Privacy-Preserving Transportation Traffic Measurement in Intelligent Cyber-Physical Road Systems

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Abstract—Traffic measurement is a critical function in transportation engineering. We consider privacy-preserving point-to-point traffic measurement in this paper. We measure the number of vehicles traveling from one geographical location to another by taking advantage of capabilities provided by the intelligent cyber-physical road systems that enable automatic collection of traffic data. The challenge is to allow the collection of aggregate point-to-point data while preserving the privacy of individual vehicles. We propose a novel measurement scheme which utilizes bit arrays to collect “masked” data and adopts maximum likelihood estimation (MLE) to obtain the measurement result. Both mathematical proof and simulation demonstrate the practicality and scalability of our scheme.

Keywords—Transportation traffic measurement, privacy, cyber-physical systems, maximum likelihood estimation

I. INTRODUCTION

New technologies in vehicular communications and networking [1], [2], [3], [4], [5], [6] have greatly advanced the design of intelligent cyber-physical road systems. To fully realize the potential of such systems as well as improving the capacity of existing infrastructures, traffic measurement is a critical function in transportation engineering [7]. There are two categories of traffic statistics, “point” statistics and “point-to-point” statistics. Point statistics describe the number of vehicles traveling a specific point (location). Various prediction models have been proposed to estimate them [8], [9], [10], [11]. Point-to-point statistics describe the number of vehicles traveling between two points (locations). They are essential inputs to a variety of studies including estimation of traffic link flow distribution as part of investment plan, and calculation of road exposure rates as part of safety analysis, etc. Though some point-to-point statistics may be inferred from point data [12], the practicality is limited by either high computation overhead or degraded measurement accuracy. As for direct measurement of “point-to-point” traffic, little work has been done especially when drivers’ location privacy is concerned.

This paper considers the important problem of privacy-preserving point-to-point transportation traffic measurement. The set of vehicles traveling from one geographical location to another is modeled as a traffic flow, and the flow size is the number of vehicles in the set. To enable automatic collection of traffic flow data, we take advantage of intelligent cyber-physical road systems (CPRS), which integrate the latest technologies in wireless communications and on-board computer processing into transportation systems [13] [14]. In particular, IntelliDrive [15] from USDOT [16] envisions a nationwide system where vehicles communicate with roadside equipments (RSE) in real time via dedicated short range communications. In CPRS, vehicles may report their IDs to RSEs when they pass by, and that information can be used by the authority to measure traffic flows. However, if a vehicle keeps transmitting its unique identifier to RSEs, that information will enable others to track its entire moving history. As more and more people concern about their location privacy, the degree of privacy that a traffic measurement scheme preserves will directly affect its applicability.

To address the concerns of privacy, there are many issues that we need to consider: First of all, we need a criterion to tell what is good privacy and what is not. In this paper, we capture the essence of privacy in traffic flow measurement, and quantify it as a probability that a potential tracker cannot identify any trace of any vehicle. Secondly, given that criterion, how can we preserve the optimal privacy? Apparently, the better the privacy, the more applicable the measurement scheme. Furthermore, to protect the privacy of vehicles, only randomized and de-identified information is collected. How can we achieve sound measurement accuracy based on information that looks totally random?

In this paper, we propose a novel scheme for privacy-preserving traffic flow measurement. It utilizes bit arrays to encode “masked” data sent from vehicles to RSEs, and adopts maximum likelihood estimation (MLE) to obtain measurement results. The measurement accuracy and preserved privacy are analyzed through both mathematical proof and simulations, which demonstrate the applicability of our scheme.

The rest of the paper is organized as follows: Section II gives the preliminaries. Section III presents our scheme and its analysis. Section IV shows simulation results. Section V summarizes related work. Section VI draws the conclusion.
II. PRELIMINARIES

A. System Model

We consider an intelligent cyber-physical road system model as illustrated in Fig. 1, which involves three types of entities: vehicles, roadside equipments (RSE), and a central server. Each vehicle has a unique ID, e.g., its Vehicle Identification Number (VIN). Each RSE also has its unique ID. Both vehicles and RSEs are equipped with computing and communication capabilities, e.g., on-board computer chips and communication modules. Vehicles communicate with RSEs in real time via dedicated short range communications (DSRC) [16]. RSEs are connected to the central server through wired or wireless means. They collect information from vehicles and transfer it to the central server on a periodical basis.

B. Problem Statement

We define a traffic flow between one RSE-equipped location and another RSE-equipped location as the set of vehicles traveling between the two locations during a measurement period. The size of the traffic flow is the number of vehicles in this set. Our problem is to measure the sizes of traffic flows in a road system between all pairs of locations where RSEs are installed while protecting vehicles’ privacy. To achieve the privacy-preserving end, we need a solution in which a vehicle never transmits any fixed identifier. Ideally, the information transmitted by the vehicles to the RSEs looks totally random, out of which neither the identity nor the trajectory of any vehicle can be pried with high probability.

We also assume that a special MAC protocol is applied to support privacy preservation such that the MAC address of a vehicle is not fixed. Vehicles may pick an MAC address randomly from a large space for one-time use when needed.

C. Threat Model

We assume a semi-honest model for the RSEs. On the one hand, all RSEs are from trustworthy authorities, which can be enforced by authentication based on PKI. The vehicles can use the public-key certificate broadcasted by RSEs, which they obtained from the trusted third parties, to verify the RSEs. On the other hand, the authorities may exploit the information collected by RSEs to track individual vehicles when they need to do so. For instance, if a vehicle transmits any fixed identifier upon each query, that identifier can be used for tracking purpose.

