Design of ETC Violation Enforcement System for Non-payment Vehicle Searching

Guo-Huang Hsu*, Liang-Rui Lin**, Rong-Hong Jan**, and Chien Chen**

*ITRI(Industrial Technology Research Institute), Hsinchu, Taiwan R.O.C.

**Department of Computer Science, National Chiao Tung University, Hsinchu, Taiwan R.O.C.

GHHsu@itri.org.tw, {ljlin, rhjan, chienchen}@cs.nctu.edu.tw

***Abstract*—As we know, the heaviest traffic congestion on highways occurs near toll gates where vehicles make a short stop to pay the toll. So an electronic toll collection (ETC) system is usually built to eliminate the traffic jams. In order to find out the non-payment vehicles, the violation enforcement usually includes cameras to capture images of license plates, and a license plate reader system to recode photographs and license plate numbers of all vehicles. Thus, automatic license plate recognition (ALPR) technology is often used in violation enforcement. However, the identification precision of ALPR is not always reliable. Human review and correction will be needed to improve the accuracy and therefore will result in extra manual operation cost. In this paper, we consider multilane-free-flow ETC systems and formulate the non-payment vehicle searching problem into a matching problem and propose a Photograph-to-Transaction matching algorithm (PT algorithm) based on bipartite graph. The PT algorithm not only can reduce the human loading to review and correct the image recognition results but also can accurately identify all non-payment vehicles. The performance of the PT algorithm was evaluated in ns-2 simulator and three different traffic scenarios: congested traffic, normal traffic and sparse traffic. The simulation results show that our algorithm greatly reduce the number of plate recognitions, and is more feasible and reliable for ETC enforcement. This will activate some consequent activities against the violation vehicles.**

***Keyword*—ETC, multilane free flow, violation enforcement, bipartite graph, matching.**

I. INTRODUCTION

Owing to the dramatic cost down on electronic components and the advances on wireless technologies, the development of Intelligent Transportation System (ITS) has drawn intensive attention in recent years from many countries.

Manuscript received June 20, 2012. This work was supported in part by the National Science Council of the Republic of China under grants NSC 100-2221-E-071-MY2.

Guo-Huang Hsu is with the Industrial Technology Research Institute, 195, Sec. 4, Chung Hsing Rd., Chutung, Hsinchu, Taiwan 31040, R.O.C.
Phone: +886-3-5915682; fax: +886-3-5836236; e-mail: GHHsu@itri.org.tw.
Liang-Rui Lin, Rong-Hong Jan and Chien Chen are with the Department of Computer Science, National Chiao Tung University, 1001 Ta Hsueh Road, Hsinchu, Taiwan 300, ROC.
Phone: +886-3-5712121; e-mail: {ljlin, rhjan, chienchen}@cs.nctu.edu.tw

The Vehicular Ad hoc Network (VANET) is a promising approach for the future ITS. In this novel architecture, the in-vehicle device (On-Board Unit, OBU) can communicate with roadside units (RSU) and with each other, referred to as vehicle-to-roadside (V2R) and vehicle-to-vehicle (V2V) communication, respectively. Due to VANETs have the characteristics of low-latency transmission and rapid topology change, 802.11 doesn't fit with above characteristics. So the Intelligent Transportation Systems (ITS) Committee of the IEEE Vehicular Technology Society (VTS) develops the IEEE 802.11p/1609.X draft and the Federal Communications Commission (FCC) of the U.S allocates 75MHZ Dedicated Short Range Communication (DSRC) spectrum within the (5.85-5.925) GHZ for VANET [19]. The overall bandwidth is divided into seven channels which are composed of one control channel (CCH) and six service channels (SCHs). The CCH is mainly used to transmit safety-critical messages and high priority messages in the form of WAVE short message. On the other hand, the SCHs are used to deliver non-safety messages.

In all applications for VANET, it can be divided into two main categories: safety and non-safety applications. The purpose of the safety application is to transmit the emergency messages and collision avoidance to decrease the traffic accident. The emergency messages are usually reserved at the specific zone for a long time so that the drivers can pay attention to the warning area. The Cooperative Collision Avoidance (CCA) [2] informs the backward vehicles the front road information so that the vehicle collision accident could be reduced. The common characteristic of the applications are that the messages should be propagated in low delay time reliably. In non-safety applications, the focus is on transmission of large data files, multi-hop communication and service provision such as the Electronic toll collection (ETC).

According to a research of traffic congestion on highways, the heaviest congestion occurs near toll gates where vehicles make a short stop to pay the toll. Hence, the primary cause of traffic jams can be eliminated by building an ETC system. Through wireless communication between OBU and the roadside antenna of a toll gate, vehicles are able to pay the toll and drive through toll gate without stopping. In general, ETC systems currently used in the world can be classified into two types: single-lane free flow (SLFF) and multilane free flow

(MLFF) as shown in Fig. 1. It is also known that MLFF ETC systems have much greater complexity than SLFF ETC systems, but the former is more convenient for faster passing due to the less restriction on vehicle speed.

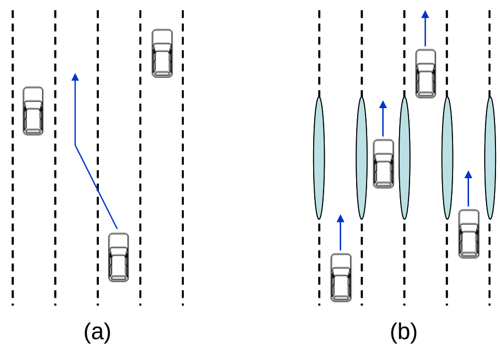

Figure 1. (a) Multilane Free Flow. (b) Single Lane Free Flow.

In Fig. 2, it shows the four components of a typical ETC system [15]. It includes 1) Automatic Vehicle Identification (AVI); 2) Automatic Vehicle Classification (AVC); 3) transaction processing; and 4) violation enforcement. The AVI component involves the use of OBU-to-RSU communications to identify the vehicle when entering the toll gate area. The type of OBU can be either a transponder or a radio-frequency identification (RFID) tag so that the vehicle can automatically be identified. The communication technology of ETC can be classified into two types of categories: Dedicated Short Range Communication (DSRC) System and Vehicle Position System (VPS). In DSRC system, it has two main communication technologies called infrared and microwave. The infrared communication technology is mature and has the features of low cost, fewer channel collision, easy installation and maintenance. But it is also easily affected by weather conditions and only suitable for SLFF. In order to increase traffic flow throughput, microwave communication is mostly adopted for MLFF in many countries now. In VPS, it combines GPS and mobile communication such that vehicles could report its real-time position to the server and the drivers could receive the bills by cell phone. Because of the high precision requirement of the vehicle position, the technique is still not matured.

