Performance Evaluation of Vehicle-Based Mobile Sensor Networks for Traffic Monitoring

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***Abstract*—Vehicle-based sensors can be used for traffic monitoring. These sensors are usually set with long sampling intervals to save communication costs and to avoid network congestion. In this paper, we are interested in understanding the traffic-monitoring performance that we can expect from such vehicle-based mobile sensor networks, despite the incomplete information provided. This is a fundamental problem to be addressed. A performance evaluation has been carried out in Shanghai, China, by utilizing the vehicle-based sensors installed in about 4000 taxies. Two types of traffic status-estimation algorithms, i.e., the link-based and the vehicle-based, are introduced and analyzed. The results show that estimations of the traffic status based on these imperfect data are reasonably accurate. Therefore, the feasibility of such an application is demonstrated.**

***Index Terms*—Global Positioning System (GPS), Intelligent Transportation System (ITS), traffic monitoring, vehicle-based mobile sensor networks.**

I. Introduction

CURRENTLY, taxi companies often deploy GPS-based sensors on their taxies for the effective dispatch of vehicles in many cities. These GPS-based mobile sensors can constitute a vehicle-based mobile sensor network, where the data sensed can be collected through either a vehicular ad hoc network or a Global System for Mobile Communications (GSM) network. The taxi companies, however, often set these sensors with long sampling intervals, such as 1–2 min, not only because they want to reduce communication costs but also because they are only interested in the general locations of the taxies for vehicle dispatch.

In this paper, we are interested in understanding what the performance for traffic monitoring would be if these sensor networks only provide sparse and incomplete real-time information [1]. Compared with stationary sensors such as loop detectors and/or video cameras, which are associated with high infrastructure and maintenance costs, vehicle-based sensor networks have the advantage of cost savings [2]. This paper is not concerned with details of the networking aspect, but primarily with data processing for traffic monitoring. We aim to explore the feasibility of such an application and the tradeoff between the accuracy of traffic status estimation and the cost of communication. Overall, available sensor data are considered as a by-product of taxi companies and are not specifically designed for traffic monitoring.

We carried out a performance evaluation study in the urban areas of Shanghai by utilizing the sensors installed in about 4000 taxies. Sensors can collect longitude and latitude coordinates, time stamp, etc. The average sampling interval is from 61 to 129 s. Two traffic status estimation algorithms, namely, the link-based algorithm (LBA) and the vehicle-based algorithm (VBA), are introduced to compute the real-time mean speed for every road segment. In total, 26 cases collected from August 2006 to May 2007 have been analyzed. The results show that the traffic status can reasonably accurately be estimated based on data from these vehicle-based sensor networks.

II. Related Work

Several works on mobile sensor for traffic monitoring have been carried out in recent years [3]–[8]. Most of them have focused on highways or freeways, where a traffic light delay is not an issue in these circumstances [2]. On the contrary, the situation is different from an urban area, where there are traffic light delays [3]. In addition, many works assumed that the sensor is set with a high sampling rate, such as 1 Hz, inevitably implying a considerable communication cost that might cancel the benefits of infrastructure cost-saving. A comparison of traffic measurement systems with stationary and mobile sensors can be found in [4]. In [5], an algorithm for the arterial road speed estimation was proposed by using taxies equipped with GPS sensors in Guangzhou, China. This work is based on a fine-grain data sampling model and only proposes the methodology of how to use sensor data to estimate the traffic status. To our best knowledge, performance and verification of the algorithm has not been reported. The work in [6] and [7] uses buses to monitor the arterial traffic status. Similarly, the work is also based on a short sampling interval, ranging from every 1 s to at most 30 s. Both works are mainly restricted to arterial roads in a metropolitan area, such as Shanghai, China. In [8], GPS

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data along a prespecified loop route with a sampling interval of 4–10 s were collected. As a comparison, the vehicle-based sensor network discussed in this paper can cover the entire road network of a metropolitan area. Overall, most of existing works are of experimental study and only proposed the methodology of vehicle-based sensors for traffic monitoring; the feasibility and real testing of accuracy are rarely found.

