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iTraffic: A Smartphone-based Traffic Information System

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***Abstract*—We propose the *i-Traffic* system that utilizes *crowd-sourced* data from smartphones for the traffic flow mining by *shockwave* techniques. *Shockwave* is the propagation phenomenon of vehicle accumulation or relief on roads between two traffic flows with different speeds. The movement data of vehicles in front of an intersection are collected via smartphones for the shockwave identification. To conquer the low penetration problem when the number of the movement data is low, a folding heuristic is proposed by using traffic light cycle information to virtually increase the penetration of movement data. We implement our system on a client-server architecture and perform a small scale field trial experiment to demonstrate the system capability. Our results showed that our system is able to compute traffic information, including red/green light transition information and vehicle arrival rate with *mean absolute errors* of $5.0/0.6$ seconds and 2.43 vehicles per minute, respectively under a low penetration rate of 1.2%.**

***Index Terms*—Crowdsourcing, green computing, intelligent transportation, location-based service.**

I. Introduction

With the advent of telematics technology, many ITS (Intelligent Transportation System) applications have been proposed in helps of traffic management such as dynamic traffic light sequence assignments in intelligent infrastructures and navigation or route guidance in driver assistances. One of the most important information required to enable these useful applications is traffic flow information. For example, in the dynamic traffic light sequence assignment, the schedule of traffic light sequence can be optimized dynamically according to the real-time traffic flow information so that the traffic throughput can be improved significantly; in the route guidance, navigation system can suggest drivers an optimal route based on the congestion information to safe traveling time.

In the past, many infrastructure-based approaches are proposed to obtain the traffic flow data, e.g., loop detectors and CCTV; however, the high cost on deployment and maintenance makes pervasive data collection difficult. Recently, a new data sourcing approach called *crowdsourcing* is proposed. Crowdsourcing approaches have lower cost both in deployment and maintenance as compared with traditional infrastructure-based approaches and thus become a new trend for pervasively data collection. In addition to crowdsourcing, mobile sensing is another new trend that makes use of communication and sensing technologies. The popularity of smartphones makes both crowdsourcing and mobile sensing possible in pervasively data collection and sensing. In this paper, we adopt mobile sensing technology in crowdsourcing data to discover traffic flow information.

Shockwave theory is a common base used in traffic flow mining. Shockwave is the propagation phenomenon of vehicle accumulation or relief on roads between two traffic flows with different speeds [1]. For example, the propagation of shockwaves in a signalized intersection can be illustrated by a time-position diagram as shown in Fig. 1. Each dash arrow represents vehicles' time-position relation with respect to the road segment. When vehicles encounter a red light, they gradually stop, forming a stop shockwave. On the light changing to green, these vehicles start to move, forming a go shockwave. From the stop/go shockwaves, important traffic flow related parameters can be discovered. Therefore, it is possible to discover traffic flow information from the movement of vehicles in front of the traffic light.

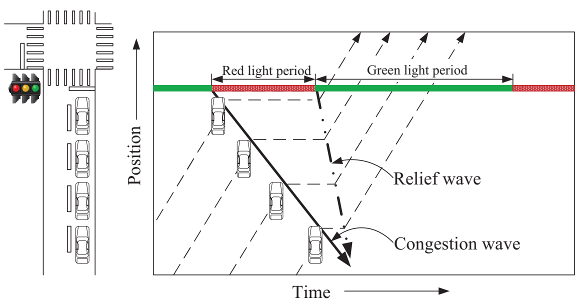

Fig. 1. Propagation of two shockwaves in a signalized road segment.

