Vehicle Cardinality Estimation in VANETs by Using RFID Tag Estimator

著者	SONG Jinhua, HSU Ching-Hsien, DONG Mianxiong, ZHANG Daqiang
journal or publication title	Internet of Vehicles - Safe and Intelligent Mobility
volume	9502
page range	3-15
year	2015
URL	http://hdl.handle.net/10258/00008921

doi: info:doi/10.1007/978-3-319-27293-1_1

Vehicle Cardinality Estimation in VANETs by Using RFID Tag Estimator

Jinhua Song[1], Robert Hsu[2], Mianxiong Dong[3], Daqiang Zhang[1*]

[1]School of Software Engineering, Tongji University, Shanghai, China
[2] Department of Computer Science, Chung Hua University, Taiwan
[3] Muroran Institute of Technology, Hokkaido, Japan
*Corresponding author, dqzhang@tongji.edu.cn

Abstract

Nowadays, many vehicles equipped with RFID-enabled chipsets traverse the Electronic Toll Collection (ETC) systems. Here, we present a scheme to estimate the vehicle cardinality with high accuracy and efficiency. A unique RFID tag is attached to a vehicle, so we identify vehicles through RFID tags. With RFID signal, the location of vehicles can be detected remotely. Our scheme makes the vehicle cardinality estimation based on the location distance of the first vehicle and the second vehicle. Specifically, it derives the relationship between the distance and the number of vehicles. Then, it deduces the optimal parameter settings under certain requirement. According to the actual estimated traffic flow, we put forward a mechanism to improve the estimation efficiency. Conducting extensive experiments, the presented scheme is proven to be outstanding in two aspects. One is the deviation rate of our model is 50% of FNEB algorithm that is the classical scheme. The other is our efficiency is 1.5 times higher than that of FNEB algorithm.

Keywords: Vehicle Estimation, VANETs, RFID tag, Privacy Preservation

1 Introduction

The automobile popularity provides much convenience for people, together with significant serious traffic problems [1], [2], [3]. In this situation, Intelligent Transportation System (ITS) [4], [5] is the direction and goal for traffic management, where many vehicles are attached with a RFID-enabled [6] module for wireless communication. ITS alleviates traffic pressure and reduces traffic accident occurrence frequency. In ITS, Internet of Vehicle (IOV) [7] achieves the two kinds of communication between vehicles and vehicles, vehicles and roads, drivers and managers. Based on the communication between the Road-Side Units (RSU) and On-Board Units (OBU) [8], the traffic manager can evaluate the traffic situation through estimating the number of vehicles and thus make more effective traffic management. Meanwhile, the drivers can access current traffic situation to adjust more effective transportation plan in time.

The 2nd International Conference on Internet of Vehicles（IOV 2015）

The RFID tag estimator can be used to estimate the number of vehicles, because one vehicle corresponds to one tag. RSU corresponds to RFID reader and OBU corresponds to independent tag in the RFID system [9], [10]. That means, estimating vehicle cardinality in IOV equals to estimating the tag cardinality in the RFID system. The correspondent relationship between the two systems is shown in Fig.1.

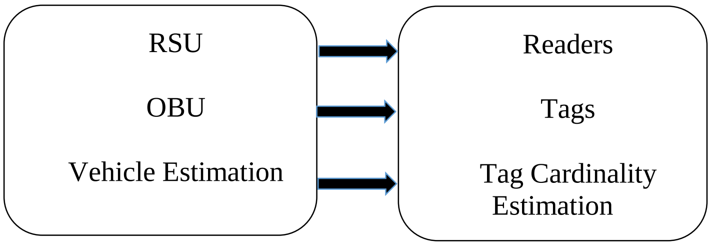

Fig. 1. Correspondent relationship between IOV and RFID systems

In view of the corresponding relation between IOV and RFID systems, we solve the vehicle estimation using the tag cardinality estimator. Intuitively, the potential scheme for this problem is supposed to satisfy two requirements. One is the high accuracy and efficiency. The other is the anonymous detection to avoid privacy leakage [11], [12], [13].

The following sections of the paper is as follows. The related work is presented in section 2. Section 3 gives the problem description and model introduction. The main idea of our scheme is stated in section 4. Section 5 reports the experiment results. Section 6 contains the final conclusion of our work.