III. Algorithms for Traffic Estimation

A. Macroscopic Traffic-Flow Theory

The macroscopic traffic-flow model includes three key characteristics: 1) flow rate; 2) mean speed; and 3) density [1]. In evaluating the quality of a trip, drivers tend to consider the mean speed more than the flow rate or density. Therefore, in this paper, mean speed is also used as a performance metric. A road network consists of a set of roads embedded in a predefined geographical region, such as the metropolitan area of Shanghai. A node is an intersection. A *link* is a road segment between two intersections. A *road* consists of several ordered links, all of which share the same road name [9].

In general, a pair of data $p(s, t_1, t_2)$ consecutively sampled by a same sensor is defined as

$$p(s, t_1, t_2) = \{s, t_1, \psi_1, t_2, \psi_2\} \tag{1}$$

where ψ_1 and ψ_2 are obtained by map matching from the consecutive data samples at t_1 and t_2, respectively. The process of locating sensing data onto a road network map due to the well-known error of GPS devices is called *map matching* [10]. A sensor s has its average mobile speed during interval (t_1, t_2), which is denoted as

$$v(s, t_1, t_2) = r(\psi_1, \psi_2)/(t_2 - t_1) \tag{2}$$

where $r(\psi_1, \psi_2)$ is the length of road traveled between ψ_1 and ψ_2.

To estimate the traffic status around time t_k, we need to utilize the data collected from a group of associated sensors. More precisely, we use the data pair $p(s, t_1, t_2)$ as input for the traffic estimation algorithm. For link L_i with length l_i, let the mean traffic speed (MTS) of link L_i at time t_k be denoted as $V_i(t_k)$, which can be obtained by following algorithms with sensor data. If $p(s, t_1, t_2)$ is used to compute the MTS of L_i around t_k, we say that $v(s, t_1, t_2)$ is a speed element (SE) for L_i. The definition of MTS is given as follows:

$$V_i(t_k) = \sum_{v \in O_i(t_k)} \left(\frac{l_i^v}{\sum\limits_{v \in O_i(t_k)} l_i^v} \times v \right) \tag{3}$$

where $V_i(t_k)$ denotes the MTS of L_i around time t_k obtained by traffic status estimation algorithms with sensor data, v represents an SE, $O_i(k)$ is the set of SEs, and l_i^v denotes the length of the segment of L_i that v covers. In addition, we aggregate sensor data from $(t_k - \tau, t_k + \tau)$ for calculation of $V_i(t_k)$ to handle asynchronous data sample timing. More precisely, $p(s, t_1, t_2)$ can be used to calculate $V_i(t_k)$ when $(t_1, t_2) \subseteq (t_k - \tau, t_k + \tau)$, where τ is a predefined constant.

In addition, we analyze the real traffic flow by videotaping to get measurement of MTS, which is regarded as the real value of MTS (RMTS). The formula used is as follows:

$$V_i^R(t_k) = \frac{l_i}{\frac{1}{|C_i(t_k)|} \sum\limits_{c \in C_i(t_k)} \Delta t_c} \tag{4}$$

where c denotes a vehicle that travels link L_i with the time cost Δt_c around time t_k. A vehicle that enters link L_i between $(t_k - \tau, t_k + \tau)$ is included in a set of vehicles $C_i(t_k)$, and $|C_i(t_k)|$ is the size of $C_i(t_k)$.

We use camcorders to capture the video of the traffic flow of the tested link. Then, we begin to analyze the traffic flow. As we mentioned, for a specific link, we sample vehicles from the video, with and without traffic lights delays, to calculate RMTS by (4). Thus, these vehicles often have different time costs for traveling the link, which may result in a large standard deviation (SD) of the value of RMTS. Considering such a property, the RMTS calculated by (4) is a statistical metric that describes the entire traffic flow.

B. Link-Based Traffic Status Estimation

First, we describe the basic idea of the LBA: The LBA is proposed with an assumption that given a link, pairs of sensor data either starting or ending around this link can best reflect the traffic status of this particular link. Based on such assumption, given a particular link L_i, the LBA only aggregates pairs of sensing data from link L_i, as well as links adjacent to either of intersection nodes of L_i for every time duration $(t_k - \tau, t_k + \tau)$. Note that every link L_i has two intersection nodes, i.e., $k_B(L_i) = k_1$ and $k_E(L_i) = k_2$. Every intersection node w defines an *adjacent set of links* as

$$A(w) = \{L_i \mid k_B(L_i) = w \vee k_E(L_i) = w\}. \tag{5}$$

The LBA is presented as a procedure $\text{Estimate}_{\text{LBA}}(L_i, t_k)$ in Fig. 1.