Both the infrastructure-based approach and the crowdsourcing-based approach are able to be used for shockwave detection. For the infrastructured-based approach, a pair of loop detectors is deployed under road surface to measure the speed and number of incoming and outgoing vehicles [2] [3]. Nevertheless, this approach can not be deployed pervasively due to the need of high cost on installation and maintenance. Besides, the shockwave is

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estimated by the position where the traffic flow changes, which is not accurate. On the other hand, the crowdsourcing-based approach makes use of GPS tracking data reported to measure the flow variation [4] [5]; however, the high requirement on percentage of reported GPS-tracking data (3%) to obtain accurate mining results makes this approach not practical in pervasive traffic flow mining [4].

In this paper, we propose a system that utilizes crowd-sourced data from smartphones for the traffic flow mining by shockwave techniques. The movement data of vehicles in front of an intersection are collected via smartphones for the shockwave identification. To conquer the low penetration problem when the number of the movement data is low, using traffic light cycle information to virtually increase the penetration of movement data used in the shockwave identification, a folding heuristic is proposed. We implement our system on a client-server architecture and perform a small scale field trial experiment to demonstrate the system capability. Our results showed that our system is able to compute traffic information, including red/green light transition information and vehicle arrival rate with *mean absolute errors* of $5.0/0.6$ seconds and 2.43 vehicles per minute, respectively under a low penetration rate of 1.2%.

The rest of this paper is organized as follows. In Section II, related works in the literature are reviewed. Section III presents the system architecture and designs. In Section IV, the system implementation is presented. In Section V, preliminary results of simulation experiments are introduced to demonstrate our system. Conclusions are given in Section VI.

II. Related Works

The shockwave theory was first proposed by Lighthill, Whitham [1] and Richards [6] for modeling highway traffic and later expanded by Stephanopolos [7] and Michalopoulos [8] for modeling signalized traffic.

The shockwave theory was applied by many works for the analyses on the dynamics of traffic flows. Based on data collection methods, researches studying in the shockwave model can be classified into two categories: infrastructure-based approaches [9][10][3][2][11] and crowdsourcing-based approaches [12][5][13][4].

Researches using infrastructure-based approaches have devoted in the development of analytical models for traffic estimation and the improvement of data collection methods. Skabardonis and Geroliminis [10] developed an analytical model for traveling time estimation in signalized arterials. Liu *et al.* [9] discovered a Queue-Over-Detector (QOD) problem in the traditional input-output approach for queue length estimation in signalized road segments, and used high resolution traffic signal data with data collected by loop detectors to estimate time-dependant queue length. Followed by Wu *et al.* [2], Oversaturated Severity Index (OSI) is defined for quantifying the effects of spillovers, and further separated to temporal OSI and spatial OSI where the temporal OSI describes the detrimental effects created by a residual queue, *i.e.*, the detrimental effects in temporal dimension, and the spatial OSI describes the detrimental effects created by spillovers, *i.e.*, the detrimental effects in spatial dimension. After that, the QOD problem in signalized arterials was further discussed in [11], Wu *et al.* found that the QOD can significantly affects the accuracy of Arterial Fundamental Diagram (AFD) and concluded that after removing the QOD effects, one can use AFD to interpret the traffic flow in signalized arterials. In [3], Geroliminis and Skabardonis proposed a method to detect spillovers in signalized intersections.

On the other hand, researches using crowdsourcing-based approaches tried to utilize the new mobile sensing technologies to find other means for traffic data collection. In [12], Herrera *et al.* proposed to incorporate GPS tracking logs with data collected from loop detector for traffic reconstruction. However, they did not discuss the penetration rate of GPS in vehicles, which directly affects the accuracy of the estimated traffic flow. In [13], Izadpanah *et al.* proposed a clustering algorithm to automatically identify the trajectories of shockwaves. However, the penetration rate would still be a performance issue in their method. After that, the penetration issue was brought back by Herrera *et al.* [4], they performed a field trial to show that a 3% penetration of GPS in vehicles is enough to provide accurate measurement data. In [5], Ban *et al.* proposed to use traveling time between intersections from GPS tracking logs, and developed an analytical model from the concept Queue Rear No-delay Arrival Time (QRNAT) to estimate queue length.