Note that there are also other ways to track a vehicle, for example, tailgating the vehicle, or setting cameras near RSEs to take photos and using image processing to recognize it. Those methods are beyond the scope of this paper. In this paper, we focus on preventing automatical tracking caused by the traffic flow measurement scheme itself.

D. Performance Metrics

In this paper, we consider three performance metrics to evaluate a traffic flow measurement scheme: measurement accuracy, computation overhead, and preserved privacy. They are defined in the following.

1) Measurement Accuracy: Let $n_c$ be the real size of a traffic flow between a pair of locations and $\hat{n}_c$ be the corresponding measurement result. We specify the measurement accuracy through a parameter $\beta$ such that, the probability for $n_c$ to fall into the interval $[\hat{n}_c \cdot (1 - \beta), \hat{n}_c \cdot (1 + \beta)]$ must be at least $\alpha$, where $\alpha$ is a pre-determined parameter in the range of [0, 1]. For a given probability $\alpha$, a smaller value of $\beta$ means better measurement results. For example, when $\alpha = 95\%$, a solution with $\beta = 0.05$ is more accurate than a solution with $\beta = 0.1$ because the former ensures the measured traffic flow size has a probability of 95% to be within $\pm 5\%$ deviation from the real value, while the latter only ensures the measured result to be within $\pm 10\%$ deviation from the real value under the same probability.

2) Computation Overhead: We consider the computation overhead for vehicles, RSEs, and the central server. For vehicles, we measure the computation overhead for each vehicle per RSE en route. For RSEs, we measure the computation overhead for each RSE per passing vehicle. For the central server, we measure the computation overhead for it to measure the traffic flow size for a pair of RSEs.

3) Preserved Privacy: We capture the essence of privacy preservation in point-to-point transportation traffic measurement, which is allowing the tracker only a limited chance of identifying partially or fully any trajectory of any vehicle. Accordingly, we quantify the privacy of a scheme through a parameter $p$ which satisfies the following requirement: the probability for any “trace” of any vehicle not to be identified must be at least $p$, where a trace of a vehicle is a pair of RSEs it has passed by. A larger value of $p$ means better privacy. Intuitively, a scheme with $p = 0.9$ is better than one with $p = 0.5$ in terms of privacy because the latter gives the tracker a better chance to link traces of a vehicle to obtain its trajectory since it allows the traces to be identified with a higher probability, i.e., $1 - p$.

III. PRIVACY PRESERVING POINT-TO-POINT TRANSPORTATION TRAFFIC MEASUREMENT

In this section, we present our novel scheme for privacy preserving point-to-point transportation traffic measurement. There are two phases for each measurement period: online coding and offline decoding. Online coding is an interaction between vehicles and RSEs to securely collect information for
traffic flow measurement. Later in the offline decoding phase, the central server will use those information to compute traffic flow sizes. We first illustrate the two measurement phases, and then evaluate our scheme with respect to the three performance metrics described in Section II-D.

A. Online Coding Phase

As presented in our previous preliminary work [17], in our scheme, each RSE $R_x$ maintains a counter $n_x$, which keeps track of the total number of vehicles passing by during the current measurement period. $R_x$ also maintains a bit array $B_x$ with a fixed length $m$ to mask vehicle identities. At the beginning of each measurement period, $n_x$ and all the bits in $B_x$ are set to zeros. In addition, each vehicle $v$ has a logical bit array $LB_v$, which consists of $s$ ($1 < s < m$) bits randomly selected from $B_x$. The indices of these bits in $B_x$ are $H(v \oplus K_v \oplus X[0], \ldots, H(v \oplus K_v \oplus X[s-1])$, where $\oplus$ is the bitwise XOR, $H(\cdot)$ is a hash function whose range is $[0,m]$. $X$ is an integer array of randomly chosen constants whose purpose is to arbitrarily alter the hash result, and $K_v$ is the private key of $v$ to protect the privacy of its logical bit array.

The online coding phase is quite simple. RSEs broadcast queries in pre-set intervals (e.g., once a second), ensuring that each passing vehicle receives at least one query and meanwhile giving enough time for the vehicle to reply. Collisions can be resolved through well-established CSMA or TDMA protocols, which are not the focus of this paper. Every query that an RSE sends out includes the RSE’s RID and its public-key certificate. Suppose a vehicle, whose ID is $v$, receives a query from an RSE, whose ID is $R_x$. The vehicle first verifies the certificate, and then uses the RSE’s public key to authenticate the RSE. After verifying that $R_x$ is from the trustworthy authority, the vehicle $v$ randomly selects a bit from its logical bit array $LB_v$ by computing an index $b = H(v \oplus K_v \oplus X[H(R_x) \mod s])$. The vehicle $v$ then sends the resulting index $b$ to the RSE $R_x$. Upon receiving the index $b$, $R_x$ will first increase its counter $n_x$ by 1, and then set the $b$th bit in $B_x$ to 1:

$$B_x[H(v \oplus K_v \oplus X[H(R_x) \mod s])] = 1.$$  

Note that the same vehicle may transmit different bit indices at two RSEs. The probability for this to happen is $1 - \frac{1}{2^s}$, which is larger when the size of $LB_v$ is larger. Different vehicles may send the same index because their logical bit arrays share bits from $B_x$. As any vehicle does not have to transmit any fixed number, we improve privacy protection. This is true even when there is a single vehicle passing through two RSEs.