C. Vehicle-Based Traffic Status Estimation

The basic idea of the VBA is described as follows: Compared to the LBA, the VBA utilizes every available data pairs and disseminates them back to all links traveled to estimate MTS. Thus, a sensor moving with a vehicle may travel over one or more links, which again can be associated with one or more roads.

The realistic data background can explain the methodology of the VBA that a long sampling interval makes two data of a data pair always far from each other. Thus, the VBA can make the most use of sensor data to calculate the traffic status, whereas the LBA only uses a portion of the sensor data. Same as the LBA, the VBA also calculates $V_i(t_k)$ by (3). The VBA for traffic estimation is presented as a procedure $\text{Estimate}_{\text{VBA}}(t_k)$ in Fig. 2.

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Procedure EstimateLBA(Li,tk) //Link-based traffic status estimation
Input: Li, tk; and all sensor data pairs collected around tk
Output: Vi(tk) // the mean traffic speed of Li at time tk
1) Construct a set of data pairs to be used
   ℘(Li, tk) = { p(s, t1, t2) | (t1,t2) ⊆ (tk-τ,tk+τ)
        and Include(Li, ψ1,ψ2) ≡ true }
where, τ is a predefined constant used to handle
asynchronous data sample timing.
2) Find the length of Li: e = r(kB(Li), kE(Li))
3) For each sensor s with p(s, t1, t2)∈ ℘(Li, tk)
   • compute its road distance over Li as l(Li,s).
     ▪ if (ψ1∈Li ∧ ψ2∈Li) l(Li,s) = r(ψ1,ψ2)
     ▪ if (ψ1∉Li ∧ ψ2∉Li) l(Li,s) = r(kB(Li), kE(Li))
     ▪ if (ψ1∈Li ∧ ψ2∈A(kE(Li))) l(Li,s) = r(ψ1, kE(Li))
     ▪ if (ψ1∈Li ∧ ψ2∈A(kB(Li))) l(Li,s) = r(ψ1, kB(Li))
     ▪ if (ψ1∈A(kE(Li)) ∧ ψ2∈Li) l(Li,s) = r(ψ2, kE(Li))
     ▪ if (ψ1∈A(kB(Li)) ∧ ψ2∈Li) l(Li,s) = r(ψ2, kB(Li))
   • compute weight of average mobile speed contributed
     ▪ βs = l(Li,s) / e; // where βs ≤ 1
   • accumulate weighted mean speed:
     ▪ R = R + βs * r(ψ1, ψ2) / (t2 – t1)
     ▪ U = U + βs
4) Compute the mean traffic speed of Li around tk:
   Vi(tk) = R / U;
Boolean Function Include(Li, ψ1,ψ2)
Input: Li, ψ1,ψ2; Output: true or false
= (ψ1∈A(kB(Li)) ∧ψ2∈A(kE(Li)) ∨ (ψ1∈A(kE(Li)) ∧
ψ2∈A(kB(Li))
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Fig. 1. LBA for traffic status estimation.