2 Related Work

In recent years, tag cardinality estimation has attracted much attention from the research community. Based on the different ways for tag coding, these schemes are divided into two approaches: uniformly distribution of hash function based and geometric distribution of hash function based.

In the first approach, Kodialam proposed a tag cardinality estimator based on probability analysis with Anonymity, which broke with the tradition of using tag identification protocol to estimate tag cardinality [14]. However, it had two drawbacks, one was the reader must read all tags in a single time round. The other was the scale of a tag set should be a known quantity. Because of these disadvantages, a FNEB model was presented [15], which makes tag cardinality estimation using the first slot chosen by tags with required accuracy. It avoided reading all tags in a frame.

Uniformly distribution of hash function for tag coding is widely used in tag cardinality estimation, but it is not the only choice. Lottery of Frame (LoF) estimator was proposed [16], which utilized the average run size of 1 to estimate tag cardinality. It used the geometric distribution of hash function for tag coding, so enlarged the estimation range.

Now, research on RFID tag cardinality estimation is still ongoing, such as Zero-One Estimator [17], Simple RFID Counting estimator [18] and Average-run-based estimator [19]. In this paper, we compare the classical FNEB algorithm with our new proposed scheme when used in VANETs, and the result shows that our scheme achieves better performance in time cost and accuracy.

3 Problem Description and System Introduction

This section presents the problem description and system introduction. The aim is to estimate the vehicle cardinality accurately and quickly without identifying each vehicle individually. We simply introduce the frame-slotted ALOHA model [20], [21], [22], [23] and its application in our paper. Then, we describe the way that vehicles choose road segment locations and the communication protocol between the RSU and OBU.

3.1 Problem Description

Assuming the OBUs are all in the communication range of RSUs, and vehicles keep static during the estimation phase. The problem is how to estimate the vehicle cardinality accurately and quickly without reading each vehicle individually. Our scheme uses two variables to define the requirement, accuracy probability and confidence interval. With the vehicle cardinality t_0, accuracy probability γ and confidence interval β, our scheme returns an estimation value t_1, which satisfies the formula $P\left[\frac{|t_1-t_0|}{t_0} \leq \beta\right] \geq \gamma$. For example, if $t_0 = 3000$,$\gamma = 90\%$ and $\beta = 10\%$, the probability of our result between 2700 and 3300 is above 90%. Table 1 introduces the symbols appeared in our paper.

Table 1. Symbol description used in the design the proposed scheme

Symbol	Description	Symbol	Description
β	Confidence interval	t_{max}	Upper bound
γ	Accuracy probability	l	Road size
t_0	Vehicle cardinality	s	Random seed
t_1	Estimated value of vehicle cardinality	ρ	Load factor
F	Location number of the first vehicle	n	Times of cycles
S	Location number of the second vehicle	$T(\cdot)$	Estimation time
W	Location number distance of the first and second vehicle	$h(\cdot)$	Hash function

3.2 System Introduction

Our scheme references the framed-slotted ALOHA protocol, whose idea is unifying user's data transmission through clock signal. By dividing time into discrete time slice, the user can only send data in the start of any time slice, which avoids sending data casually and reduces the probability of data conflict. In our scheme, we will divide a road length into discrete road segments. All road segments are numbered uniquely and sequentially, then a vehicle chooses one of them.

The RSU and OBU communicate with each other through multiple roads, and every road is composed of multiple segments. Here, a single road corresponds to a collection cycle. Firstly, the RSU transmit a random seed s and a road size l to the OBU. If the road size is l, there are l road segments numbered by l consecutive integers that can be chosen in a road. Then, the vehicles within reception range choose any road segment in the road, which decides the location of a vehicle. The OBU in a vehicle uses road size l, random number s, OBU ID and uniformly distributed hash function $h(f, R, ID)$ to decide which segment to choose in this collection cycle. In essence, each vehicle selects a road segment number from the uniformly distributed integers between 1 and l randomly.

As each vehicle choose a road segment independently, there may be segments without any vehicle choosing or multiple vehicles choosing. However, the road here are all single-lane road, so we do not consider the collision problem. According to different states, road segments can be divided into two categories: empty and full. This process can be seen in Fig.2. After executing the query of a road, the RSU will get a binary sequence with 0 and 1, such as the Fig.2 results to a sequence of 011101, in which, 1 represents full segment and 0 represents empty segment.