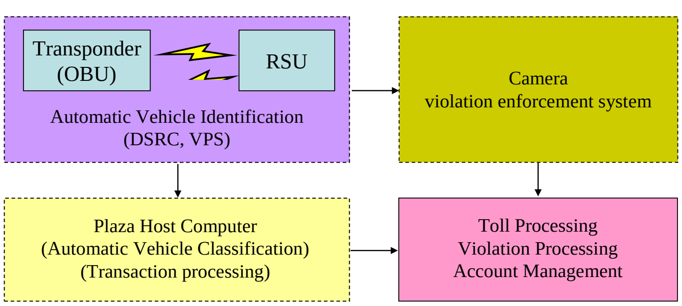

Figure 2. Electronic toll collection Architecture.

For AVC component, vehicle class can be determined by the vehicle's physical characteristics, such as the number of axles. A higher toll is usually imposed on a vehicle with more axles. Larger commercial trucks or vehicles pulling trailers, therefore, would likely pay a higher toll. Transaction processing entails debiting the toll from the customer's account and addressing customer inquiries. Violation enforcement usually includes cameras to capture images of license plates, and a license plate reader system to recode photographs and license plate numbers of all vehicles. Thus, automatic license plate recognition (ALPR) technology is often used in violation enforcement. In addition to taking and recognizing pictures, the most common current practice in violation enforcement involves determining and sending out written notices for each violation. The determining can be performed by matching the transaction data with the correct license plate number recognized by ALPR. As the factors of dirty plate surface, weather or equipment, so the identification precision of ALPR is not always reliable. For this reason, human review and correction will be needed to improve the accuracy of the license plate recognition. However, employing a lot of human labor for recognizing a large number of photographs will increase the extra manual operation cost. In SLFF, the violation enforcement system is easy to match the vehicle's transaction record to its image record correctly because the two records must take place at the same lane; however, in MLFF, it is relatively complicated to match the vehicle's transaction record to its image record because the transaction location can be anywhere in the highway toll gate area.

In this paper, we consider the violation enforcement of MLFF ETC systems and focus on improving the efficiency of finding the non-payment vehicles. As we known, ALPR technology is one of the important factors for matching the vehicle's transaction data to its license plate image data. However the precision of the ALPR is not always reliable as mentioned above. So human loading will be increase. In order to reduce the count of executing ALPR, we formulate the non-payment vehicle searching problem into a bipartite graph matching problem and propose a Photograph-to-Transaction matching algorithm (PT algorithm). PT algorithm not only can reduce the human loading to review and correct the image recognition results but also can accurately identify the vehicles that drive through a highway toll gate area without paying for toll. The rest of this paper is organized as follows: Section 2 provides previous results and system model. Based on the system model, the PT algorithm for identifying all violations is proposed in Section 3. In Section 4, we show and discuss the simulation results. Finally, our conclusions are given in Section 5.

II. PRIOR WORKS AND SYSTEM MODEL

A. Prior Works

Currently in the world, many countries and cities have conducted the MLFF system, and many related techniques have been proposed [3-13, 16-18]. Some of these researches were proposed for AVI components. In [12], the authors designed in-pavement antennas with carrier frequency 915MHZ. The tag is on the lower edge of the front license plate, and the in-pavement antennas are buried under the road. The transmission range is one meter wide and 2 meter high. It support variable bits packet for several operations. However, it is not sufficient for congested traffic. In [9] the authors proposed MLFF architecture for ETC. The gantry is 6.2m height cross the width of three lanes and the transceivers are with carrier frequency 5.8GHz. In [10] the authors proposed a novel architecture by employing millimeter-wave range in MLFF. Each lane is equipped with antennas and the frequency of each is different. The proposed scheme utilized high resolution in lateral directions to track the vehicle's direction. This is for separating the packets into segments so that can communicate with RSU consecutively. The communication range may overlap on the intersection of adjacent lane.

Some of researches were proposed for AVC components. In [16], the authors proposed a wire device that can get the electronic signal when vehicle passing. The device can classify type of vehicles by the variation signal information. ETC System can utilize the information to toll different amount of money.

For violation enforcement system, some of papers were also proposed to study the performance in MLFF. In [6], Lee et al. designed and implemented a MLFF system based on VPS techniques. As shown in Fig. 3, a virtual toll zone is a rectangle area identified by a pair of coordinates $\{(x_1,y_1), (x_2,y_2)\}$, and consists of notification area, toll area and enforcement line. The vehicle moving into the notification area will be notified that a tolling transaction is going to be carried out, and the debit transaction is going on when the vehicle passing through the toll area. Enforcement line has enforcement devices such as cameras, vehicle classification sensors installed on it in order to identify the vehicle class and capture the vehicle license plates. Camera modules take pictures for every vehicle entering the toll area and ALPR module recognizes every license plate number in order to discriminate the registered and un-registered vehicles by matching the license plate number with the tolling transaction data. Since all the missions should be done in nearly real time, it is a computing critical task for the enforcement system. The authors, therefore, propose a match pre-processing skill to reduce the computing capacity in license plate recognition and arise the pre-matching accuracy. The license plate number is sent to the enforcement system immediately by querying the registered user database in the backend system when it receives 'TS' message, an online debit message send tracks in toll zone, from a vehicle. Thus whenever the vehicle passes through the enforcement line, the enforcement system has the capability of 'prediction' the next coming registered vehicle license plate. This action improves the efficiency and accuracy of ALPR and match pre-processing. The match pre-processing is done when the license plate number received from the backend is matched to the license plate number recognition, and all the images of unrecognized vehicle is stored in the backend database for the post matching and violation processing.

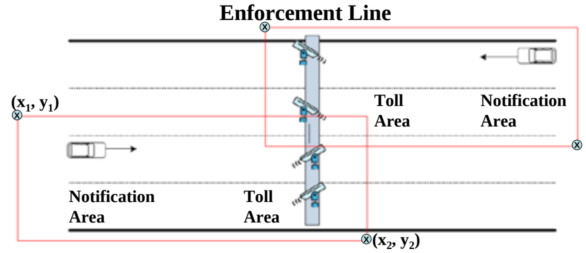

Figure 3. Virtual toll zone configuration in VPS system.