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Procedure EstimateVBA(tk) //Vehicle-based traffic estimation
Input: tk; and all sensor data pairs collected around tk
Output: Vi(tk) for every links // mean traffic speeds at tk
1) For each link Li, find the length of Li: ei = r(kB(Li), kE(Li))
2) Construct a set of data pairs to be used
   ℘(tk) = { p(s, t1, t2) | (t1,t2) ⊆ (tk-τ,tk+τ) }
3) For each sensor s with p(s, t1, t2)∈ ℘(tk),
   • compute weight of average mobile speed
   v(s, t1, t2) = r(ψ1, ψ2) / (t2 – t1)
   • construct an ordered list of links
   Q(s, tk) = [L1, L2, …, Lq], where q ≥1
   Q(s, tk) is an ordered list of links over which sensor s
   moved through during time (tk, tk+1).
   • for every Li∈ Q(s, tk)
     i) compute road distance traveled over Li as l(Li,s),
        ▪ l(Li,s) = r(ψa, ψb), where
          ❖ψa = (Li = L1) ? ψ1 : kB(Li)
          ❖ψb = (Li = Lq) ? ψ2 : kE(Li)
     ii) compute weight of average mobile speed contributed
        ▪ βs(Li) = l(Li,s) / ei; // where βs(Li)≤ 1
     iii) accumulate weighted mean speed:
        ▪ R(Li) = R(Li) + βs(Li)* v(s, t1, t2)
        ▪ U(Li)= U(Li) + βs(Li)
4) For each link Li, compute the mean traffic around tk:
   • Vi(tk) = R(Li) / U(Li);
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Fig. 2. VBA for traffic status estimation.

IV. Performance Evaluation

A. System Description

A practical vehicle-based mobile sensor system has been designed and implemented, which is called the Intelligent Traffic Information Service (ITIS). Normally, ITIS collects the real-time GPS data from the vehicle-based mobile sensors, and a preprocessing step directs them onto right links and roads by map matching. Then, we use these processed data to estimate the real-time traffic status. The scalability and latency of traffic status-estimation algorithms is important because such algorithms are to be used on a city-scale sensor network. ITIS was implemented as a distributed system that aims to process massive real-time data and provide information services with short latency. In addition, we tested the delay of data and found out that it took at most 5 s in transmission from the sensor device to ITIS. Meanwhile, the running time of algorithms is very short, which can be neglected.

B. Testing Results of Traffic Status Estimation Algorithms

Testing was carried out on several links that belong to different types of roads, including arterial and inferior roads: ZhaoJiaBang road (LinkID = 20822, Case A-1 to A-6, Date: 2006-8-11 10:10-10:40, 117 m, arterial short link; FengLin road (LinkID = 8373, Case B-1 to B-4, Date: 2006-10-24 09:25-09:50, 99 m, inferior short link); W.TianMu road (LinkID = 5322, Case C-1 to C-8, Date: 2007-05-20 09:35-10:15, 154 m, arterial short link); and HengFeng road (LinkID = 3942, Case D-1 to D-8, Date: 2007-05-20 10:30-11:10, 244 m, arterial long link). Some cases are not consecutive in time series. In addition, Cases A and B are based on the average sampling interval of 129 s, whereas the rest of the cases are based on the average sampling interval of 61 s. A map-matching algorithm is adopted from [10].

We do not present the comparison of performances between our algorithms and existing mechanisms in previous works because they are based on different assumptions and data basis. We mainly carried out a performance evaluation study with large-scale testing cases from the real world, which aims to demonstrate the feasibility of such an application. We focus on the MTS of unidirection for links around t_k, $\tau = 2.5$ min. Meantime, we calculate the average of results at t_k and t_{k-1}. The average of the LBA is denoted as the LBA-Avg, and the average of the VBA is denoted as the VBA-Avg. It aims to explore how many improvements can be made with historical information.

First, we describe how to estimate the traffic status. When algorithms begin to run, for every calculation approach, the first time t_k, which has data pairs for calculation, is regarded as their respective "initial time." The results of the LBA-Avg and VBA-Avg are the same with the LBA and VBA, respectively, at "initial time" because of no historical information. If no data pairs are to be used for calculation around t_k, we use the latest historical MTS of $t_{k'}$ as result of t_k when $(t_k - t_{k'}) < 15$ min. Next, we explain the methodology of testing. Fig. 3(a)–(d) shows that the RMTSs of links, which are regarded as real MTSs, often have large SDs; thus, we tend to evaluate our results of the algorithms by using the following criterion: If the difference of the calculation result and RMTS is less than the SD of RMTS, we regard it as a reasonable result. Thus, the VBA and VBA-Avg have reasonable results in most of 26 testing cases, but many results of the LBA and LBA-Avg are not.