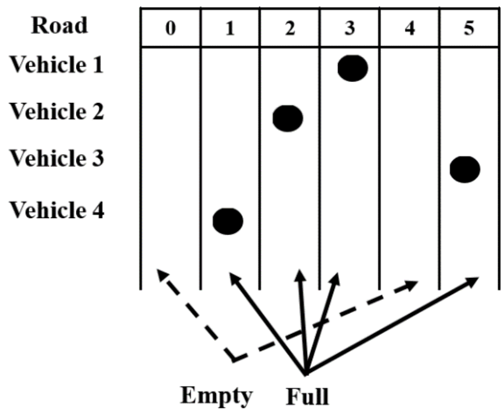

Fig. 2. Process of vehicles choosing road segments

4 Design of Our Scheme

Our vehicle cardinality estimation scheme includes four parts. The first part is to derive the estimation formula, and that is to get the mathematical relationship between expectation of location distance and number of vehicles, where the location distance is the location number difference of the second vehicle and first vehicle. The second part is to determine the times of cycles according to the requirement. The third part is to decide the road size by means of minimizing estimation time. The fourth part is to adjust the upper bound of vehicle cardinality according to the actual estimated traffic flow. The whole process of our model is illustrated in Fig.3.

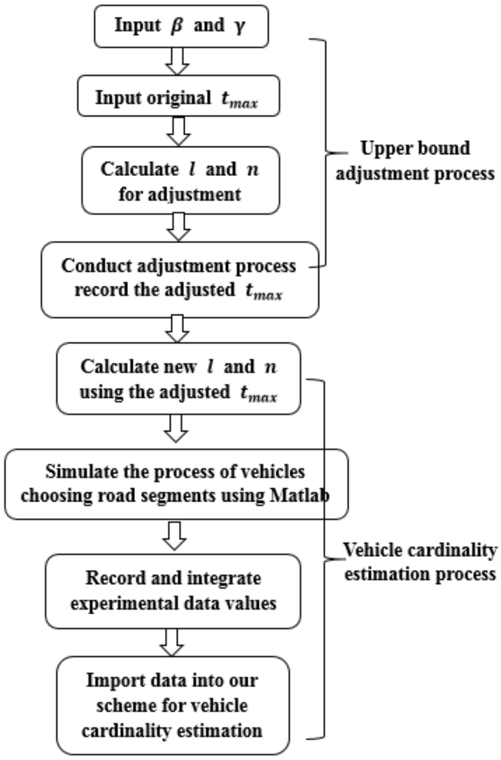

Fig. 3. Whole scheme illustration

4.1 Deriving Mathematical Formula for Estimation

Each vehicle chooses a segment number in a road randomly and independently, which means the probability of any segment being selected by any vehicle equals to each other. That is to say, the probability of any segment being empty or full is the same. We define the probability of any segment being empty as P_0,

$$P_0 = \left(1 - \frac{1}{l}\right)^{t_0} \tag{1}$$

When the road size l is large, P_0 can be simplified to

$$P_0 \approx e^{-\rho}, \text{ where } \rho = \frac{t_0}{l} \tag{2}$$

The location number of the first vehicle is defined as F and the location number of the second vehicle is defined as S respectively, by the probability formula of independent events, we can get

$$P[F = u] = {P_0}^{u-1}(1 - P_0) \tag{3}$$

$$P[S = v] = (v - 1){P_0}^{v-2}(1 - P_0)^2 \tag{4}$$

The location number difference of the first vehicle and the second vehicle is defined as W, by the probability formula of discrete random variable, we can get

$$P[W = w] = {P_0}^{w-1}(1 - P_0)\left(1 - {P_0}^{l-w}\right) \tag{5}$$

The expectation of W is

$$E(W) = \sum_{w=1}^{l-1} wP(W = w) = \sum_{w=1}^{l-1} w{P_0}^{l-1}(1 - P_0)\left(1 - {P_0}^{l-w}\right) \approx \frac{1}{1 - P_0} \tag{6}$$

According to the mathematical relationship between $E(W)$ and t_0, we can estimate the value of vehicle cardinality through the observation value of W. However, there exists variance between expectation value and observation value, so we need to get the average of many observation values of W to substitute $E(W)$. Conducting n collection cycles, we get W_1,W_2…..W_n, and the average value V is

$$V = \sum_{i=1}^{n} \frac{W_i}{n} \tag{7}$$

Where W_i is the ith observation value of W.