B. Offline Decoding Phase

At the end of each measurement period, all RSEs will send their counters and bit arrays to the central server, which then performs the offline measurement. We employs the maximum likelihood estimation (MLE) [18] to measure the sizes of traffic flows based on the counters and bit arrays.

Suppose the set of vehicles that pass RSE $R_x$ ($R_y$) is denoted as $S_x$ ($S_y$) with cardinality $|S_x| = n_x$ ($|S_y| = n_y$). Clearly, the set of vehicles that pass both RSE $R_x$ and $R_y$ is $S_x \cap S_y$. Denote its cardinality as $n_o$, which is the value that we want to measure. Furthermore, denote by $S$ the subset of vehicles in $S_x \cap S_y$ that happen to set the same bit in $B_x$ and $B_y$, where $B_x$ and $B_y$ are the bit arrays at $R_x$ and $R_y$, respectively. Let $n_o$ be the cardinality of $S$, i.e., $n_o = |S|$. Clearly, $S \subseteq S_x \cap S_y$ and $0 \leq n_o \leq n_c$. For any vehicle, it has the same probability $\frac{1}{2}$ to set any bit in its $s$-bit logical bit array. As a result, the probability for an arbitrary vehicle $v$ from $S_x \cap S_y$ to select the same bit in both $B_x$ and $B_y$ is $s \times \frac{1}{2} \times \frac{1}{2} = \frac{s}{4}$. Therefore, the number of such vehicles, $n_o$, is binomially distributed according to $B(n_c,\frac{1}{2})$. Accordingly, the probability for $n_o = z (0 \leq z \leq n_c)$ is

$$P(n_o = z) = \binom{n_c}{z} \left(\frac{1}{2}\right)^z \left(1 - \frac{1}{2}\right)^{n_c-z}.$$  

Given the counters $n_x$ and $n_y$, and bit arrays $B_x$ and $B_y$, we measure $n_c$ as follows: First, take a bitwise AND of $B_x$ and $B_y$, and denote the resulting bit array as $B_c$. Namely, $B_c[i] = B_x[i] \land B_y[i], \forall i \in [0,m-1]$.

We can easily find out the number of 0’s in $B_c$, denoted by $U_c$. In the following, we will analyze the probability for an arbitrary bit in $B_c$ to remain ‘0’ after the online coding phase, and use it to establish the likelihood function for us to observe $U_c$ ‘0’ bits in $B_c$. Maximizing that likelihood function with respect to $n_o$ will give the MLE estimate of $n_c$.

Clearly, the event for an arbitrary bit $b$ in $B_c$ to remain ‘0’ after online coding is equivalent to the combination of the following two events: (1) Event 1: None of the vehicles in $S$ has chosen $b$ at $R_x$ and $R_y$. If a vehicle $v \in S$ chooses $b$, then bit $b$ in $B_x$ and $B_y$ are both set to ‘1’ by $v$ (hence bit $b$ in $B_c$ is also ‘1’). Since each vehicle has probability $\frac{1}{2}$ to set bit $b$ to ‘1’, the probability for the vehicle not to choose bit $b$ is $1 - \frac{1}{2}$. There are $n_o$ vehicles in $S$. Therefore, the probability for the first event to happen is the following:

$$q_1 = \left(1 - \frac{1}{2}\right)^{n_o}.$$  

(2) Event 2: Either none of the vehicles in $S_x - S$ has chosen $b$ at $R_x$ or none of the vehicles in $S_y - S$ has chosen $b$ at $R_y$. Otherwise, bit $b$ in both $B_x$ and $B_y$ will be ‘1’ (hence bit $b$ in $B_c$ is ‘1’). The probability for bit $b$ not chosen by any vehicle in $S_x - S$ is \(1 - \frac{1}{m}\)^{n_x-n_o}, and the probability for bit $b$ not chosen by any vehicle in $S_y - S$ is \(1 - \frac{1}{m}\)^{n_y-n_o}. Therefore, the probability for the second event to happen is:

$$q_2 = 1 - \left(1 - \frac{1}{m}\right)^{n_x-n_o} \times \left(1 - \frac{1}{m}\right)^{n_y-n_o} = \left(1 - \frac{1}{m}\right)^{n_x-n_o} + \left(1 - \frac{1}{m}\right)^{n_y-n_o} - \left(1 - \frac{1}{m}\right)^{n_x+n_y-2n_o}.$$  

Combining above analysis, the conditional probability for bit $b$ in $B_c$ to remain ‘0’ given $n_o = z$ is $q_1 \times q_2$, namely,
Given \( q(n_c|n_o = z) \) and the distribution of \( n_o \), the overall probability \( q(n_c) \) for an arbitrary bit \( b \) in \( B_c \) to remain ‘0’ is
\[
q(n_c) = \sum_{z=0}^{n_o} q(n_c|n_o = z) \times P(n_o = z) = \sum_{z=0}^{n_o} q(n_c|n_o = z) \times \left( \frac{1}{S} \right)^z \left( 1 - \frac{1}{S} \right)^{n_o-z} = \left( \frac{1}{S} \right)^s + \left( \frac{1}{S} \right)^y - \left( \frac{1}{S} \right)^{s+y} C^n_c,
\]
where \( C \) is a value determined by \( s \) and \( m \) only:
\[
C = \left( \frac{1}{S} \right)^s + \frac{1}{S} \times \frac{1}{1 - \frac{1}{S}}.
\]