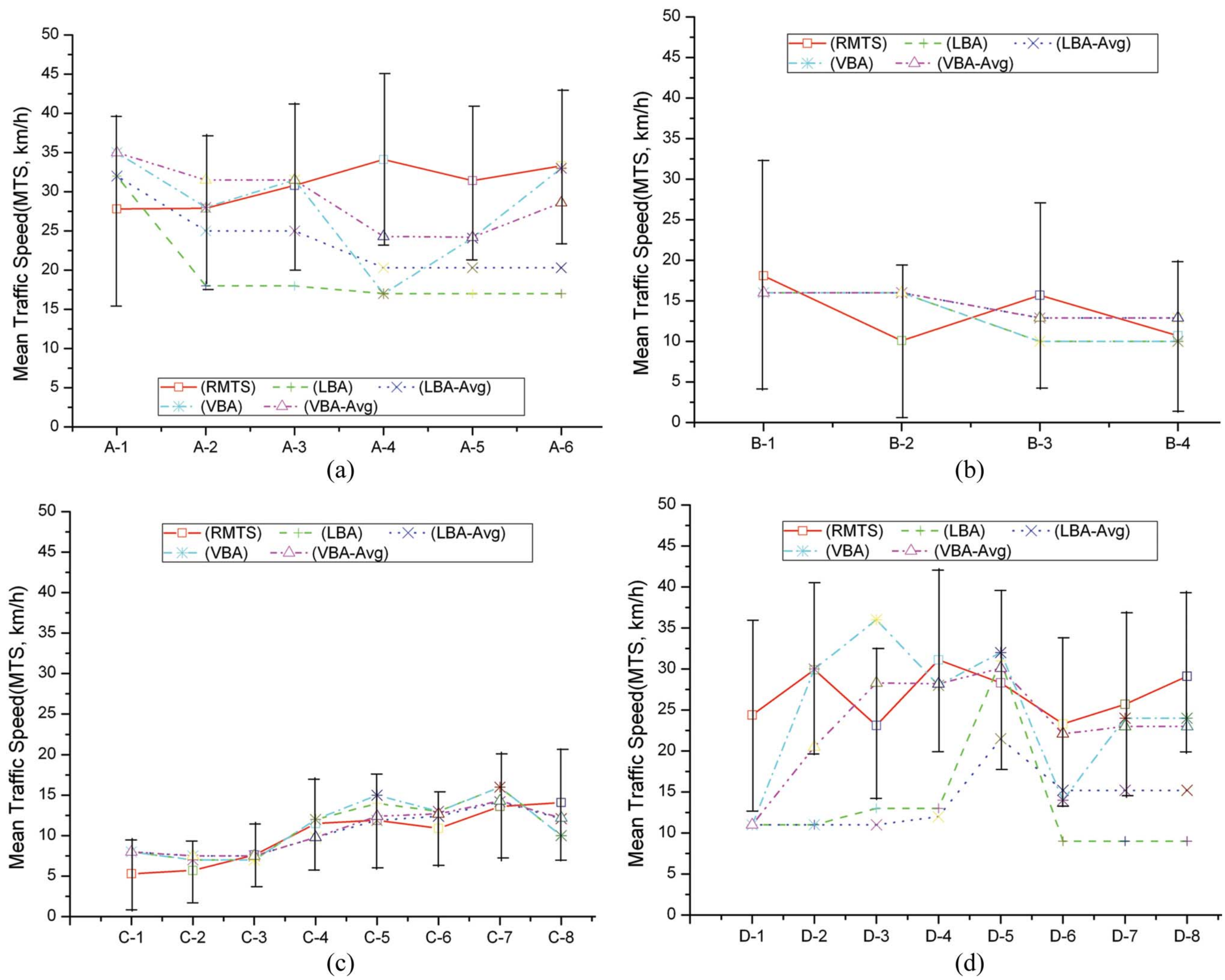

Fig. 3. (a)–(d) Testing results of 26 cases on different links.

More particularly, for several testing cases, although LBA-based results can be regarded as reasonable, they still performed worse than VBA-based results because of the large fluctuation, whereas VBA-based results often a have similar trend with RMTS. In addition, Case C has very small SDs, whereas other cases had large SDs; we will discuss such a phenomenon and give the insight later in this paper.

