, 30, 40, 50, 60, 70, 80, 90, 100, 200]$ **do**
6: Divide the DS_c with TR, SR, get DS_d.
7: **for** each $N \in [1, 2, 3, 4, 5, 6, 7]$ **do**
8: $c = 0$
9: $m = 0$
10: **while** $c <$ *Count* **do**
11: Sample N spatio-temporal points P_n from DS_c
12: **if** len(matched(P_n, DS_d)) == 1 **then**
13: m += 1
14: **end if**
15: c += 1
16: **end while**
17: $\epsilon = m$ / *Count*
18: R.append((TR, SR, N, ϵ))
19: **end for**
20: **end for**
21: **end for**
22: **return** R

Table 2. Data Sample from Shenzhen's Taxicab

ID	*Time*	*Longitude*	*Latitude*
B00T12	2011/04/18 00:00:18	113.984566	22.560133
B00T12	2011/04/18 00:01:14	113.994598	22.556467
...	...	...	...
B001B2	2011/04/20 00:01:55	113.881699	22.742943
B001B2	2011/04/20 00:02:55	113.880867	22.739964
...	...	...	...
B02S48	2011/04/23 19:54:42	114.262413	22.711182
B02S48	2011/04/23 19:55:22	114.261932	22.715206
B02S48	2011/04/23 19:56:39	114.261513	22.718210
...	...	...	...

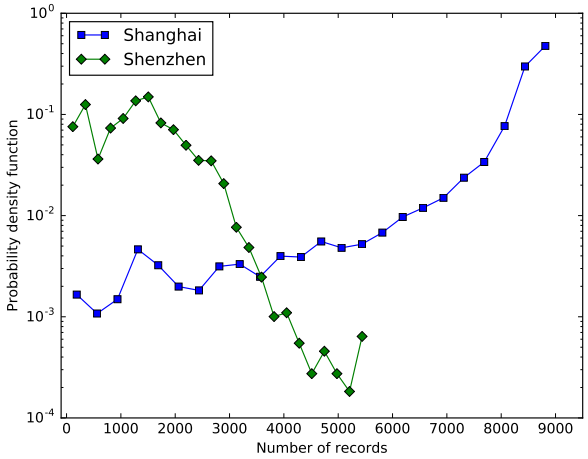


Figure 13. Probability Density Function of the Average Number of a Taxi Trajectory Records Per Day.

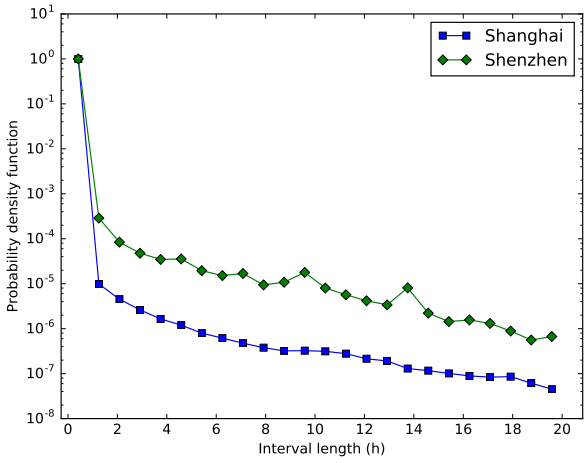


Figure 14. The Distribution of Interval Length of Two Adjoined Records.

the length of intervals is decreasing progressively. For records that are collected every ten seconds or less, the taxi location barely changes numerically on longitude and latitude, which means a high redundance in our data. We can vote one point on behalf of all the points within a specific threshold of time. For example, if we set the threshold to be 20 minutes, then the mobilities in 20 minutes can be summarized to one spatio-temporal point.

5. Discussion

The experimental result shows that 95.35% of uniqueness can be achieved if 4 spatio-temporal points are exposed to adversaries. With the growing of the number, the possibilities rapidly increase to 99%. Also, we find both spatial and temporal generalization methods help to protect the trajectory privacy and lower the possibilities of being re-identified. When the level of spatial and temporal resolution increases, the information contained in the data goes vague and the dataset becomes useless, which will end up with one spatio-temporal point standing for all taxis and none can be identified. Our result shows four spatio-temporal points are sufficient for re-identifying a taxi with a moderate level of spatial and temporal resolution, which suggests that the data after this level generalization be sufficiently useful for LBS providers.