Knowing that each bit in \( B_c \) has a probability \( q(n_c) \) to remain ‘0’, we can establish the likelihood function for us to observe \( U_c \) ‘0’ bits in \( B_c \) (hence \( m - U_c \) ‘1’ bits in \( B_c \)):
\[
\mathcal{L} = (q(n_c))^U_c \times (1 - q(n_c))^{m-U_c}.
\]

The MLE estimate of \( n_c \) is the optimal value of \( n_c \) that maximizes the likelihood function in (9):
\[
\hat{n}_c = \arg \max_{n_c} \{ \mathcal{L} \}.
\]

To find \( \hat{n}_c \), we take logarithm on both sides of (9):
\[
\ln \mathcal{L} = U_c \times \ln q(n_c) + (m - U_c) \times \ln (1 - q(n_c)).
\]

Take the first order derivative of (11), we have:
\[
\frac{d \ln \mathcal{L}}{dn_c} = \left( \frac{U_c}{q(n_c)} - \frac{m - U_c}{1 - q(n_c)} \right) \times q'(n_c),
\]
where \( q'(n_c) \) can be computed from (7) as follows:
\[
q'(n_c) = \frac{dq(n_c)}{dn_c} = -\left( 1 - \frac{1}{S} \right)^{s+y} \times C^n_c \times \ln C.
\]

To compute \( \hat{n}_c \), we set the right side of (12) to 0:
\[
\left( \frac{U_c}{q(n_c)} - \frac{m - U_c}{1 - q(n_c)} \right) \times q'(n_c) = 0.
\]

Observe from (13) that \( q'(n_c) \) cannot be 0 when \( m > 1 \) and \( s > 1 \). Therefore, we have:
\[
\frac{U_c}{q(n_c)} = \frac{m - U_c}{1 - q(n_c)} = 0.
\]

Substituting (7) to (15), we obtain the MLE estimator \( \hat{n}_c \) of the desired traffic flow size \( n_c \) as follows:
\[
\hat{n}_c = \frac{1}{\ln \left( \frac{1}{S} \times \frac{1}{1 - \frac{1}{S}} \right)} \left\{ \left. \left(- (s+y) \frac{m - U_c}{1 - q(n_c)} \right) \ln \left( 1 - \frac{1}{S} \right) \right\} + \ln \left( \left( \frac{1}{S} \right)^s + \left( \frac{1}{S} \right)^y - \frac{U_c}{m} \right) \right\}.
\]

### C. Measurement Accuracy

In the following subsections, we discuss the performance of our scheme with respect to the three performance metrics described in Section II-D. We start with analyzing the measurement accuracy. The standard theory of MLE [19] tells when \( m, n_x, y \), and \( n_y \) are large enough, the MLE estimator \( \hat{n}_c \) approximately follows the normal distribution:
\[
\hat{n}_c \sim \text{Norm} \left( n_c, \frac{1}{\mathcal{I}(\hat{n}_c)} \right),
\]
where \( \mathcal{I}(\hat{n}_c) \) is the fisher information of \( \mathcal{L} \), defined as:
\[
\mathcal{I}(\hat{n}_c) = -E \left[ \frac{d^2 \ln \mathcal{L}}{dn_c^2} \right].
\]

We compute the second-order derivative of \( \ln \mathcal{L} \) from (12):
\[
\frac{d^2 \ln \mathcal{L}}{dn_c^2} = \left( -\frac{U_c \cdot q'(n_c)}{q^2(n_c)} - \frac{(m - U_c) \cdot q'(n_c)}{(1 - q(n_c))^2} \right) \times q'(n_c)
\]
\[
+ \frac{U_c}{q(n_c) - \frac{m - U_c}{1 - q(n_c)}} \times q'(n_c) \cdot \ln C,
\]
where \( C \) is the confidence interval of our measurement is
\[
\hat{n}_c = \frac{1}{\mathcal{I}(\hat{n}_c)} = \frac{q(n_c)(1 - q(n_c))}{m(q'(n_c))^2}.
\]

Therefore, the confidence interval of our measurement is
\[
\hat{n}_c \pm Z_\alpha \times \sqrt{\frac{q(n_c)(1 - q(n_c))}{m(q'(n_c))^2}},
\]
where \( \alpha \) is the confidence level and \( Z_\alpha \) is the \( \alpha \) percentile for the standard Gaussian distribution [20]. For example, when \( \alpha = 95\% \), \( Z_\alpha = 1.6 \).

### D. Preserved Privacy

Next, we evaluate the preserved privacy of our measurement scheme. Note that in our scheme, the only information that a vehicle \( v \) ever transmits to an RSE en route is an index of a bit \( b \) randomly selected from its \( s \)-bit logical bit array, \( LB_v \). From the tracker’s point of view, it can only identify the trace of a vehicle passing by two RSES \( R_x \) and \( R_y \) through the observation of the bits that are set to ‘1’ in both \( B_x \) and \( B_y \); these bits will be ‘1’ in \( B_c \). Therefore, the preserved privacy of our scheme is actually a conditional probability which tells
to what degree an observed ‘1’ in $B_{c}$ does not represent a common vehicle passing by both $R_{x}$ and $R_{y}$. We derive this conditional probability in the following.