III. System Architecture and Designs

The proposed system is composed of crowd side and server side as shown in Fig. 2. The crowd side is a vehicle that installs smartphones, GPS, IMU (inertial measurement unit) and OBD (OnBoard Diagnostics). Among these devices, smartphones provide general computation capability, display interface to show traffic flow information and communication interfaces such as 3G and WiFi; GPS provides vehicle position information; both IMU and OBD provide vehicle movement information such as acceleration and speed. The crowd side uses these devices to sense vehicle movement state, i.e., halt and move states, by mobile sensing technology and provides these crowdsourced data to the server side. The server side is a collection of servers including database (DB) servers, data analysing (DA) servers and traffic information provision (TIP) servers. The DB server provides a storage interface that collects crowdsourced data from the crowd side and store estimated traffic flow information; the DA server has the capability to mine traffic flow information from the crowd side, and the TIP server provides an interface for road users to obtain traffic flow information in the DB server.

A. System Designs

Fig. 3 illustrates the system work flow. The system work flow is separated into the crowd side and the server side. In the beginning, the crowd side detects its movement state (halt or move) and reports the stop/go events including movement state, location and time to the server side. These stop/go events are stored in the DB server; later on, the DA server mines traffic flow information from the stop/go events by

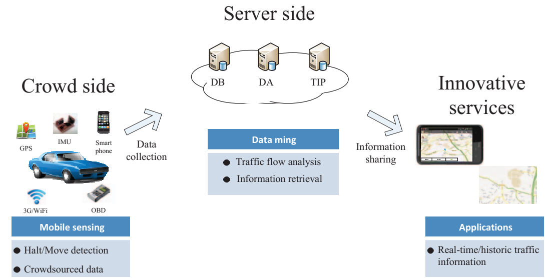

Fig. 2. The proposed system architecture.

the shockwave technique and event folding mechanism, and stores the information in the DB server. Finally, the TIP server provides a query interface to share the traffic flow information in the DB server among the crowd side. In the following, we present the key tasks in the work flow. The halt/move detection in the crowd side, and the traffic flow mining technique and folding heuristic in the server side.

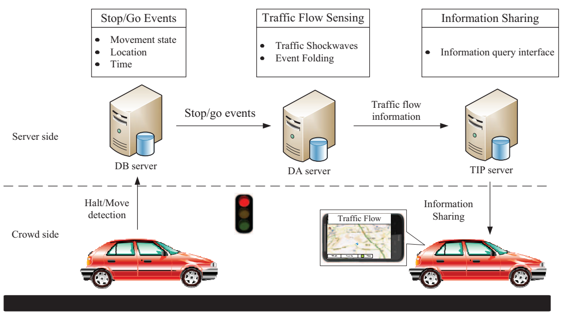

Fig. 3. The system work flow.

B. Halt and Move Detection

To provide crowdsourced data that are useful in traffic flow mining, the crowd side needs to sense the movement state associated to the traffic light ahead. In a journey of a vehicle, the journey is composed of a sequence of alternative halt periods and move periods divided by stop events and go events. A stop event indicates a vehicle transits from move to halt which can be described by the time and position pair that a vehicle stops. Similarly, a go event indicates a vehicle transits from halt to move which can also be described by the time and position pair that a vehicle starts to go. Practically, it is not so definitely that the stop and go events can be detected. In this work, a *Finite State Machine* (FSM) is used to model the status of a vehicle and also to sketch an algorithm detecting the stop and go events. See Fig. 4. The GO state means the vehicle is moving, and the STOP state means the vehicle is stopped. As mentioned before, the moving speed reported by GPS is more or less inaccurate and somewhat with delay. Even more, vehicles may move slowly before stopped. So, there exists a grey area between the GO and STOP states. To reflect these