If we focus on taxis that cannot be identified in our experiments, we find that several spatio-temporal points from those taxis trajectory can still match two or three taxis, which means those taxis' identities can be decided by making a choice from two or three entities. So adversaries can still identify those taxis with several attempts. In our experiments, we utilize trajectory data from taxis instead of private cars. Generally speaking, the trajectory of a taxi is less regular as compared to a private car. Under this observation, we can predict that private cars have even more serious privacy problems than taxis. Thereby, we can conclude that VLBS is confronted with a noteworthy privacy problem.

There may be a doubt that the vehicle quantity we have used in experiments is too little to support our conclusion. Nowadays, the number of VLBS applications are growing rapidly, such as Here Maps, Google Maps, Foursquare, etc. We assume that millions of vehicles are driven around in the city, only some of which are distributed in various VLBSs applications. For a single application, the number of vehicles that its server serves could be very small in the city. Hence, our datasets are enough for most cases.

We provide several suggestions for drivers and VLBS providers to reduce the risk of privacy leakage.

- *Advice 1*: Use VLBS applications only when it is necessary. Most LBS-related applications keep on uploading users' location data under specific frequency while running in backend. Most of drivers are familiar with the roads, but they may still keep using the application unintentionally when driving. Some of them may want to use the application for a second, for example, just in order to find POIs (Place Of Interests) nearby, but fail to turn it down.

- *Advice 2*: Do not reveal personal information to LBS-related applications. For example, when you register Google Maps account, you are not supposed to reveal unnecessary personal information.

- *Advice 3*: In principle, using different accounts and different applications is helpful for privacy protection.

Here are also several advices for the VLBS providers.

VLBS's Advice 1: Lower the information collection frequency if it dose not harm basic services.
VLBS's Advice 2: Adopt more advanced cryptographic algorithm and store less sensitive information on the server.

With the efforts of both drivers and VLBS providers, users' privacy can be protected better.

6. Conclusion and Future Work

Based on investigating two real world datasets of taxi traces, we found that with the help of urban road maps, four spatio-temporal points are sufficient to uniquely identify vehicles, achieving an accuracy over 95%. Then, we can draw a conclusion that in a VLBS environment, the privacy protect is a critical challenge even though the queries are sparse.

People may have different concerns about their privacy when using LBS-related applications. For our future work, we plan to provide customized privacy strategies with different privacy levels. In detail, we would turn to machine learning methods to automatically learn users' habits and preferences, which can aid in adaptable choice among different privacy levels.

Acknowledgement. The research of authors is partially supported by the National Natural Science Foundation of China (NSFC) under Grants 61571331, the Integrated Project for Major Research Plan of the National Natural Science Foundation of China under Grant 91218301, Fok Ying-Tong Education Foundation for Young Teachers in the Higher Education Institutions of China under Grant 151066, "Shuguang Program" from Shanghai Education Development Foundation under Grant 14SG20, the Shanghai Science and Technology Innovation Action Plan Project under Grant 16511100901, and the Shanghai Innovation Action Project under Grant 16DZ1100200. We thank all anonymous reviewers for their insightful comments.

References

[1] Wang, C., Tang, S., Yang, L., Guo, Y., Li, F. and Jiang, C. Modeling data dissemination in online social networks: A geographical perspective on bounding network traffic load. In *Proc. ACM MobiHoc 2014*.

[2] Wang, C., Shao, L., Li, Z., Yang, L., Li, X. and Jiang, C. (2015) Capacity scaling of wireless social networks. *IEEE Transactions on Parallel and Distributed Systems* **26**(7): 1839–1850.

[3] Shin, K.G., Ju, X., Chen, Z. and Hu, X. (2012) Privacy protection for users of location-based services. *IEEE Wireless Communications* **19**(1): 30–39.