In [17], the authors proposed a tolerant algorithm to match the license plate number with the tolling transaction data. The steps of this algorithm are as follows: 1) for all license plate numbers recognized by ALPR, if there exists a transaction data which can fully match with the digits of the license plate number, the license plate image is a paid vehicle. 2) For remaining license plate numbers, if there exists a transaction data which can match with four or more digits, the license plate image also can be seen a paid vehicle. 3) Discriminate all unmatched license plate numbers to be paid or unpaid by manual operation. In [18], the authors also consider the MLFF system based on VPS and proposed an automatic matching method to improve the performance of violation enforcement. As shown in Fig. 4, the vehicle equipped with GPS receiver will report the location information per second when passing through the toll area. The lane location where the vehicle is taken a picture at can be estimated by two location points at the left and right sides closest to the enforcement line. Then the enforcement system only needs to check the image data captured by the camera located at the same lane location, and the computing capacity can be reduced.

We observe that the methods discussed in previous literatures about improving the performance in violation enforcement system still need to recognize all the image data. Human review and correction is still needed to improve the identification precision of ALPR. In contrast, our algorithm not only can reduce the human loading but also can accurately identify all non-payment vehicles.

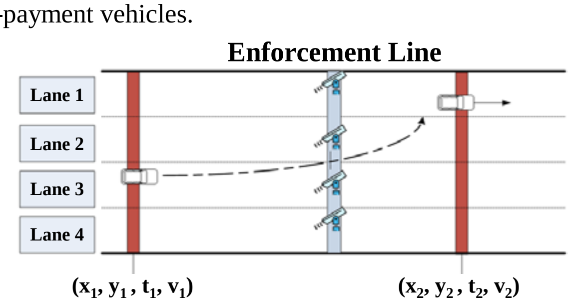

Figure 4. Two location points to estimate the lane position.

B. *System Model*

In this paper, we consider the MLFF ETC system and propose a PT algorithm to identify all violations. As shown in Fig. 5, the scenario of the road is a highway with 4-lanes. There is a RSU to provide the AVI service and transaction processing, and each lane is equipped with a camera at the enforcement line. For PT algorithm, the primary step is to create a bipartite graph representation of the relation between license plate image data and transaction data. The flow for creating a bipartite graph is described as follows. Consider Fig. 5. A vehicle equipped with an OBU is driving on a highway. When the vehicle enters the highway toll gate area identified by the RSU, the OBU can use wireless communication to pay the toll to the RSU and then the RSU sends the transaction data to the enforcement system. The transaction data includes the time of transaction and license plate ID information. When the vehicle passes through the gate, the enforcement line will take a picture of the license plate in order to get the license plate image data. At the same time, the enforcement system gets the speed of the vehicle and uses the time of taking the picture (T1) to infer the times of entering (T2) and exiting (T3) the toll gate area. All the transaction data from T2 to T3, said the possible matching targets, will be connected to the image data. As the shown example in Fig. 5, there are five transaction data from T2 to T3. So the image data has five possible matching targets. In Fig. 6, for each image data, we can connect it with the corresponding transaction data and then a maximum connected bipartite graph G(P∪T, E) is created, where the set of vertices P represents image data, the set of vertices T represents transaction data and the set of edges E represents links between P and T.

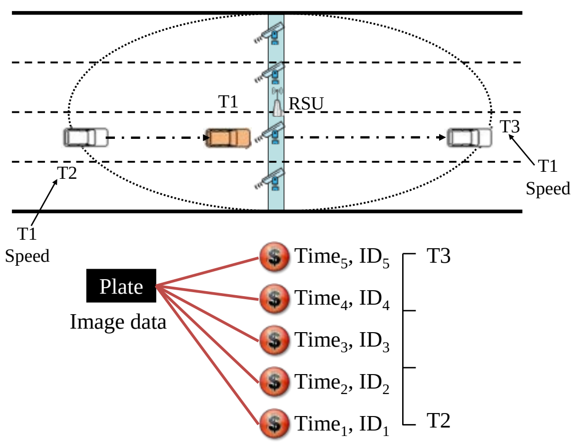

Figure 5. An image data and the possible matching targets.

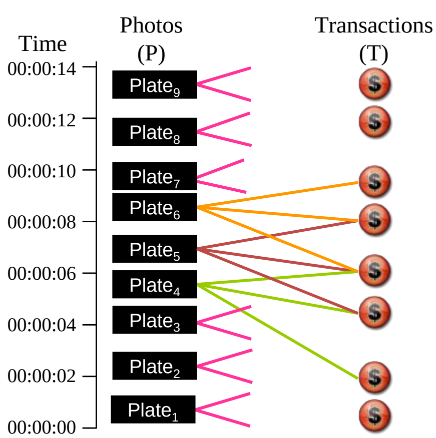

Figure 6. A bipartite graph representation of the relation between image and transaction.

III. THE PT MATCHING ALGORITHM

Throughout this paper, we focus on an undirected graph without loops and follow [14] for graph theoretical definitions and notations. Let G(V, E) be a graph and v∈V(G) be a vertex. We use the notation N(v) and E(v) to denote the set of vertices connected to v and the set of edges incident with v, respectively. The cardinality |E(v)| is called the degree of v, denoted by deg(v). Consider a maximum connected bipartite graph G(P∪T, E) representing the relation between license plate image data and transaction data. Then G(P∪T, E) has the following properties:

Property 1. The number of vertices of the image data set P must be greater or equal to the number of vertices of the transaction data set T.

1.1 If |P| = |T|, all the vertices in P are legal vehicles. The legal vehicle means that it drives through the toll gate area with paying for toll.

1.2 If |P| > |T|, there exists at least one illegal vehicle in P without paying for toll.

Property 2. For a vertex v in P, if v is a legal vehicle, the transaction data of v must be in N(v). It means that the transaction data of v is in the set of possible matching targets of v.

Property 3. For a vertex v in P, if deg(v) = 0, v must be an illegal vehicle.

Property 4. For a vertex u in T, the image data of u must be in N(u).

Property 5. For a vertex u in T, if deg(u) = 1 and vertex v is the only neighbor of u, v must be a legal vehicle and u is the transaction data of v.

Consider an example of a bipartite graph as shown in Fig. 7(a). The degree of the transaction data with the license plate ID P01802 is one and $Plate_1$ is the only neighbor. So $Plate_1$ must be a legal vehicle and the other two edges adjacent to $Plate_1$ can be ignored. Using the same method, the transaction data with the license plate ID B00010 and A21787 also have degree one. Hence we can say that $plate_2$ is mapping to B00010 and $plate_3$ is mapping to A21787. After removing irrelevant edges, the bipartite graph can be simplified as shown in Fig. 7(b).

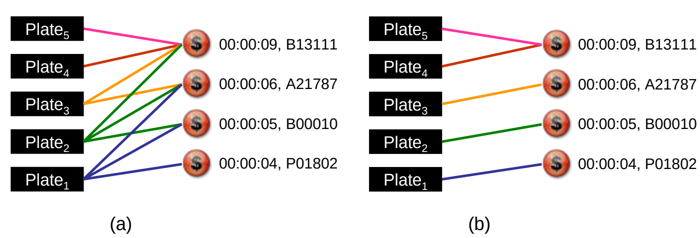

Figure 7. (a) Initial bipartite graph.
(b) Removing irrelevant edges by Property 5.