For some cases, the LBA can only use historical results because of no SEs for the LBA to calculate MTS. The data background explains this situation that most of sensor data pairs have a long time interval that makes them not on the same link or on the links directly connected with each other. Thus, these data pairs cannot be used in the LBA, whereas they can contribute to the VBA. Moreover, we found out that it is very effective to use the latest historical results while there are no SEs used for calculation in the current case. The result around t_k can remain valid for the following time because the traffic flow does not have a considerable change in a short time, e.g., we deem that it remains valid in 15 min in our work.

It is also shown in Fig. 3(a)–(d) that the performance of the LBA-Avg and VBA-Avg are better than that of the LBA and VBA, respectively. In other words, the results of the $*$-Avg type are more accurate than only using the current results, particularly in such a situation that there are few SEs used for calculation and these SEs have abnormal values, such as taxies stop for taking passengers for few minutes, etc. We calculate the average error of the VBA-Avg in all 26 cases, which can be within only 21.7%, a reasonably accurate estimation of the traffic status. It demonstrates the feasibility of such vehicle-based mobile sensor networks for traffic monitoring.

Now, we analyze the relationship between the SE data size and accuracy of algorithms. Fig. 4 shows the fact that as the data size becomes larger, the average error becomes smaller (size $= 0$ means that there are no data for calculation, but only historical results will be used). This is easy to explain that the more data for calculation, the more accurate the result of the algorithm will be because the vehicles in the sample vehicle set include various driving experiences. Thus, as shown in Fig. 4, the average error is 18.8% when the data size is 3, i.e., a fairly well estimation can be obtained when the data size reaches 2 to 3. In these testing cases, the number of vehicles is about 1% to 2% of the total traffic for a given link. This result is similar to [11],

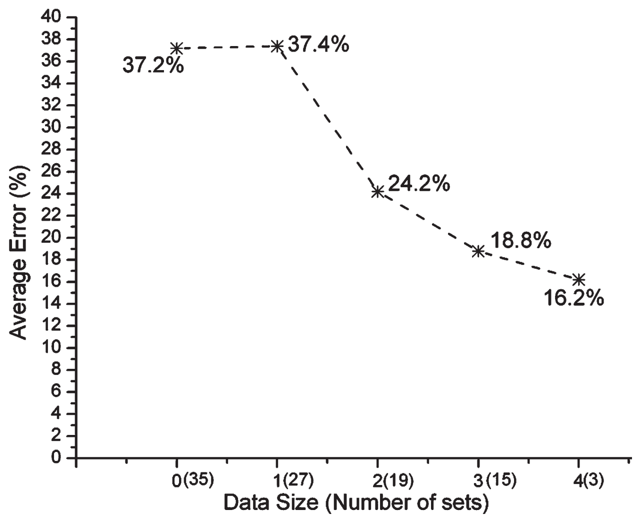

Fig. 4. Average error of the same data size.

which proved that observations from only 1% of the probe vehicles can provide accurate travel time estimation.

On the other hand, we point out that although we can collect sensor data from 4000 taxies, the average number of such vehicles on each link is only 0.12 vehicle/link because of totally 32 920 links in the road network of Shanghai. More particularly, for most of taxies, they always appear on arterial roads and downtown area; thus, some inferior roads cannot be well covered, which leads to no data for calculation during a certain time interval.

In addition, we carried out an investigation in the Shanghai Traffic Information Center and gained some statistical data. Currently, nearly 65 000 public transport vehicles are equipped with GPS-based sensors, including 50 000 taxies and 15 000 buses. The sensing data (the size of each data is about 70 bytes) is collected through a GSM network. It is said that with a small sampling interval of 10 s, the total data volume is about 13.049 TB/year, which incurs a considerable communication cost. Thus, taxi companies prefer long sampling intervals because of lower communication expenses. Meanwhile, they are only interested in the general locations of taxies for vehicle dispatch.