Firstly, consider the probability for the tracker to observe an arbitrary bit, $b$, to be set to ‘1’ in both $B_{x}$ and $B_{y}$ (event A), $P(A)$. Obviously, the probability $P(A)$ equals 1 minus $q(n_{c})$ given our analysis in Section III-B:

$$P(A) = 1 - \left(1 - \frac{1}{m}\right)^{n_{x} + n_{y}} \times C^{n_{c}},$$

(24)

where $C$ is given in (8).

Secondly, consider the conditional probability for such a bit, $b$, to not represent a common vehicle passing both $R_{x}$ and $R_{y}$ (event E), $P(E|A)$. This is the privacy $p$ that we want to derive. Note that event $E$ happens if and only if bit $b$ in $B_{x}$ is set only by vehicles passing only RSE $R_{x}$ (i.e., in set $S_{x} - S_{y}$), and bit $b$ in $B_{y}$ is set only by vehicles passing only RSE $R_{y}$ (i.e., in set $S_{y} - S_{x}$). Denote these two events as $E_{x}$ and $E_{y}$, respectively. There are $n_{x}$ ($n_{y}$) vehicles passing $R_{x}$ ($R_{y}$), and $n_{c}$ vehicles among them pass both $R_{x}$ and $R_{y}$. Since each vehicle has a probability $\frac{1}{m}$ to set bit $b$ to ‘1’, the probability for $E_{x}$ ($E_{y}$) to happen is:

$$P(E_{x}) = \left(1 - \frac{1}{m}\right)^{n_{x} - n_{c}} \times \left(1 - \frac{1}{m}\right)^{n_{c}},$$

(25)

$$P(E_{y}) = \left(1 - \frac{1}{m}\right)^{n_{y} - n_{c}} \times \left(1 - \frac{1}{m}\right)^{n_{c}}.$$  

(26)

Combining the above analysis, we have the formula for the preserved privacy of our scheme as follows:

$$p = P(E|A) = \frac{P(E_{x}) \times P(E_{y})}{P(A)} = \frac{\left(1 - \frac{1}{m}\right)^{n_{x} - n_{c}} \times \left(1 - \frac{1}{m}\right)^{n_{y} - n_{c}} \times C^{n_{c}}}{P(A)}$$

(27)

where $P(A)$ is given in (24).

Observe that there are 2 parameters, $s$ and $m$, that determine the value of $P(E|A)$. Among them, $s$ only appears in the denominator $P(A)$, and it influences $P(E|A)$ through varying the value of $P(A)$, $m$ influences both the denominator and the numerator. In the following, we first examine the influence of $s$ on $P(A)$ (hence on $P(E|A)$), and then analyze how $m$ affects the value of $P(E|A)$.

1) Influence of $s$ on $P(A)$: To examine how $s$ affects $P(A)$, we take partial derivative of (24) with respect to $s$:

$$\frac{\partial P(A)}{\partial s} = -\left(1 - \frac{1}{m}\right)^{n_{x} + n_{y}} \times \frac{n_{c}}{m^{2}} C^{n_{c} - 1},$$

(28)

where $C$ is given in (8). Clearly, $\frac{\partial P(A)}{\partial s} < 0$. Therefore, with the increment of $s$, the value of $P(A)$ decreases, and in turn, the value of $P(E|A)$ increases. In other words, the privacy will be better with a larger value of $s$. The numerical results are shown in Fig. 2 where $n_{x} = n_{y} = n = 50,000$, $n_{c} = 5,000$, and $s = 2, 5, 10$, corresponding to three curves in each plot. Clearly, as $s$ increases, the probability $P(A)$ decreases.

Another observation from the numerical results is that when $s > 5$, the difference in probability $P(A)$ under different $s$ becomes quite small. For instance, with $m \in [5n, 20n]$, the difference in $P(A)$ when $s = 5$ and $s = 10$ is smaller than 0.0005 (see the two lower curves in the right plot of Fig. 2). When $n > 10$, that difference becomes negligible. Therefore, when we analyze the effect of $m$ on $P(E|A)$ in the following subsection, and later when we set up the parameters for our simulations, we will only consider the cases of $s = 2, 5, 10$, with an established understanding that larger values of $s$ will only make negligible difference.

2) Influence of $m$ on $P(E|A)$: To examine the effect of $m$ on $P(E|A)$, we take the partial derivative of (27) with respect to $m$ and obtain the following:

$$\frac{\partial P(E|A)}{\partial m} = \frac{\frac{\partial P(E)}{\partial m} \times P(A) - \frac{\partial P(A)}{\partial m} \times P(E)}{P(A)^{2}},$$

(29)

where $P(E) = P(E_{x}) \times P(E_{y})$. $P(E_{x})$ and $P(E_{y})$ are given in (25) and (26), respectively. Therefore, the partial derivative of $P(E)$ with respect to $m$ is:

$$\frac{\partial P(E)}{\partial m} = \frac{1}{m(m-1)} \left[\left(n_{x} + n_{y}\right)\left(1 - \frac{1}{m}\right)^{n_{x} + n_{y}} + 2n_{c}\left(1 - \frac{1}{m}\right)^{n_{c} + n_{x}} - \left(n_{c} + n_{x}\right)\left(1 - \frac{1}{m}\right)^{n_{c} + n_{y}}\right].$$

(30)