According to the properties mentioned above, a Photograph-to-Transaction matching algorithm is proposed for determining the non-payment vehicles in MLFF system. Fig. 8 shows the execution of each step of the algorithm. The main spirit of the algorithm here is the use of Property 1. When the number of vertices of the image data set is equal to the number of vertices of the transaction data set, it can determine all the image data are legal vehicles quickly and reduce the number of image recognitions. On the other hand, if the number of image data is greater to the number of the transaction data, there exists at least one illegal vehicle in image data set. In this case, the image recognition processing can make that the two sets have the same number of vertices or disconnect the bipartite graph into several disjoint components. For each component, it is recursive and used as the input of the algorithm.

```
1   Input: a maximum connected bipartite graph G(P∪T, E).
2   Output: two sets of illegal vehicles and legal vehicles.
3   Input (G(P∪T, E)) {
4     If |P| = |T|
5       move u into the set of legal vehicles, ∀u∈P;
6       exit;
7     If |P| = 1 and |T| = 0
8       move u into the set of illegal vehicles, where u∈P;
9       exit;
10    run Check_Degree_One_Vertices_In_T;
11    If G is disconnected and has G1, G2, …, Gn components
12      ∀Gi, Input(Gi(Pi∪Ti, Ei)), i = 1, 2, …, n;
13    else {
14      while (G is connected and G is not empty) {
15        take the middle node u∈P;
16        Image_Recognition(u);
17        If (License_check(u) = true)
18          move u into the set of legal vehicles;
19        else {
20          move u into the set of illegal vehicles;
21          If |P| = |T|
22            move u into the set of legal vehicles, ∀u∈P;
23            exit;
24        }
25        run Check_Degree_One_Vertices_In_T;
26      }
27      If G is not empty and has G1, G2, …, Gn components
28        ∀Gi, Input(Gi(Pi∪Ti, Ei)), i = 1, 2, …, n;
29    }
30  }
```

Figure 8. The Photograph-to-Transaction matching algorithm.

The details are described as follows.

- line 1 and 2: Explain the input and output.
- line 3: The input is a maximum connected bipartite graph G(P∪T, E)
- line 4 ~ line 6: Apply Property 1.1 to check whether the number of vertices of image data set is equal to the number of vertices of transaction data set or not. If agree, all image data are legal and moved to the set of legal vehicles.
- line 7 ~ line 9: Apply Property 3 to check whether the number of vertices of image data set is equal to one and the number of vertices of transaction data set is equal to zero. If agree, the only image data is illegal and moved to the set of illegal vehicles.
- line 10: Run the Check_Degree_One_Vertices_In_T function. By Property 5, for a vertex in transaction data set with degree one, the only neighbor of this vertex must be legal and can be moved to the set of legal vehicles.
- line 11 ~ line 12: If G is disconnected and has some components after the steps above, the components can be recursive and used as the input of the algorithm.
- line 13 ~ line 29: Use the image recognition processing repeatedly until the two sets of image data and transaction data have the same number of vertices or G is disconnected.

Now we take two examples to explain how the PT Algorithm can reduce the count of executing ALPR. Consider Fig. 9. The set of image data has nine vertices and the set of transaction data has eight vertices. By Property 1.2, there exists one illegal vehicle in P. To find the illegal vehicle, we take the middle vertex plate5 of the set P to execute ALPR first and the result is A21787. As shown in Fig. 9(a), we can find that the transaction data of plate5 is in its possible matching targets. So plate5 is a legal vehicle. Next, we remove plate5 from the set P and the transaction data with the license plate ID A21787 from the set T. After removing the two vertices, the bipartite graph is still connected and the number of vertices of the image data set is still greater than the number of vertices of the transaction data set. So we take the middle vertex plate4 of the set P to execute ALPR again and the result is B01610 as shown in Fig. 9(b). In this time, we can not find the transaction data of plate4 in its possible matching targets. So plate4 is an illegal vehicle and can be removed from the set P. Now, we can see that the two sets have same number of vertices. By Property 1.1, all the vertices in set P are legal vehicles. In this example, the system performs only twice ALPR to identify which vehicles are legal or illegal.

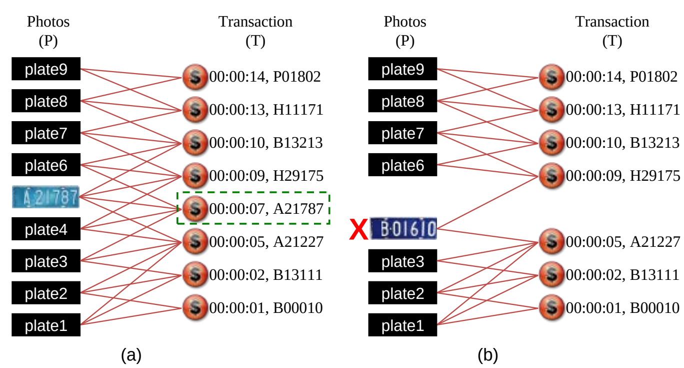

Figure 9. (a) Plate5 is recognized as legal.
(b) Plate4 is recognized as illegal.

Consider another example shown in Fig. 10. We assume that the vertex B01610 is legal. After removing B01610 from the set P and the transaction data with the license plate ID B01610 from the set T, the bipartite graph is disconnected as shown in Fig. 10(b). There are two components with four and three vertices, respectively. By Property 1.1, all the vertices in the subgraph with four vertices are legal. On the other hand, the subgraph with three vertexes exists one illegal vehicle by Property 1.2. The components can be recursive and used as the input of the algorithm to find remain illegal vehicle.

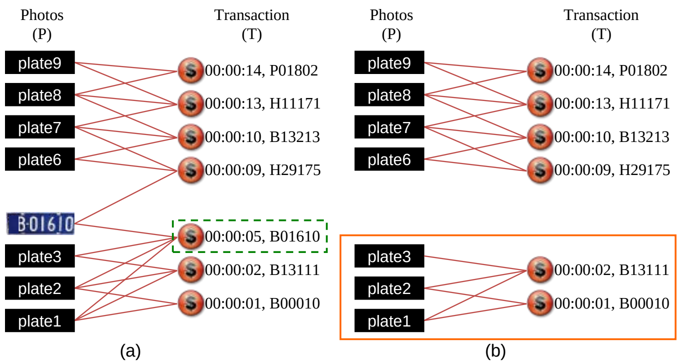

Figure 10. (a) B01610 is legal.
(b) Remain two bipartite subgraphs.