According to $E(W_i) = E(W)$, and $W_1 \sim W_n$ is't correlated mutually, we can get

$$E(V) = \frac{\sum_{i=1}^{n} W_i}{n} = E(W) \quad = \frac{1}{1-P_0} = \frac{e^{\rho}}{e^{\rho}-1} \tag{8}$$

That is

$$t_0 = l \cdot ln \frac{E(V)}{E(V)-1} \tag{9}$$

Simplifying $E(V)$ to V, we can derive the vehicle cardinality estimation value t_1 is

$$t_1 = l \cdot ln \frac{V}{V-1} \tag{10}$$

There is a special case when $V = 1$, which means the second vehicle is next to the first vehicle. In that circumstance, we can get that the real-time traffic condition can't be worse without estimating vehicle cardinality.

4.2 Determining Times of cycle n

Collecting data process should be conducted repeatedly, because there exists variance between $E(V)$ and V. We can determine the times of cycles n through the variance of $E(V)$.

Based on the calculation formula of variance [24], [25], we can get

$$Var(W) = E(W^2) - E^2(W) \quad = \frac{1+P_0}{(1-P_0)^2} - \left(\frac{1}{1-P_0}\right)^2 = \frac{P_0}{(1-P_0)^2} \tag{11}$$

As $Var(W_i) = Var(W)$ and $W_1 \sim W_n$ is not correlated mutually,

$$Var(V) = \frac{Var(\sum_{i=1}^{n} W_i)}{n^2} = \frac{Var(W)}{n} \tag{12}$$

The expectation of V is defined as ε and standard deviation is defined as τ,

$$\varepsilon = E(V) \tag{13}$$

$$\tau = (Var(V))^{\frac{1}{2}} = (Var(W)/n)^{\frac{1}{2}} \tag{14}$$

According to mathematical theorem, we can get

$$T = \frac{V-\varepsilon}{\tau} \tag{15}$$

Where the distribution of parameter T is normal and standardized, we can get cumulative distribution function [26], [27] of T as

$$\emptyset(x) = \frac{1}{\sqrt{2\pi}}\int_{-\infty}^{x} e^{-\frac{u^2}{2}}du \tag{16}$$

A constant h can be found to make

$$P[|Z| \le h] = erf\left(h/\sqrt{2}\right) = \gamma \tag{17}$$

Where we can figure out h through $erf(\ )$. If $\gamma = 95\%$, correspondingly, we can get $h = 1.96$.

The requirement defined by β and γ can be described as

$$\begin{aligned} P[|t_1 - t_0| \le \beta t] &= P[(1-\beta)t_0 \le t_1 \le (1+\beta)t_0] \\ &= P\left[(1-\beta)t_0 \le l \cdot ln\frac{V}{V-1} \le (1+\beta)t_0\right] \qquad (18) \\ &= P\left[\frac{e^{\rho(1+\beta)}}{e^{\rho(1+\beta)}-1} \le V \le \frac{e^{\rho(1-\beta)}}{e^{\rho(1-\beta)}-1}\right] \end{aligned}$$

Combine the formula (16) and（17），we need to satisfy the following two conditions

$$\frac{\frac{e^{\rho(1+\beta)}}{e^{\rho(1+\beta)-1}}-\mu}{\tau} \le -h \text{ and } \frac{\frac{e^{\rho(1-\beta)}}{e^{\rho(1-\beta)}-1}-\mu}{\tau} \ge h$$

Then we can get the times of cycles n

$$n = \frac{h^2 e^{tmax/l}\left(e^{\beta \cdot tmax/l} - e^{-tmax/l}\right)^2}{\left(1-e^{\beta \cdot tmax/l}\right)^2} \tag{19}$$

4.3 Determining Road Size l

The total estimation time is decided by collection cycle times and each cycle's execution time. Our scheme requires the RSU identify the first vehicle and the second vehicle, so we use the location number of the second vehicle, defined as S, to measure each cycle's execution time. The total estimation time can be simplified to the product of n and $E(S)$.