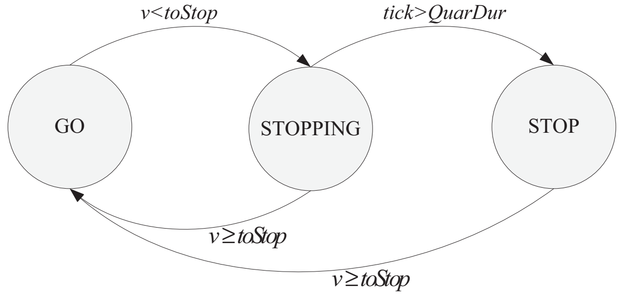

Fig. 4. The finite state machine that is used to recognize SG events from GPS tracking logs.

facts, we add one more state called STOPPING to quarantine the entrance to the STOP state as the speed is low. To sum up, in the FSM, there are three states, GO, STOP and STOPPING, and two parameters, $toStop$ and $QuarDur$. Let v denote the current speed of the vehicle and $tick$ denote the duration after entering the STOPPING state. The vehicle is in the GO state whenever $v \geq toStop$. In the GO state, if v goes below the threshold $toStop$, *i.e.*, $v < toStop$, the FSM transits to the STOPPING state, and at the same time, $tick$ is reset. In the STOPPING state, as v stays below $toStop$ for $QuarDur$ unit time, *i.e.*, $tick = QuarDur$, the FSM transits to the STOP state. Remind that no matter when, as soon as $v \geq toStop$, the FSM goes to the GO state. As the FSM transits from the STOP state to the GO state, a go event with the location and the time of the transition is reported. As the FSM transits from the STOPPING state to the STOP state, a stop event with the location and the time of the previous transition from the GO state to the STOPPING state is reported. After the stop/go events are detected, the crowd side reports the stop/go events to the DB server.

C. Traffic Information Mining Technique

After collecting the crowdsourced stop/go events, the DA server will mine traffic flow information from the stop/go events in the DB server. Let $\{s_i = (t_i^s, p_i^s)\,|i = 1, 2, ..., n\}$ be a collection of stop events, where t_i^s and p_i^s are the time and position of the stop event s_i, respectively, and $\{g_i = (t_i^g, p_i^g)\,|i = 1, 2, ..., n\}$ be a collection of go events, where t_i^g and p_i^g are the time and position of the go event g_i, respectively. If these stop events are put together, a linear trend called the stop shockwave may exist. Similarly, a linear trend called the go shockwave may exist among these go events $g_i = (t_i^g, p_i^g)$.

The stop and go shockwaves can thus be expressed by equations

$$L^s : p^s \doteqdot \alpha^s t^s + \beta^s \quad (1)$$

$$L^g : p^g \doteqdot \alpha^g t^g + \beta^g, \quad (2)$$

respectively.

We take stop events as an example to show how to determine the stop shockwave equation. Assume $\{s_1, s_2, \cdots, s_n\}$ are stop events due to a red light period. For any $1 \leq i \leq n$, $s_i = (t_i^s, p_i^s)$ fits to a stop shockwave

$$L^s : p_i^s \doteqdot \alpha^s t_i^s + \beta^s. \tag{3}$$

Let

$$\mathbb{T}^s = \begin{bmatrix} t_1^s & 1 \\ t_2^s & 1 \\ \vdots & \vdots \\ t_n^s & 1 \end{bmatrix}, \mathbf{p}^s = \begin{bmatrix} p_1^s \\ p_2^s \\ \vdots \\ p_n^s \end{bmatrix}, \text{ and } \mathbf{x}^s = \begin{bmatrix} \alpha^s \\ \beta^s \end{bmatrix}. \tag{4}$$

The linear system can be written as $\mathbb{T}^s \mathbf{x}^s \doteqdot \mathbf{p}^s$. Since this is an approximately system, we apply the *Least Square Method* (LSM) to find the linear regression equation for L^s. It follows that

$$(\mathbb{T}^s)^T \mathbb{T}^s \mathbf{x}^s = (\mathbb{T}^s)^T \mathbf{p}^s, \tag{5}$$

and we have

$$\mathbf{x}^s = \left((\mathbb{T}^s)^T \mathbb{T}^s \right)^{-1} \left((\mathbb{T}^s)^T \mathbf{p}^s \right). \tag{6}$$

Similarly, the go shockwave equation can be determined by the similar way from the go events $\{g_1, g_2, \cdots, g_n\}$.