IV. SIMULATION RESULTS

A. Simplify Bipartite Graph

Before showing the simulation results, we first introduce two methods to simplify the bipartite graph in order to improve the performance of our algorithm. Since the speed of vehicles driving in the congested traffic environment is lower than the speed in the normal or sparse environment, the number of vehicles staying in the toll gate area will be increased. It means that the degree of each image data in the bipartite graph created based on the congested environment will be higher. In order to decrease the degree and simplify the bipartite graph, we assume the vehicle would report their location information when the tolling transaction is finished. According to the location information, the enforcement system can determine whether the tolling transaction is finished before the time of taking picture or not. As shown in Fig. 11, there are two types of vehicles paid road-user charges in the toll gate area. One finishes the tolling transaction at the left side of the enforcement line, and the other at the right side.

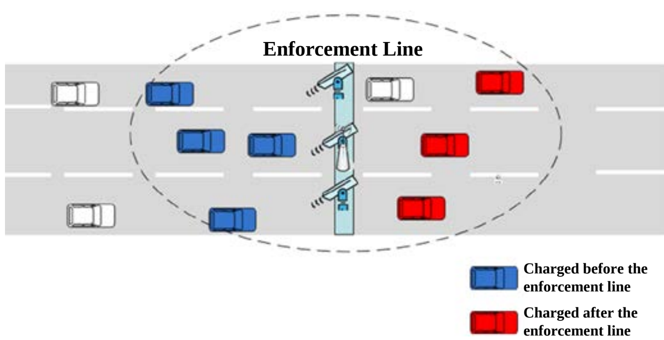

Figure 11. Two types of paid vehicles.

For the vehicles at the left side, the time of image data must occur after the time of transaction data; in the same way, the time of image data must occur before the time of transaction data at the right side. According to above characteristics, the unnecessary edges of each image data can be eliminated and further the bipartite graph will be simplified. Consider an example as shown in Fig. 12, the red vertices are the transaction data finished at the right side of the enforcement line and the blue vertex is finished at the left side. Since the transaction time of the blue vertex is 00:00:05, the time of taking the picture must be after 00:00:05, and therefore the blue vertex is only connected to plate5. Using the same method, the time of taking pictures of the red vertices transacting at the right side must be before 00:00:01 and 00:00:03, respectively. Therefore, the degree of red vertices can be decreased as shown in Fig. 12(b).

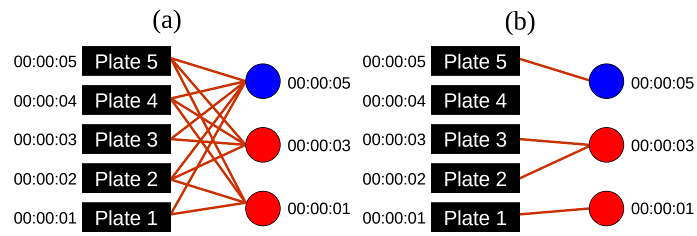

Figure 12. (a) Initial graph.
(b) After eliminate the unnecessary edges.

In addition to the location information of transaction data, we can apply the lane prediction technique [18] as shown in Fig. 4 to estimate the lane ID where the vehicles are taken pictures at. Then the image data and transaction data can be classified by the lane ID. The number of lanes is four, for example, we can divide the original bipartite graph into four subgraphs. This would eliminate the unnecessary edges and decrease the degree of each vertex again. To simplify the bipartite graph would decrease the number of ALPRs that can reduce the human loading to find the illegal vehicles. The impact of the factor to our algorithm will be investigated in simulation.

B. Simulation Environment

The simulation environment is described in this section. In [1], the mobility generator tool is a set of mobility scenario generators including Random Waypoint model, Reference Point Group Mobility model, Freeway mobility model and Manhattan mobility model. The Freeway model is used in our algorithm to generate mobility scenario. The simulation scenario is in a 4 km highway with four lanes. We conduct the simulation using the ns-2 simulator [21] in three scenarios: congested traffic, normal traffic and sparse traffic, and compare the number of ALPRs of orginal bipartite graph and simplified graphs, respectively. The main different parameters among these scenarios are velocity, number of vehicles and acceleration. Table 1 shows the details.

Table 1. Simulation Parameters.

The Length of Highway	4 km
Number of lanes	4 lanes
Number of Vehicles	[4410, 3286, 2519]
Velocity	V_{max}:[108, 80, 54]Km/h V_{min}:[90, 72, 36] Km/h
Acceleration Speed	[0.4, 0.8, 1.2]m/s^2
Simulation times	1800s
Transmission Range	100m
Location of the camera	2000m
Location of the RSU	2000m

In rush hour, the tolerance of the traffic flow in Taiwan ETC is 2,210 vehicles per hour [20]. As shown in Fig. 13, the maximum traffic flow appears from 7 a.m. to 7 p.m., and it is almost 8000 vehicles per hour for all lanes. Electronic toll collection has been implemented in Taiwan for five years. The proportion of illegal vehicles which are not equipped OBUs to total traffic flow is shown in Fig. 14. In recent years, the average error rate is closed to 0.06%. In our simulation, we utilized the error rate from 0.06% to 3.0% in the three scenarios.

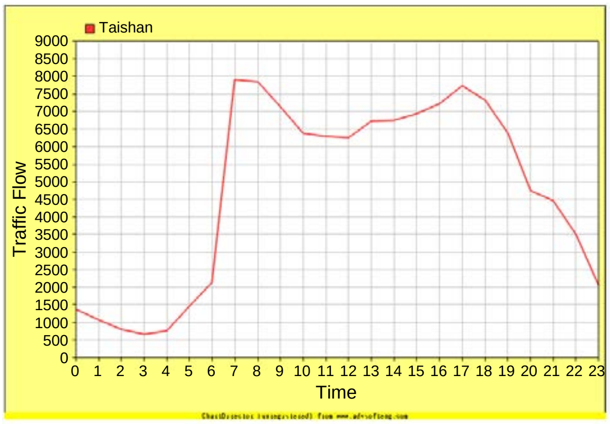

Figure 13. The traffic flow at Taishan Toll Station a day.

http://211.79.135.72/volume/drawday.htm

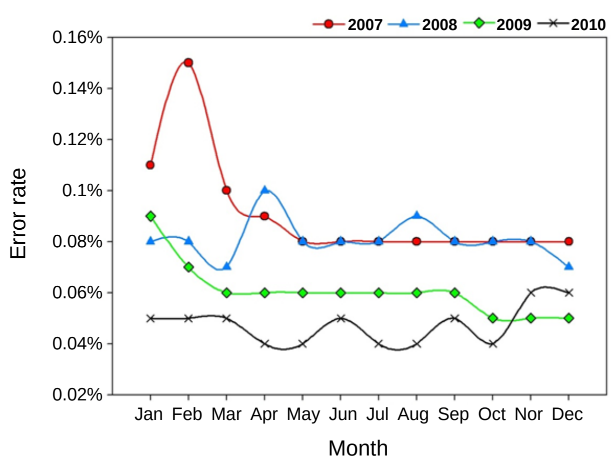

Figure 14. The proportion of illegal vehicles.