The expectation of S is

$$\begin{aligned} E(S) &= \sum_{v=2}^{l} v \cdot (v-1){P_0}^{v-2}(1-P_0)^2 \qquad (20) \\ &= \frac{2}{1-P_0} = \frac{2e^{\rho}}{e^{\rho}-1} \end{aligned}$$

Based on the formula (19) and (20), we can get the calculation formula of estimation time as

$$T(t_0, l) = n \cdot E(S) \ = \frac{2h^2\left[e^{(1+\beta)\cdot\rho}-1\right]^2}{\left(1-e^{\beta\rho}\right)^2 \cdot (e^{\rho}-1)} \tag{21}$$

Where h calculated by error function $erf(\ )$ [28], [29] and β defined as confidence interval are all known quantities, so the estimation time $T(t_0, l)$ is only dependent on the load factor ρ. We minimize $T(t_0, f)$ to find the optimized load factor ρ using the matlab tool. Then, as given above $\rho = \frac{t_0}{l}$, we can get the optimized road size l through ρ and t_{max}.

4.4 Adjusting Upper Bound t_{max}

When the given upper bound of vehicle cardinality is too large, there will be more empty road segments in the road. It causes the location of the first vehicle and second vehicle backward, which means the RSU needs to identify more road segments, that is, more time cost. We utilize the location number of the first vehicle F to judge whether the original upper bound t_{max} is too large for the current traffic flow. If so, we will shrink the upper bound t_{max} adaptively. For the randomness [30], we need to collect F many times and get the average $\bar{F}$. Through several experiments, we find $\bar{F}$ can get a stable value when the data collections reach 50 times. Hence, we use the average value $\bar{F}$ of 50 collected F_i to adjust the upper bound t_{max} in the simulation. The flow chart of the adjustment process is in Fig.4.

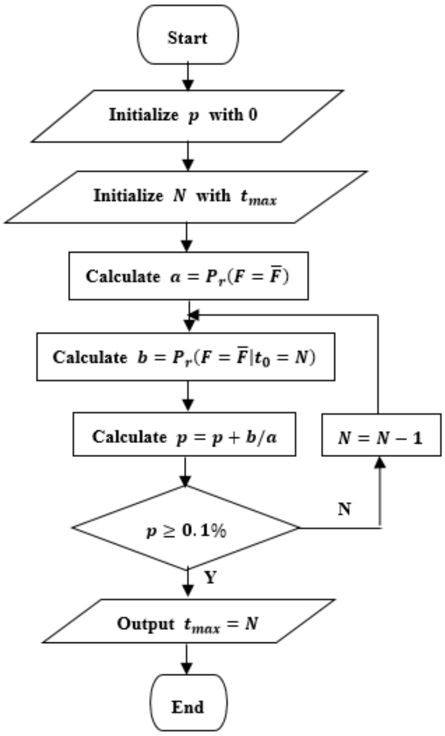

Fig. 4. Adjustment process of upper bound

F is defined as the location number of the first vehicle, and in the ith cycle, we will get a F_i. We decrease N from t_{max} to 1 to traverse all possible vehicle cardinality. Every time, we calculate $P_r(t_0 = N|F = \bar{F})$, which is the probability of vehicle cardinality is N when the location number of the first vehicle is $\bar{F}$. With the decreasing of N, we accumulate $P_r(t_0 = N|F = \bar{F})$ calculated in each cycle, defined as p. p is the probability of vehicle cardinality t_0 between N and t_{max}, written as $P_r[N \leq t_0 \leq t_{max}]$. When p is limited in a certain range, such as 0.1%, that is, the probability of vehicle cardinality larger than N is very low(0.1%). In other words, there are high probability(99.9%) of vehicle cardinality less than N. Therefore, we can shrink upper bound t_{max} to N.

5 Simulation and Evaluation

In order to evaluate the performance of our vehicle cardinality estimation scheme, we simulate estimating different traffic flows using the Matlab R2012a. The evaluation is conducted in two aspects, accuracy and time efficiency. We do not consider any collision and interference problems. In the simulation, we set the confidence interval as 5%, accuracy probability as 99%, vehicle cardinality from 500 to 5000, the original upper bound as 10000. The simulation experiment is conducted as followed. Firstly, in order to get the location number of the first vehicle and the second vehicle, we use the process of Matlab generating random number to represent vehicles choosing road segments. The smallest random number represent the location number of the first vehicle and the second smallest represent the location number of the second vehicle. Secondly, we conduct several simulation experiments to record and integrate experimental data, and then import the data into our proposed scheme for estimation. In the end, we compare the performance of our scheme with the FNEB algorithm in both accuracy and time cost aspects.