From these shockwave equations, many useful traffic related information parameters can be found. For example, if we regard the position of the traffic light as the origin, the moment of $p^s = 0$ indicates the start time of a red light period. So, from $0 = \alpha^s t^s + \beta^s$, $t^s = -\beta^s/\alpha^s$ is the start time of a red light period. Similarly, $t^g = -\beta^g/\alpha^g$ is the start time of a green light period. In addition, the arrival and departure rates of vehicles can be discovered from α^s and α^g in the shockwave equations, respectively. Let H be the average space headway between vehicles and L be the number of lanes in a direction. Since the arrival rate of vehicles is defined as the number of incoming vehicles per unit time, and $|\alpha^s|$ is the vehicle accumulating distance per unit time per lane, $|\alpha^s| \times L/H$ is therefore the average arrival rate of vehicles. After the traffic related information parameters are estimated, these parameters are stored in the DB server and the crowd side can access these parameters from the interface provided by the TIP server.

D. Folding Heuristic

Note that the above discussion is based on the stop/go events caused in the same traffic light period; however, in practice, only a small portion of vehicles will participate in the crowdsourcing activity, so there may not be enough events for determining the shockwave equations. Observing that similar stop/go shockwaves will repeat every cycle if the vehicle arrival and departure patterns are stable and the traffic light cycle length is not change, we are possible to reduce the required penetration rate by utilizing the traffic light cycle information. We propose a *folding heuristic* to reduce the required penetration rate of stop/go events.

Fig. 5 illustrates an example of collected stop/go events in a signalized road segment. It appears that the linear trend can be easily observed in Fig. 5 (a) if all the stop and go events are known. However, in practice, there may only be a portion of events reported as the events marked in black in Fig. 5 (b), resulting in the difficulty of finding the linear trend of the

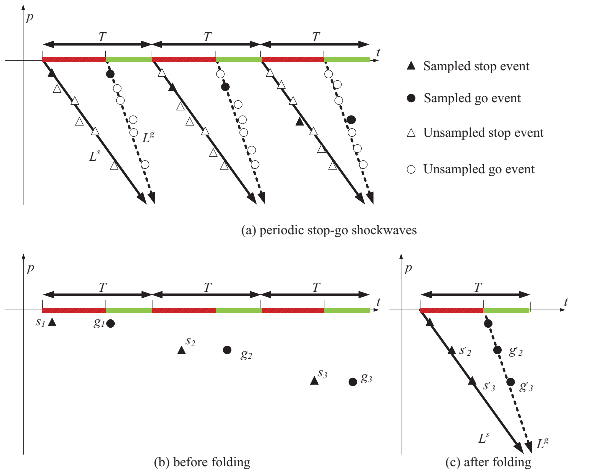

Fig. 5. An example of collected stop/go events in a signalized road segment.

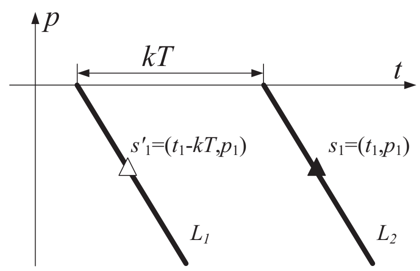

Fig. 6. An example to illustrate the folding technique.

stop/go shockwaves from these stop and go events. We call this the penetration rate issue.