C. Result Analysis

In this section, we show the simulation results for the three traffic models in terms of the number of ALPRs, and of the distribution of average degree.

***1) Congested Traffic Analysis*:** Fig. 15 shows the number of ALPRs over different ratios of illegal vehicles and the number is increasing with the growing of the ratio. The origin represents that the input of PT algorithm is the original bipartite graph. The two simplified methods as mentioned in the beginning of this section are named PCL and PCL+PL. The simplified method related to the partition by the camera's location is PCL, and partition by the combination of the camera's location and lane ID is PCL+PL. We can observe that in the worst case, the ratio of illegal vehicles is 3% and the number of ALPRs is almost close to the number of total vehicles in origin. The reason is that our algorithm has to repeat the ALPR step continuously until the number of vertices of the image data set is equal to the number of vertices of the transaction data, or the bipartite graph becomes disconnected. In other words, it has to recognize a large number of image data to achieve the termination condition of the algorithm in congested traffic environment. On the other hand, the simplified bipartite graphs can get better performance than origin. Using PCL and PCL+PL methods, the numbers of ALPRs compared to origin can be reduced by 15% and 60%, respectively. In the bipartite graph simplified by PCL+PL, it is divided into four subgraphs and each lane has its own independent bipartite graph. So PCL+PL can get less number of ALPRs. Fig. 16 shows the number of ALPRs of each lane by utilizing PCL and PL. Obviously, it gets larger when the error rate grows up. In Fig. 17, it shows the distribution of the average degree of the three methods. The average degree of original bipartite graph is more than eight times the average of PCL+PL during 300s to 500s. This claims that the degree is an impact factor for PT algorithm.

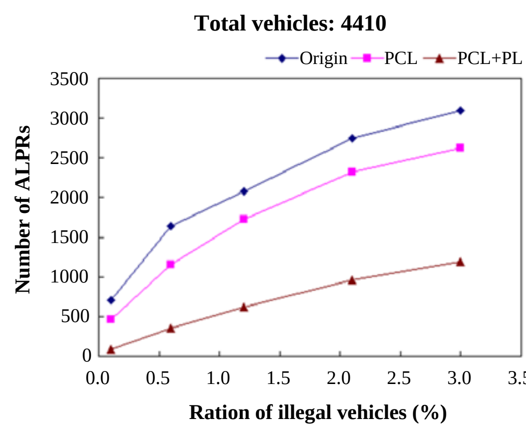

Figure 15. The number of ALPRs in congested traffic.

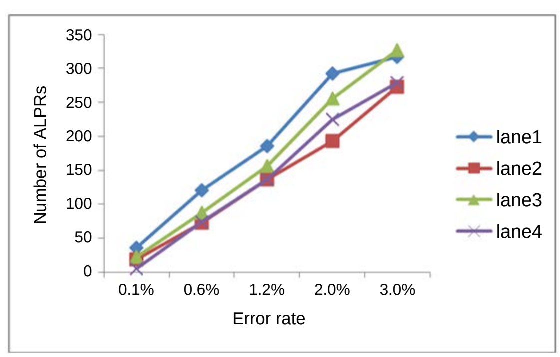

Figure 16. The number of ALPRs of each lane in congested traffic.

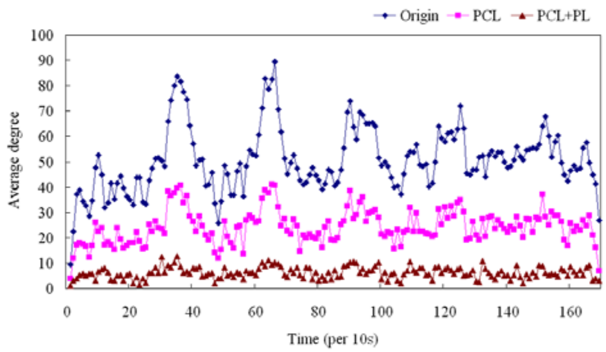

Figure 17. The distribution of average degree in congested traffic.

2) Normal Traffic Analysis： In Fig. 18, it shows that the number of ALPRs of the origin is still half of the total vehicles in worst cast. But, compared with the congested traffic, the ratio number of ALPRs is relatively small. By utilizing PCL and PCL+PL methods, the numbers of ALPRs compared to origin can be reduced by 23% and 80%, respectively. In Fig. 19, it presents the number of ALPRs of each lane by utilizing PCL+PL. The numbers in the worst case of normal traffic are one-third to congested traffic. In Fig. 20, it shows the distribution of the average degree of origin, PCL and PCL+PL. In normal traffic, the average degree is half of the degrees in congested traffic. So the number of ALPRs required in PT algorithm is relatively small.

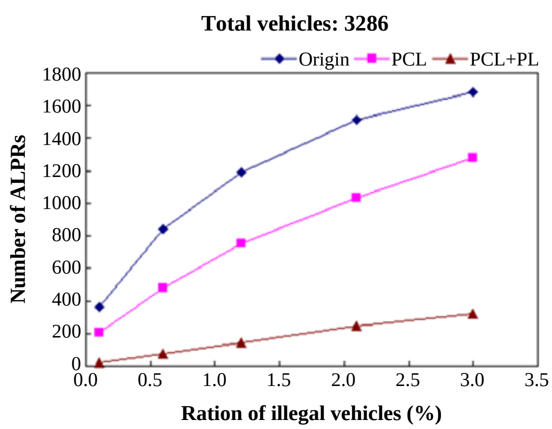

Figure 18. The number of ALPRs in normal traffic.

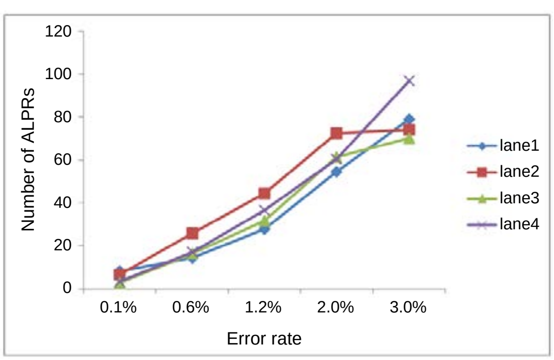

Figure 19. The number of ALPRs of each lane in normal traffic.