The adjustment of upper bound is crucial in our scheme, so it is necessary to simulate the adjustment process before comparison. In the experiment, we simulate adjusting the upper bound of a traffic flow with 500 vehicles, and record the adjusted upper bound in each cycle. The whole adjustment process can be seen in Fig.5. As shown in Fig.4, in view of the significant reduction on upper bound, we can see the adjustment process is very necessary. The adjustment algorithm achieves high efficiency, especially in the former 10 cycles, which shrinks the upper bound sharply. After these 50 cycles, there is no need for further adjustment, as the upper bound tends to be stable.

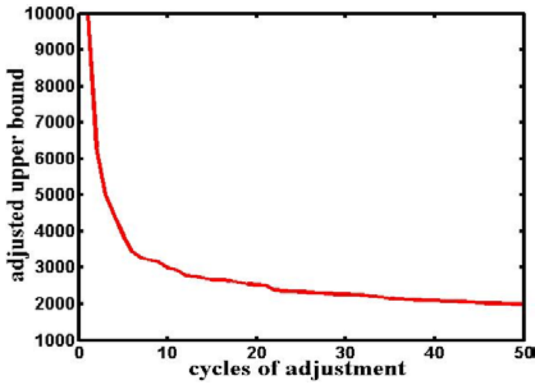

Fig. 5. Upper bound adjustment of vehicle cardinality

It is known that estimation time implies the scheme's efficiency. Fig.6 gives the three-dimensional relations between accuracy rate, vehicle cardinality and estimation time, which shows the time cost when estimating different traffic flows with different accuracy requirement .As seen in Fig.6, the higher accuracy rate results in longer estimation time, because higher accuracy rate means more times of cycles, thus, more estimation time. Similarly, the smaller vehicle cardinality results in longer estimation time. That's because vehicles are uniformly distributed in the road, so less vehicles lead to the location of the first vehicle and the second vehicle go backward, which means the RSU needs to identify more road segments, that is, more estimation time.

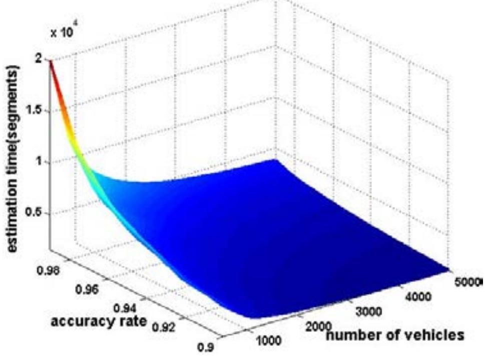

Fig. 6. Estimation time of our scheme

After that, our proposed scheme and FNEB algorithm are used to estimate different traffic flows respectively, whose cardinality is from 500 to 5000. Based on the result of experiments, we will compare these two tag estimators in aspects of deviation rate and time efficiency.

For comparison, we define deviation rate as d, which can be calculated with $d = |t_1 - t_0|/t_0$. Experimental results of deviation rate d are shown in Fig.7. Viewed as a whole， the deviation rate of our scheme is stable and keeps lower than 0.05, however, the FNEB's arises more than 0.1, even close to 0.35. Observing the specific data values, the deviation rate of our scheme is at least 50% lower than that of the FNEB algorithm, which proves superiority of our scheme in the aspect of accuracy. That's because our scheme leverages the location number difference of the second vehicle and the first vehicle to estimate vehicle cardinality, while FNEB algorithm only leverages the location of the first vehicle. The randomness of the former is much less than the latter, so it can reflect the distribution of vehicles in the road more accurately, which means higher accuracy in vehicle estimation.