In addition, from (24), we can compute the derivative of $P(A)$ with respect to $m$:

$$\frac{\partial P(A)}{\partial m} = \frac{1}{m^{2}} \left[-n_{x}\left(1 - \frac{1}{m}\right)^{n_{x} - 1} - n_{y}\left(1 - \frac{1}{m}\right)^{n_{y} - 1} + \left(1 - \frac{1}{m}\right)^{n_{x} + n_{y} - 2} \cdot C^{n_{c}} \cdot \left(n_{x} + n_{y}\right)\left(1 - \frac{1}{m}\right)^{-n_{c}} \cdot s \cdot C\right].$$

(31)

We have proved that $\frac{\partial P(A)}{\partial m} < 0$, which means $P(A)$ will decrease with the increment of $m$. In addition, $\frac{\partial P(E)}{\partial m}$ will also be negative when $m$ exceeds a certain value, which means $P(E)$ will also decrease with the increment of $m$ afterwards. Intuitively, increasing $m$ gives each vehicle a smaller chance $\frac{1}{m}$ to set an arbitrary bit, $b$. Hence, $P(E)$ and $P(A)$ also drop. The effect that $m$ has on $P(E|A)$ is twofold: on one hand, the increment of $m$ decreases the denominator $P(A)$, which improves the privacy; on the other hand, the increment of $m$ decreases the numerator $P(E)$, which reduces the privacy. With the combination of the two effects, the partial derivative of $P(E|A)$ with respect to $m$ can be positive, negative, or 0, according to (29). Therefore, given a value of $s$, we can choose an optimal $m$ to achieve the best privacy. The optimal $m$ is obtained by setting the right side of (29) to 0.

Fig. 3 shows the numerical results for the probability $P(E)$ and the preserved privacy $p = P(E|A)$ under different $m$ when $n_{x} = n_{y} = n = 50,000$, $n_{c} = 5,000$, and $s = 2, 5, 10$. From the left plot, one can see that the three different values of $s$ yield the same curve of $P(E)$ (or the three curves of $P(E)$ corresponding to $s = 2, 5, 10$ overlap completely). In other
words, the value of $s$ is irrelevant to the probability $P(E)$, which is consistent with our previous analysis. The value of $m$, on the other hand, has a clear impact on the value of $P(E)$. Specifically, there exists an optimal point where $m^*$ produces a maximum value of $P(E)$. When $m < m^*$, the value of $P(E)$ increases dramatically with the increment of $m$. When $m > m^*$, the value of $P(E)$ decreases with a slower and slower pace. In the figure, $m^* = 0.39n$ results in an optimal value of $P(E) = 0.4856$. Recall from Fig. 2 that the value of $P(A)$ always decreases with the increment of $m$. Combining these results, we learn that as $m$ exceeds a certain value $m^*$, the probability $P(E)$ and $P(A)$ will both drop if we further increase $m$, which is also consistent to our theoretic analysis.

Finally, the right plot of Fig. 3 gives the combined effect of $s$ and $m$ on $P(E|A)$, the privacy of our scheme. The smallest value of $s = 2$ yields the bottom curve that represents the least privacy, while the largest value of $s = 10$ yields the top curve that represents the best privacy, which agrees with our previous analysis that a larger value of $s$ brings better privacy. Clearly, in each curve, $P(E|A)$ first increases quickly and then decreases slowly with respect to $m$. There is an optimal value of $m$ that gives the optimal privacy. For instance, $m = 3.6n$ gives the optimal privacy 0.7661 when $s = 10$. Another observation is, when $s$ is large (5 or 10), there always exists a smooth interval of $m$ near its optimal point that can achieve near-optimal privacy. For example, when $s = 10$, the values of $m$ in the interval $[3.6n, 11.2n]$ achieve privacy that is within 5% drop of the optimal privacy 0.7661. In practice, this smooth interval allows us to adjust the value of $m$ to achieve better measurement results while preserving near-optimal privacy.

E. Computation Overhead

We conclude the discussion about the performance of our measurement scheme by a quick remark on the computation overhead incurred to each group of entities involved in the system. In our scheme, when a vehicle $v$ passes an RSE $R_x$, the vehicle $v$ only needs to compute two hashes to obtain an index of a random bit in its logical bit array $LB_v$, and the RSE $R_x$ only needs to set one bit in its bit array $B_x$, as described in Section III-A. Therefore, the computation overhead for each vehicle per RSE as well as that for each RSE per vehicle are both $O(1)$. As for the central server, in order to compute the traffic flow size between a pair of locations, it only needs to perform a bitwise AND operation over two $m$-bit arrays, count the number of ‘0’s in the resulting bit array, and use formula (16) to compute the MLE estimator. Therefore, the computation overhead for the central server is $O(m)$.

IV. SIMULATION

In this section, we evaluate the performance of our scheme through simulations. The simulation platform is a PC featured with an Intel Core i7-3770 CPU and 8GB RAM. The simulations are performed under five system parameters, $n_x$, $n_y$, $n_c$, $s$, and $m$. For a pair of RSEs, $R_x$ and $R_y$, $n_x$ ($n_y$) is the number of vehicles passing by $R_x$ ($R_y$). There are $n_c$ vehicles passing both $R_x$ and $R_y$, which means the real traffic flow size is $n_c$. $s$ is the number of bits in each vehicle’s logical bit array, and $m$ is the number of bits in each RSE’s bit array. Our simulations consist of two parts. For each part, we first describe the settings of the system parameters, then report the simulation results and the analysis.
TABLE I
VALUES FOR m TO ACHIEVE OPTIMAL p UNDER DIFFERENT s.