[4] Pan, J., Zuo, Z., Xu, Z. and Jin, Q. (2015) Privacy protection for lbs in mobile environments. *International Journal of Security and its Applications* **9**(1): 249–258.

[5] Zhu, J., Kim, K.H., Mohapatra, P. and Congdon, P. An adaptive privacy-preserving scheme for location tracking of a mobile user. In *Proc. IEEE SECON 2013*.

[6] Corser, G., Fu, H., Shu, T., D'Errico, P. and Ma, W.J. Endpoint protection zone (epz): Protecting lbs user location privacy against deanonymization and collusion in vehicular networks. In *Proc. IEEE ICCVE 2013*.

[7] Gkoulalas-Divanis, A. and Stephenson, M. (2015), Method and system for anonymization in continuous location-based services. US Patent 9,135,452.

[8] Song, D., Sim, J., Park, K. and Song, M. (2015) A privacy-preserving continuous location monitoring system for location-based services. *International Journal of Distributed Sensor Networks* **2015**: 14.

[9] Montazeri, Z., Houmansadr, A. and Pishro-Nik, H. Defining perfect location privacy using anonymization. In *Proc. IEEE CISS 2016*.

[10] Feldman, D., Sugaya, A., Sung, C. and Rus, D. idiary: from gps signals to a text-searchable diary. In *Proc. ACM SenSys 2013*.

[11] Zhang, Y., Tan, C.C., Xu, F., Han, H. and Li, Q. (2015) Vproof: Lightweight privacy-preserving vehicle location proofs. *IEEE Transactions on Vehicular Technology* **64**(1): 378–385.

[12] Lu, R., Li, X., Luan, T.H., Liang, X. and Shen, X. (2012) Pseudonym changing at social spots: An effective strategy for location privacy in vanets. *IEEE Transactions on Vehicular Technology* **61**(1): 86–96.

[13] Lu, R., Lin, X., Liang, X. and Shen, X. (2012) A dynamic privacy-preserving key management scheme for location-based services in vanets. *IEEE Transactions on Intelligent Transportation Systems* **13**(1): 127–139.

[14] Forster, D., Lohr, H. and Kargl, F. Decentralized enforcement of k-anonymity for location privacy using secret sharing. In *Proc. IEEE VNC 2015*.

[15] Sweeney, L. (2002) k-anonymity: A model for protecting privacy. *International Journal of Uncertainty, Fuzziness and Knowledge-Based Systems* **10**(05): 557–570.

[16] Gruteser, M. and Grunwald, D. Anonymous usage of location-based services through spatial and temporal cloaking. In *Proc. ACM MobiSys 2003*.

[17] Beresford, A.R. and Stajano, F. Mix zones: User privacy in location-aware services. In *Proc. IEEE PerCom 2004*.

[18] Gedik, B. and Liu, L. Location privacy in mobile systems: A personalized anonymization model. In *Proc. IEEE ICDCS 2005*.

[19] Rebollo-Monedero, D., Forné, J., Pallarès, E. and Parra-Arnau, J. (2013) A modification of the lloyd algorithm for k-anonymous quantization. *Information Sciences* **222**: 185–202.

[20] Qiu, F., Wu, F. and Chen, G. Slicer: A slicing-based k-anonymous privacy preserving scheme for participatory sensing. In *Proc. IEEE MAAS 2013*.

[21] Stokes, K. and Farràs, O. (2014) Linear spaces and transversal designs: k-anonymous combinatorial configurations for anonymous database search notes. *Designs, Codes and Cryptography* **71**(3): 503–524.

[22] de Montjoye, Y.A., Radaelli, L., Singh, V.K. *et al.* (2015) Unique in the shopping mall: On the reidentifiability of credit card metadata. *Science* **347**(6221): 536–539.
[23] de Montjoye, Y.A., Hidalgo, C.A., Verleysen, M. and Blondel, V.D. (2013) Unique in the crowd: The privacy bounds of human mobility. *Scientific reports* **3**.
[24] Google Maps, https://www.google.com/maps.