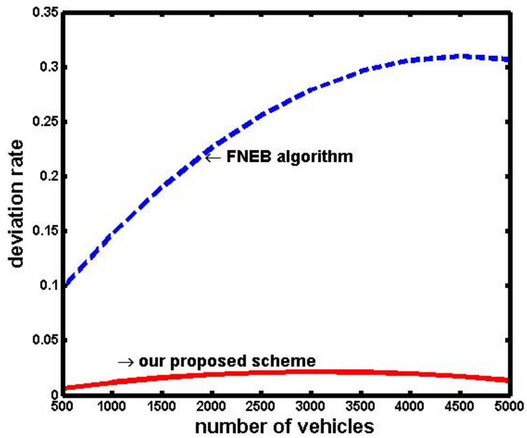

Fig. 7. Deviation rate comparison of our scheme and FNEB algorithm

Fig.8 shows the time cost of our scheme and FNEB algorithm while estimating different traffic flows with vehicle cardinality from 500 to 5000. Viewed as a whole， the time cost of our scheme is less than that of the FNEB algorithm in all traffic flows. Especially in the cases of vehicle cardinality is relatively small, our time cost is almost half of the FNEB's. While with the vehicle cardinality increasing, our scheme's gain in time cost shrinks. Observing the specific data values, the time cost of FNEB is almost 1.5 times of our scheme, that is, time efficiency of our algorithm is 1.5 times of FNEB algorithm, which proves the time efficiency advantage of our scheme. That's owing to the process of adjusting the upper bound, making the upper bound closer to the actual vehicle cardinality. The road size l and times of cycles n calculated by the adjusted upper bound will be more accurate, which contributes to higher time efficiency.

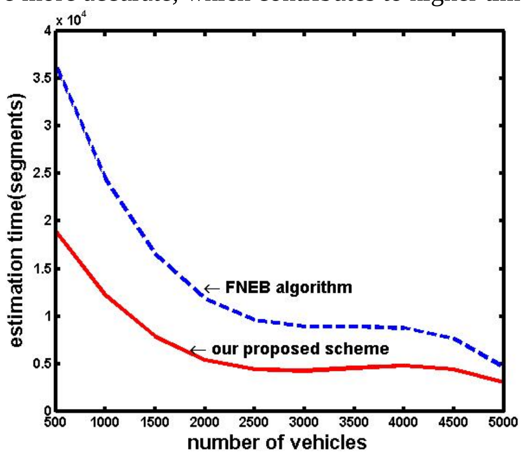

Fig. 8. Time efficiency comparison of our scheme and FNEB algorithm

6 Conclusion

This paper proposes a newly-fashioned scheme based on the location distance between the first vehicle and the second vehicle to estimate the number of vehicles. When the scheme is applied in VANETs, we can estimate vehicle cardinality without identifying vehicles one by one, which avoids the privacy-leakage. Both theoretical analysis and extensive simulations prove our scheme achieves high accuracy and time efficiency.

Acknowledgement

This work is partially supported by the National Science Foundation of China (Grant No. 61472283), the Fok Ying-Tong Education Foundation, China (Grant No. 142006), the Fundamental Research Funds for the Central Universities (Grant No. 2013KJ034, 2100219043 and 1600219246). This project is also sponsored by the Scientific Research Foundation for the Returned Overseas Chinese Scholars, State Education Ministry. JSPS KAKENHI Grant Number 26730056, JSPS A3 Foresight Program.

Reference

1. Nakamura K, Hayashi Y.: Strategies and instruments for low-carbon urban transport: An international review on trends and effects. J. Transport Policy. 29, 264-274(2013)
2. Kockelman, K.: Traffic Congestion. Transportation Engineering Handbook (2011).
3. Subbe, C. P., Jones, S.: Predicting speed at traffic lights—the problem with static assessments of frailty. J. Age and ageing .44(2), 180-181(2015)
4. Agarwal, P. K., Gurjar, J., Agarwal, A. K., Birla, R.: Application of Artificial Intelligence for Development of Intelligent Transport System in Smart Cities. J. International Journal of Transportation Engineering and Traffic System. 1(1), 20-30 (2015)
5. Sunmonu, O. F.: Intelligent Transportation System. In10 th Research Seminar Series Workshop(2011)
6. Hu, J., Lewis, F. L., Gan, O. P., Phua, G. H., Aw, L. L.: Discrete-Event Shop-Floor Monitoring System in RFID-Enabled Manufacturing. J. IEEE Transactions on Industrial Electronics, 61(12), 7083-7091(2014)
7. Xie, L. S., Chen, X. Y., Lin, Y. Z.: Bus Safety Regulatory System Design Based on Internet of Vehicles Technology. In: Applied Mechanics and Materials, pp. 114-117(2014)
8. Chuang, M. C., Lee, J. F.: PPAS: A privacy preservation authentication scheme for vehicle-to-infrastructure communication networks. In: 2011 International Conference on CECNet, pp. 1509-1512. IEEE (2011)
9. Navarro, W., Ternera, Y., Velez, J. C., Candelo, J. E.: RFID system on electrical substation equipment. In: 2015 IEEE 15th International Conference on EEEIC, pp. 15-20. IEEE (2015)
10. Athalye, A., Savic, V., Bolic, M., Djuric, P. M.: Novel semi-passive RFID system for indoor localization. J. Sensors Journal, IEEE,13(2), 528-537(2013)
11. Krishnamurthy, B., Naryshkin, K., Wills, C.: Privacy leakage vs. protection measures: the growing disconnect. In: Proceedings of the Web, pp. 1-10(2011)