<table>
<thead>
<tr>
<th>s</th>
<th>2</th>
<th>5</th>
<th>10</th>
</tr>
</thead>
<tbody>
<tr>
<td>m</td>
<td>1.7n</td>
<td>2.6n</td>
<td>3.6n</td>
</tr>
<tr>
<td>m</td>
<td>0.7258</td>
<td>0.7513</td>
<td>0.7661</td>
</tr>
</tbody>
</table>

A. Measured Traffic Flow \( \hat{n}_c \)

We first measure traffic flows, and observe how different parameters influence the gap between the measured flow sizes and the real sizes when the optimal privacy is preserved. We choose the five parameters as follows: \( n_x = n_y = n = 50,000, 100,000, \) or \( 500,000, \) and \( n_c \) varies from \( 1\%n \) to \( 50\%n \), with a step size of \( 0.1\%n; s = 2, 5, 10, \) and \( m \) is chosen to achieve the optimal privacy, as determined in Section III-D. Table I lists the values of the bit array size \( m \) to achieve the optimal privacy \( p \) under different values of \( s \).

Fig. 4, 5, and 6 show our simulation results when \( n = 50,000, 100,000, \) and \( 500,000, \) respectively. For each figure, there are three plots, corresponding to the results of three sets of simulations controlled by parameter \( s \), where \( s = 2, 5, \) and \( 10 \). Each plot shows the measured traffic flow sizes \( \hat{n}_c \) (y-axis) with respect to different real traffic flow sizes \( n_c \) (x-axis) under a given setting of \( n, s, \) and \( m \), where \( m \) is chosen as described in Table I so that the optimal privacy is achieved. We also draw the equality line \( y = x \) in each plot for reference. Clearly, the closer a point is to the equality line, the more accurate the measurement result.

From the three figures, one can see that our scheme is quite accurate because most of the points in all plots of the three figures lie closely to the equality line. In particular, given other parameters, our scheme produces almost perfect results when \( s = 2 \) (the first plot in Fig. 4, 5, 6). When \( s \) becomes larger, there are slightly more points deviating from the equality line (the third plot in Fig. 4, 5, 6), which indicates larger values of \( s \) yield less accurate measurement results.

Recall that a larger value of \( s \) brings better privacy (Table I). For example, the optimal privacy is 0.7661 when \( s = 10 \), better than the optimal privacy of 0.7258 when \( s = 2 \). This implies a tradeoff between the privacy and the accuracy. From Section III-D, we know when \( s \) is large, there always exists a smooth interval of \( m \) near its extreme point that can achieve comparable privacy as the optimal. For example, when \( n_x = n_y = n = 50,000, n_c = 5,000, \) and \( s = 10, \) the values of \( m \) within the interval \([3.6n, 11.2n]\) achieve privacy that is within just 5% of the optimal privacy 0.7661. In reality, one can choose a relatively large value for \( m \) (e.g., 5 or 10), and adjust the value of \( m \) to achieve better measurement results while still preserving comparable privacy as the optimal.

Finally, the measurement results are more accurate with larger values of \( n \). There are fewer points deviating from the equality line \( \hat{n}_c = n_c \) in the three plots of Fig. 6 than those of Fig. 4. This is also a natural phenomenon given that the result is measured through a statistical MLE estimator.

B. Measurement Bias and Relative Standard Error

Next, we study the measurement accuracy of the MLE estimator \( \hat{n}_c \) in terms of bias and relative standard error. Similar to the previous part, there are three sets of simulations, corresponding to \( n_x = n_y = n = 50,000, 100,000, \) and \( 500,000 \). For each set, there are three simulations controlled by different values of \( s \), where \( s = 2, 5, 10. m \) is still chosen to achieve the optimal privacy \( p \) under each fixed \( s \), as listed in Table I. We conduct 5,000 independent runs for each simulation to observe statistical effects. For each run, we randomly choose a value for \( n_c \) from the range of \([0, 0.5n]\), and apply our scheme to obtain the corresponding value for \( \hat{n}_c \). Now, we try to figure out the measurement bias \( E(\hat{n}_c - n_c) \) and relative standard error \( \frac{\sqrt{\text{Var}(\hat{n}_c)}}{n_c} \) of our MLE estimator from the result of the 5,000 independent runs of each simulation.

To better illustrate the simulation results, we divide the range of \( n_c \) \([0, 0.5n]\), into 50 measurement scales, each of width \( 1\%n \), and group the values of \( n_c \) and corresponding \( \hat{n}_c \) from different runs into these 50 scales, and then numerically evaluate the measurement bias and relative standard error of \( \hat{n}_c \) with respect to each scale of \( n_c \). The simulation results are presented in Fig. 7 - 12, where the first three figures (Fig. 7, 8, 9) show the measurement bias and the remaining three figures (Fig. 10, 11, 12) show the relative standard error.