Fortunately, since the traffic flow pattern (arrival rates for stop shockwaves and departure rates for go shockwaves) has similarity in a short period and the phase plan of a traffic light system has a fixed schedule in the same time period during a day, the shockwaves of the same type in different traffic light cycles should have similar slopes. In other words, we can assume these shockwaves are parallel to each other. Given a shockwave $L_1 : p = \alpha t + \beta$ with the traffic light cycle of length T, the shockwave that occurs after k cycles will be $L_2 : p = \alpha (t - kT) + \beta$ since the x-axis intercept is kT behind. Let $s_i = (t_i, p_i)$ be an event on the shockwave L_2, and we have $p_i = \alpha (t_i - kT) + \beta$. A virtual event $s_i' = (t_i - kT, p_i)$ will be a solution to the shockwave equation L_1. This idea is called the folding technique and illustrated in Fig. 6. In the figure, L_2 is the shockwave k cycles behind L_1 and $s_1 = (t_1, p_1)$ is an event in L_2. By applying the folding technique, $s_1' = (t_1 - kT, p_1)$ will fall in the shockwave equation L_1. Fig. 5 (c) shows the folding result of Fig. 5 (b). After folding, stop events s_2 and s_3 are folded to s_2' and s_3' by adding T and $2T$, respectively. Similarly, go events g_2 and g_3 are folded to g_2' and g_3', respectively. The folding technique can effectively reduce the requirement on the penetration rate.

IV. SYSTEM IMPLEMENTATION

In this section, we present the preliminary results of the implementation of our system. We implement our prototype system on 3G networks that contains a server on the Internet and several crowd ends on smartphones.

The crowd side is implemented on an Android platform based smartphone embedded with a GPS receiver. The android platform provides several APIs for user interface, map, location and connectivity services which are useful to implement the FSM for the halt and move detection, and access and display traffic information from the server. Fig. 7 illustrates our system snapshot.

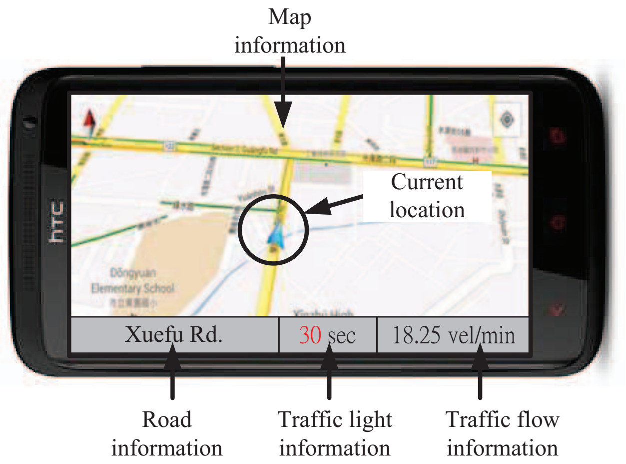

Fig. 7. The iTraffci service screenshot.

The server side is implemented in an IBM x3550 system and comprises a WWW server and a PostgreSQL server. The DA server and TIP server are implemented as web services in the WWW server, and the DB server is implemented in the PostgreSQL server. The WWW server uses PHP for the communication between the server end and the crowd end, e.g., reporting stop/go events to the DB server and querying traffic information from the DB server via the TIP server. PostgreSQL is used for data storages. In our system, the traffic information parameters estimated by our system are stored in the PostgreSQL server. PostgreSQL also provides several geographic related APIs that are useful in geographic computing.