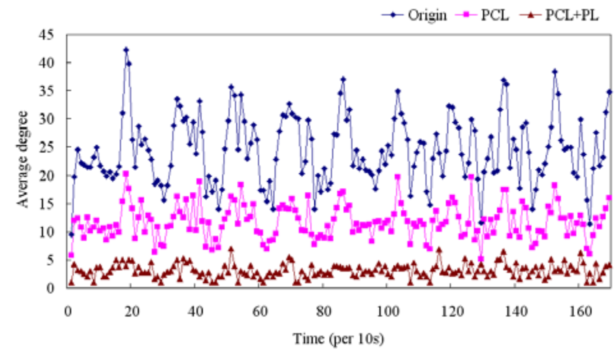

Figure 20. The distribution of average degree in normal traffic.

3) Sparse Traffic Analysis： Fig. 21 shows the simulation results in the sparse traffic environment. The number of ALPRs is the smallest of three scenarios and it can be reduced by 36% and 87% in the original bipartite graph simplified by PCL and PCL+PL, respectively. Even in the worst case, only five percent of image data need to perform ALPR in PCL+PL method. Since the velocity is faster and the density is lower in the sparse traffic, the degree of each vertex is small. Under this condition, the bipartite graph can more easily be disconnected. In Fig. 22, it presents the number of APLRs of each lane under PCL with PL. Compare to another two scenarios, The number is much lower. In Fig. 23, it shows the distribution of the average degree per ten seconds in the three methods. We observe that all the average degrees in PCL+PL are smaller than five. So PT algorithm doesn't need to recognize many image data in order to disconnect the graph. On the other hand, the enforcement system can create many smaller bipartite graphs in sparse traffic environment, and some of them have exactly the same numbers of vertices of image data set and transaction data set. That is the reason why PT algorithm has a better efficiency in sparse traffic.

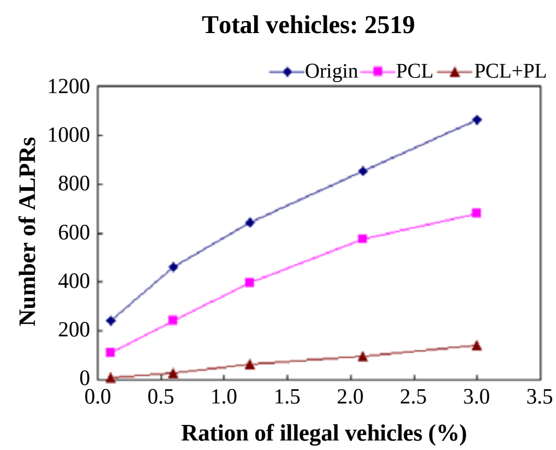

Figure 21. The number of ALPRs in sparse traffic.

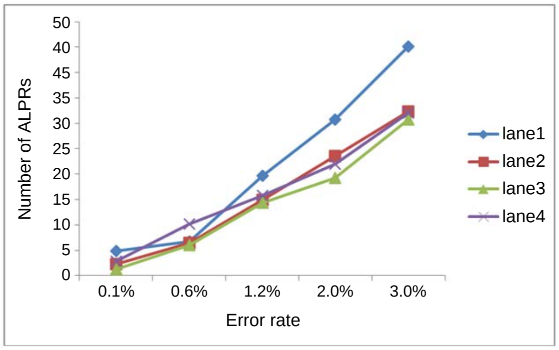

Figure 22. The number of ALPRs of each lane in sparse traffic.

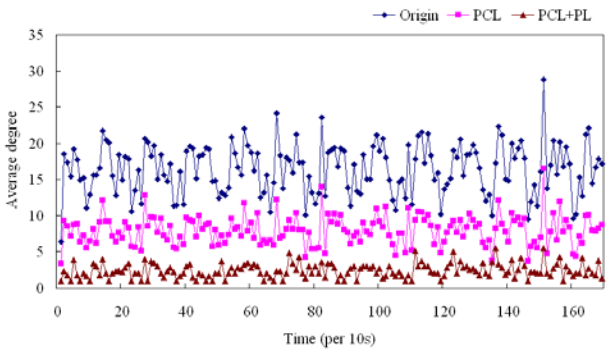

Figure 23. The distribution of average degree in sparse traffic.

4) The degree Analysis：Fig. 24 shows the number of degree in three scenarios with original graph and simplified graphs. The number of degree is the most by exploiting original graph. It seen to has closed number of degree by utilizing PL with PCL in each scenario, but our simulation show the number of degree in dense is ten times more than in sparse. This is because the number of vehicles in dense is much more than in sparse during the same time period. In other words, it has to check as many as vertices so that the bipartite graph could be disconnected.

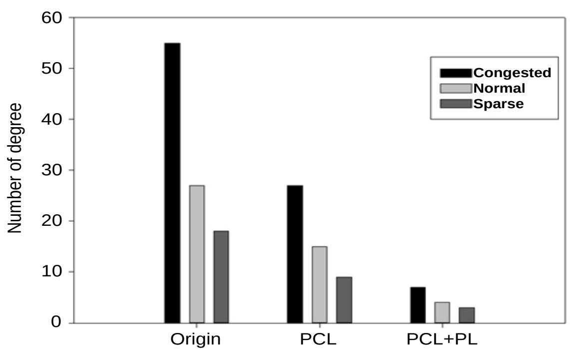

Figure 24. The average number of degree in each scenario.

V. Conclusions

In this paper, we proposed a Photograph-to-Transaction matching algorithm based on bipartite graph for the violation enforcement of MLFF ETC system. Our algorithm can accurately find all non-payment vehicles and decrease the number of license plate recognitions such that human loading can be reduced. The simulation results shows that the original bipartite graph without simplifying, it has the worst performance in the congested scenario. So we proposed two methods, called PCL and PCL+PL, to simplify the bipartite graph. PCL method is based on the location of transaction data relative to enforcement line, and PCL+PL is based on the lane location where images are captured by cameras. Simulation results show that PCL+PL method has the best performance and the size of degree is an important impact factor. Although our searching method can reduce human loading, there is an important limitation – camera modules must take pictures for every vehicle passing through the enforcement line. How to surmount this limitation is a worth investigation in the future.

References

[1] F. Bai, N. Sadagopan, and A. Helmy, “User Manual for IMPORTANT Mobility Tool Generators in ns-2 Simulator,” University of Southern California, February 2004.