Fig. 7, 8, and 9 show the measurement bias of \( \hat{n}_c \) with respect to each scale of \( n_c \), under different values of \( n \), where \( n = 50,000, 100,000, \) and \( 500,000. \) Each figure consists of three plots, each corresponding to a fixed value of \( s \), where \( s = 2, 5, 10 \). For each plot, the y-axis represents the measurement bias \( E(\hat{n}_c - n_c) \), and the x-axis represents the mean value of \( n_c \) in each scale. The y-coordinate is within 2.5% of \( n_c \), i.e., ranging from \(-2.5\%n \) to \( 2.5\%n \). Note that the optimal privacy is always guaranteed for all simulations by setting \( n \) in accordance with \( s \). From the figures, one can see that the measurement bias fluctuate around the zero-bias line for different scales of \( n_c \). In addition, observed from the three plots of each figure, under a fixed \( n \), the measurement bias tend to fluctuate more often with higher amplitudes for larger values of \( s \) (e.g., compare the first plot of Fig. 7, 8, and 9 with the third plot of the same figures), which implies larger values of \( s \) will result in more \( \hat{n}_c \) deviating from \( n_c \), and in turn, yield less accurate measurement results. This observation agrees with our simulation results from the previous part. Furthermore, if we compare the plots from different figures (e.g., first plot of each figure), it is clear that under the same value of \( s \), increasing the value of \( n \) will reduce the fluctuation amplitudes of \( \hat{n}_c \), which means our scheme will produce more stable and accurate measurement results for larger-scale systems.

Fig. 10, 11, and 12 show the relative standard error of \( \hat{n}_c \) with respect to each scale of \( n_c \), under different values of \( n \), where \( n = 50,000, 100,000, \) and \( 500,000 \). There are also three plots in each figure, each corresponding to a fixed value of \( s \), where \( s = 2, 5, 10 \). For each plot, the y-axis represents the relative standard error of \( \hat{n}_c, \sqrt{\text{Var}(\hat{n}_c)} \), and the x-axis represents the mean value of \( n_c \) in each scale. Still, optimal privacy is guaranteed through setting appropriate \( m \). The major observation is that, given \( n \), when \( s \) becomes larger, the relative standard error of \( \hat{n}_c \) with respect to each scale of \( n_c \) also becomes larger. For instance, when \( n = 50,000 \), the relative standard error of \( \hat{n}_c \) is about 0.017 for the scale of \( n_c \) ranging from \([8500, 9000]\) when \( s = 2 \), while its value
reaches to about 0.13 when \( s = 10 \), almost 8 times higher than the former value. Since the relative standard error for each scale of \( n_c \) becomes larger, the variance of \( \hat{n} \) also becomes larger, which means the measured traffic flow sizes will be more spread out from the real flow sizes. This observation also agrees with our previous simulation results, where there are relatively more points not close to the equality line for larger values of \( s \) under fixed \( n \). Similarly, the variance becomes smaller when we increase the number \( n \) of vehicles. One can see that the relative standard errors are closer to 0 in Fig. 12 than those in Fig. 10, assuming the same value of \( s \) is applied.

V. RELATED WORK

A. Transportation Traffic Measurement

In the area of transportation traffic measurement, various prediction models have been proposed to measure “point” traffic statistics, using data recorded by automatic traffic recorders (ATR) installed at road sections. For example, the multiple linear regression model in [8], artificial neural network in [9], spatial statistical method in [10], support vector regression in [11], etc. Those solutions, though elegant, are not appropriate for “point-to-point” transportation traffic measurement. As stated in the introduction, “point-to-point” traffic measurement is also critical in traffic engineering. However, few research efforts exist in literature that focus on this problem while preserving the location privacy of individual vehicles in the meantime. The recent work in [12] tries to infer “point-to-point” statistics from “point” data, but the high computation overhead limits its practicability. Our previous work [21] utilizes an encryption method to preserve vehicles’ location privacy, and measures point-to-point traffic based on the encrypted vehicle IDs. The
computation efficiency is improved to $O(n_x n_y)$ for each pair of RSEs, where $n_x$ and $n_y$ denote the number of vehicles passing them, respectively. This overhead is still too high for today’s large-scale road networks. Although Google recently announced to provide real-time traffic data service in Google maps [22], their approach cannot assure vehicle’s privacy since it uses GPS and Wi-Fi in phones to track locations [23].

### B. Network Traffic Measurement

Another branch of research that relates to (but is also significantly different from) ours is network traffic measurement, where researchers have proposed various methods for traffic flow measurement in the network environment, i.e., to measure the network traffic between two network routers. The solutions can be summarized into two categories. One is indirect estimation based on link load and network routing, by employing statistical techniques [24] [25]. These methods cannot achieve high accuracy since their estimations are based on the unknown traffic volume. The other is direct measurement by different counting methods [26] [27]. In particular, Li et al. [27] develop a bitmap-based counting method for traffic flow measurement, which is most related to our work. However, all these solutions are not appropriate for our problem, because they measure traffic in the network environment where the privacy of packets is not a concern, and counting can be done directly based on the packet IDs. In our problem, the privacy of vehicles is the major concern. Therefore, the solutions must incorporate...
randomization and de-identification techniques to protect vehicles’ privacy, and do counting based on information that looks totally random.

VI. CONCLUSION

In this paper, we focus on privacy-preserving “point-to-point” transportation traffic monitoring in intelligent cyber-physical road systems. We formalize “point-to-point” traffic as traffic flows, and quantify privacy as a probability. We propose a novel scheme which allows the collection of aggregate traffic flow data while preserving the privacy of individual vehicles. The proposed scheme utilizes bit arrays to collect “masked” data and adopts maximum likelihood estimation (MLE) to obtain the measurement result. Its feasibility and scalability are shown by both mathematical proofs and simulations.

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REFERENCES


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