V. Further Discussion on Practical Issues

We carried out an in-depth study to investigate the phenomenon that results in performance differences in terms of MTS. Several factors account for the different performances of our algorithms on links. First, links have different densities of taxies, which incur diverse densities of SEs to be utilized. Second, due to the errors of GPS devices, various surroundings of links (buildings and trees) lead to performance discrepancy of map matching. In fact, if sensor data are allocated to a wrong link by map matching, it negatively impacts on the traffic status estimation of at least two links. That is, for the link where the data should be on, information is lost for better traffic estimation, whereas for the link where the data are falsely allocated, such data often lead to an unexpected outcome of traffic estimation. In either case, incorrect matching can largely degrade the accuracy of traffic status estimation.

In addition, several reasons are responsible for the diverse SDs of RMTS in the testing cases. First is the distinct signal schedule of traffic lights, which leads to different proportions of vehicles with or without a traffic delay at the intersections. For example, for some links, most of vehicles can travel through without a traffic delay because of the long time duration of a green light in one direction. For other links, however, majority of vehicles may have to stop for a red light during traveling at this intersection. Second, real-time traffic conditions also have an influence on SDs. As previously discussed in this paper, the congested traffic can alleviate the influence of the traffic light, which means that most of vehicles will have a similar time cost for traveling the link under congested traffic. Accordingly, we can get the RMTS of this link with a small SD, as shown in Case C.

In addition, we discuss the lessons we learned in our work.

1) Map Matching: In fact, if sensor data are allocated on a wrong link by map matching, it leads to a negative impact on the traffic status estimation. Four main causes are identified to be responsible for the incorrect map matching. First, some vehicles are within a park; thus, they can be mismatched to the road. Second, some links are parallel and nearby to each other; thus, it is hard to use angle information to match the correct link. Third, there are many elevated roads in Shanghai. As our GPS data only have 2-D coordinates, it is almost impossible to identify whether a taxi is on the elevated road or the road below. Finally, the error of GPS devices can cause mismatching.

2) Traffic Light: It can be seen that RMTSs often have large SDs in our testing cases because a real traffic flow may include two kinds of vehicles, which travel through a link with or without a traffic light delay. Based on such characteristics of the real traffic flow, we analyze why the VBA usually delivers a more accurate result than the LBA does. First, more SEs can be utilized by the VBA than that of the LBA. As shown in 26 testing cases, the VBA often has SEs to calculate MTS, whereas the LBA has to use historical results since the corresponding SEs are not available. Second, vehicles can travel across two or more intersections during a long sampling interval; at the same time, they may or may not have a delay at the different intersections. This could reduce the influence of the traffic light delay and the error of traffic status estimation. Consequently, the corresponding SEs will be more accurate to reflect the real traffic status. By utilizing these SEs, the VBA can make a good estimation of the traffic status. The LBA, however, cannot use these SEs because the LBA only aggregates pairs of sensing data from link L_i, as well as links adjacent to either of the intersection nodes of L_i. In addition, it is interesting that our algorithms can make more accurate estimation in a congested traffic condition than in a light traffic condition because the waiting time for the traffic light in congested traffic cannot take a large proportion of the total time of traveling the link, as shown in Case C.

3) Events in the Real World: Various events in the real world still need more elaboration. For example, we found out that the MTS of a link at 3 a.m. was about 11 km/h, which implied that the road has congestion in such early morning! For curiosity, we have found out that drivers of taxies would like to keep a very low speed to cruise on roads during late nights because of no traffic surveillance.

VI. Conclusion

In this paper, we have carried out a performance evaluation study by utilizing the existing vehicle-based sensors in taxies for traffic monitoring. The sensors used have been set with long sampling intervals to reduce the communication cost and network congestion. We have adopted two types of traffic status-estimation algorithms, namely, link-based and vehicle-based. The testing result shows that the traffic status can be fairly well estimated; therefore, it demonstrates the feasibility of such an application in many cities.

Several issues remain to be further addressed. First, we have not been able to correlate between the accuracy of traffic estimation and the number of SEs provided. How to construct an accurate model is another challenging issue. Next, either the LBA or the VBA is considered to be a simple baseline algorithm to serve as a guideline for deploying such an application. How to improve and design an advanced yet effective algorithm for traffic monitoring in this environment setting is a topic for future work.

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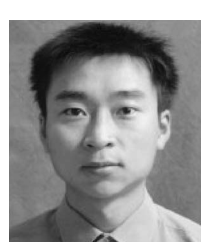

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