[2] S. Biswas, R. Tatchikou, and F. Dion, “Vehicle-to-vehicle wireless communication protocols for enhancing highway traffic safety,” *IEEE Communications Magazine*, vol. 44, no. 1, pp. 74-82, 2006.

[3] W. Du and W. Chen, “ETC development pushes combination of RFID and ITS,” *13th International Conference on Advanced Communication Technology (ICACT)*, pp.1515-1518, 2011.

[4] Z. Feng, Y. Zhu, P. Xue and M. Li, “Design and realization of expressway vehicle path recognition and ETC system based on RFID,” *3rd IEEE International Conference on Computer Science and Information Technology (ICCSIT)*, vol. 7, pp.86-90, 2010.

[5] W.H. Lee, B.S. Jeng, S.S. Tseng, and C.H. Wang, “Electronic toll collection based on vehicle-positioning system techniques,” *in: Proc. 2004 IEEE Int. Conf. Networking, Sensing, and Control*, pp. 643-648, 2004.

[6] W.H. Lee, S.S. Tseng, and C.H. Wang, “Design and Implementation of Electronic Toll Collection System Based on Vehicle Positioning System Techniques,” *Computer Communications*, vol. 31, no. 12, pp. 2925–2933, 2008.

[7] Y. Li, L. Jiang, Y. Yin, F. Liu, H. Yu and Z. Ji, “System optimization of a 5.8 GHz ETC receiver using Memetic algorithm,” *2011 IEEE Workshop on Memetic Computing (MC)*, pp. 1-5, 2011.

[8] D.W. Lim and J.S. Jun, “Free-flow multi-lane ETC system using real-time individual vehicle tracking,” *in Proc. 5th Asia-Pacific Intelligent Transportation System (ITS) Forum*, Seoul, Korea, pp. TS1-TS3, 2002.

[9] M.A.S. Mustafa, M. Pitsiava-Latinopoulou, and G.A. Giannopoulos, “The multilane electronic toll collection system in Thessaloniki: Evaluation of its first 6 months of operation,” *in Proc. IEEE Vehicle Navigation and Information Systems Conf.*, pp. 699–703, 1994.

[10] W.Y. Shieh, W.H. Lee, S.L. Tung, and C.D. Ho, “A Novel Architecture for Multilane-Free-Flow Electronic-Toll-Collection Systems in the Millimeter-Wave Range,” *IEEE Trans. Intell. Transp. Systems*, vol. 6, no. 3, pp. 294–301, Sep. 2005.

[11] W.Y. Shieh, W.H. Lee, S.L. Tung, B.S. Jeng, and C.H. Liu, “Analysis of the optimum configuration of roadside units and onboard units in dedicated short-range communication systems,” *IEEE Trans. Intell. Transp. Systems*, vol. 7, no. 4, pp. 565-571, 2006.

[12] C. M. Walker and W. K. Brockelsby, “Automatic Vehicle Identification (AVI) technology design considerations for highway applications,” *in Proc. 41st IEEE Vehicular Technology Conf., Gateway to the Future Technology in Motion*, pp. 805–811, 1991.

[13] W. Wang, Y. Zhang, W. Yao and S. Wang, “The propagation model of RFID systems in ETC,” *2009 IEEE International Conference on Communications Technology and Applications (ICCTA)*, pp. 54-57, 2009.

[14] D.B. West, Introduction to Graph Theory, Prentice Hall, 2001.

[15] Z.H. Xiao, Z.G. Guan, and Z.H. Zheng, “The Research and Development of the Highway's Electronic Toll Collection System,” *International Workshop on Knowledge Discovery and Data Mining*, pp. 359-362, 2008.

[16] Bertrand, Jean and Dicko, Mamadou, “Method and device for classifying vehicles,” U.S. Patent, NO. 20030163263.

[17] Chunghwa Telecom, “A Multiple Experts Style for Multilane Free Flow Electronic Toll Collection Systems,” Republic of China (Taiwan) Patent Application, NO. 200415528.

[18] Chunghwa Telecom, “A Method for Improving the Success Rate of Automatic Matching Operation for Transaction Data and Enforcement Data in Electronic Toll Collection Based on Vehicle Positioning System,” Republic of China (Taiwan) Patent Application, NO. 200839652.

[19] L. Armstrong, “Dedicated Short Range Communications (DSRC),” [Online]. Available: http://www.leearmstrong.com/dsrc/DSRCHome.htm

[20] (2011) Taiwan Area National Freeway Bureau. [Online]. Available: http://www.freeway.gov.tw

[21] (2011) The network simulator: NS-2. [Online]. Available: http://www.isi.edu/nsnam/ns/

Guo-Huang Hsu received the BS degree in electronic engineering from National United University, Taiwan, Republic of China, in 2002, and the MS and PhD degrees in computer and information science from National Chiao Tung University, Taiwan, Republic of China, in 2004 and 2009, respectively. He is currently an engineer in the Information and Communication Research Laboratories of Industrial Technology Research Institute. His research interests include telematics, interconnection networks, analysis algorithms, and graph theory.

Liang-Rui Lin received the BS degree in Department of Computer Science and Information Engineering from National Taiwan Normal University, Taiwan, Republic of China, in 2009 and the MS degree in computer and information science from National Chiao Tung University, Taiwan, Republic of China, in 2011, respectively. He is currently an assistant Clerk in Data Communications Business Group of Chunghwa Telecom.

Rong-Hong Jan received the B.S. and M.S. degrees in Industrial Engineering, and the Ph.D. degree in Computer Science from National TsingHua University, Hsinchu, Taiwan, in 1979, 1983, and 1987, respectively. He joined the Department of Computer Science, National Chiao Tung University, in 1987, where he is currently a Professor. During 1991-1992, he was a Visiting Associate Professor in the Department of Computer Science, University of Maryland, College Park, MD. His research interests include wireless networks, mobile computing, distributed systems, network security, and network reliability.

Chien Chen received his B.S degree in Computer Engineering from National Chiao Tung University in 1982 and the M.S. and Ph.D. degrees in Computer Engineering from University of Southern California and Stevens Institute of Technologies in 1990 and 1996. Dr Chen hold a Chief Architect and Director of Switch Architecture position in Terapower Inc., which is a terabit switching fabric SoC startup in San Jose, before joining National Chiao Tung University as an Assistant Professor in August 2002. Prior to joining Terapower Inc., he is a key member in Coree Network, responsible for a next-generation IP/MPLS switch architecture design. He joined Lucent Technologies, Bell Labs, NJ, in 1996 as a Member of Technical Staff, where he led the research in the area of ATM/IP switch fabric design, traffic management, and traffic engineering. His current research interests include vehicular ad-hoc networks, content-centric networks, and cloud computing.