V. EXPERIMENTAL RESULTS

To evaluate the accuracy of the traffic information estimated by our framework, we perform a small scale field trial experiment. In the experiment, two vehicles go around on a two-lanes road segment of length 650 m to collect stop and go events happening before a signalized intersection as illustrated in Fig. 8. The road segment is part of BaoShan Road near NCTU in Hsinchu City from A to B. The experiment is performed in a rush hour from 7:37 am to 8:20 am. The traffic light is located at B and two vehicles go along the black line from A to B to collect the stop and go events. The vehicles then take U turns at B and go back to A to start another round of data collection. Totally, ten rounds were performed in the experiment. Meanwhile, the traffic light cycle is 48 seconds for a red light period, including a 3-seconds-long yellow light period, and 102 seconds for a green light period. The total average vehicle arrival rate is 24 vehicles per minute in which the average vehicle arrival rate of the left lane is 18.6 vehicles per minute. The average vehicle arrival rate is counted from recorded video. Note that, the experiment is performed in the left lane since the traffic flow in Taiwan is mixed with heavy vehicles, passenger vehicles and motorcycles, and motorcycles usually drive in the right lane. In addition, in the ten-round experiment, there are total ten samples among the 43-minute-length experiment and there are about $42.5 \times 18.6 = 790.5$ vehicles during the experiment. Therefore, the penetration rate is $10/790.5 \approx 1.2\%$.

TABLE I
TRFFIC INFORMATION ESTIMATION FOR SHOCKWAVE EQUATIONS

Parameters	arrival rate (vel/min)		Red transition time (second)	Green transition time (second)
	$h = 6.10$	$h = 9.14$		
Measured	18.63		0	49
Estimated	19.51	12.83	5	49.6

A. Halt and Move Detection

We first evaluate the performance of the halt and move detection algorithm. The thresholds $toStop$ and $QuarDur$ used in the algorithm are set to 3.6 km/hr and 3 seconds according to our experience. The speed from OnBoard Diagnostics (OBD) with sampling rate 10Hz is used to detect the ground truth from GPS data.

The performance of the algorithm will be evaluated in terms of hitting rates and false detection rates based on the stop/go events detected by OBD. The hitting rate is defined as the ratio of the number of the stop/go events correctly reported by the algorithms to the number of stop/go events detected by OBD. The false detection rate, including the positive false detection rate and the negative false detection rate, is defined as the ratio of the number of the false stop/go events to the number of stop/go events detected by OBD. The hitting rate is $7/9$ and the positive false detection rate is $0/9$, and the negative false detection rate is $2/9$. The results show that the proposed stop/go event detection algorithms can detect most stop/go events with a small false detection rate.

B. Traffic Information Mining

To further verify the traffic information estimated by our system, Table I lists traffic parameters. The parameters include the average vehicle arrival rate and the length of the red light period. The average arrival rate is estimated by $|\alpha^s| \times l/h$ where $l = 1$ in the experiment. As suggested in [14], a reasonable vehicle head space h is from 6.10 to 9.14 meters. The average vehicle arrival rate is 19.51 vehicles per minute if $h = 6.10$ meters, and 12.83 vehicles per minute if $h = 9.14$ meters. The mean absolute errors of the vehicle arrival rate

Fig. 8. The road segment for field trial experiments.

are therefore 2.43 vehicles per minute. We can see that the vehicle arrival rates are around the measured one. The red and green light transition times are estimated by $-\frac{\beta^s}{\alpha^s}$ and $-\frac{\beta^g}{\alpha^g}$, respectively, and the mean absolute errors of red and green light transition time are 5 and 0.6 seconds, respectively. The estimated red light transition time is a little bit higher due to the driver's behavior. The results indicate that the framework proposed in this work can properly estimate traffic information parameters.

VI. Conclusions

In this paper, we propose a system that adopts crowdsourced data from smartphones for traffic information mining by the shockwave technique. We implemented a prototype system on 3G networks and evaluate the accuracy of the traffic information parameters estimated by our system. The contribution of our works are two folds. First, we have evaluated the accuracy of traffic information parameters including traffic flow and traffic light phase transition time estimated by the proposed system via field trial experiment. Second, our experiments show that 1.2% penetration rate is enough to discover the traffic information parameters. However, there are still many works need to study such as multi-lane traffic scenario, stop-go events that may not caused by traffic lights.

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