12. Yeh, K. H., Lo, N. W., Fan, C. Y.: An analysis roadwork for information loss and privacy leakage on Android applications. In: 3rd Global Conference on Consumer Electronics, pp. 216-218. IEEE(2014)
13. Chae, C. J., Shin, Y., Choi, K., Kim, K. B., Choi, K. N.: A privacy data leakage prevention method in P2P networks. J. Peer-to-Peer Networking and Applications.1-12(2015)
14. Zheng, Y., Li, M.: Towards more efficient cardinality estimation for large-scale RFID systems. J. IEEE Transactions on Networking. 22(6), 1886-1896(2014)
15. Han H., Sheng B., Tan C., et al.: Counting RFID tags efficiently and anonymously. In: IEEE INFOCOM'2010, pp. 1-9. IEEE (2010)
16. Qian, C., Ngan, H., Liu, Y., Ni, L. M.: Cardinality Estimation for Large-scale RFID Systems. J. IEEE Transactions. 22(9), 1441-1454. (2011)
17. Zheng, Y., Li, M.: Towards more efficient cardinality estimation for large-scale RFID systems. J. IEEE Transactions on Networking. 22(6), 1886-1896(2014)
18. Jiang, W., Zhu, Y.: A Unified Approach for Fast and Accurate Cardinality Estimation in RFID Systems. In: 11th International Conference on Mobile Ad Hoc and Sensor Systems, pp. 407-415. IEEE (2014)
19. SV, V. K., Manjunath, T. N. A View on Fast and Accurate Estimation of RFID Tags (2015)
20. Luo, W., Chen, S., Li, T., Chen, S.: Efficient Missing Tag Detection in RFID Systems. In: 2011 Proceedings IEEE, pp. 356-360. IEEE (2011)
21. Wang, C. Y., Lee, C. C., Lee, M. C. An enhanced dynamic framed slotted ALOHA anti-collision method for mobile RFID tag identification. J.JCIT. 6(4), 340-351 (2011)
22. Deng, D. J., Tsao, H. W.: Optimal dynamic framed slotted ALOHA based anti-collision algorithm for RFID systems. J. Wireless Personal Communications. 59(1), 109-122 (2011)
23. Tong, Q., Zhang, Q., Min, R., Zou, X.: Bayesian estimation in dynamic framed slotted ALOHA algorithm for RFID system. J.COMPUT MATH APPL.64(5), 1179-1186(2012)
24. Markowitz, H.: Mean–variance approximations to expected utility. J. European Journal of Operational Research. 234(2), 346-355(2014)
25. Fadnis, C., Jain, A., Charhate, S.: Higher order statistics for discrete Weibull fading channel: An alternate formulation. In: 2014 9th International Conference on Industrial and Information Systems, pp. 1-4. IEEE (2014)
26. Wagener, T., Pianosi, F., Sarrazin, F.: Global sensitivity analysis using a new approach based on cumulative distribution functions. In: AGU Fall Meeting Abstracts, pp. 1025. (2014)
27. Markello T C, Carlson-Donohoe H, Sincan M, et al.: Sensitive quantification of mosaicism using high density SNP arrays and the cumulative distribution function. J. MOL GENET METAB. 105(4), 665-671(2012)
28. Ding, C., Kong, D.: Nonnegative matrix factorization using a robust error function. In: 2012 IEEE International Conference on Acoustics, Speech and Signal Processing, pp. 2033-2036. IEEE(2012)
29. Endres, F., Hess, J., Engelhard, N., Sturm, J., Cremers, D., Burgard, W.: An evaluation of the RGB-D SLAM system. In: 2012 IEEE International Conference on Robotics and Automation, pp. 1691-1696. IEEE(2012)
30. Halko, N., Martinsson, P. G., Tropp, J. A.: Finding structure with randomness: Probabilistic algorithms for constructing approximate matrix decompositions. J.SIAM review. 53(2), 217-288(2011)