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Overview Paper

Using high-resolution event-based data for traffic modeling and control: An overview

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ABSTRACT

Research on using high-resolution event-based data for traffic modeling and control is still at early stage. In this paper, we provide a comprehensive overview on what has been achieved and also think ahead on what can be achieved in the future. It is our opinion that using high-resolution event data, instead of conventional aggregate data, could bring significant improvements to current research and practices in traffic engineering. Event data records the times when a vehicle arrives at and departs from a vehicle detector. From that, individual vehicle's on-detector-time and time gap between two consecutive vehicles can be derived. Such detailed information is of great importance for traffic modeling and control. As reviewed in this paper, current research has demonstrated that event data are extremely helpful in the fields of detector error diagnosis, vehicle classification, freeway travel time estimation, arterial performance measure, signal control optimization, traffic safety, traffic flow theory, and environmental studies. In addition, the cost of event data collection is low compared to other data collection techniques since event data can be directly collected from existing controller cabinet without any changes on the infrastructure, and can be continuously collected in 24/7 mode. This brings many research opportunities as suggested in the paper.

1. Introduction

With the continuing increase in traffic volume and the constrained funding for new highway facilities in urban, intercity, and rural areas, traffic engineers are keenly searching for innovative approaches to maximize the efficiency and capacity of existing transportation networks. Among them, collecting better and more informative traffic data plays a vital role in attacking traffic congestion problem. This is simply because the decisions for traffic management and transportation planning are based on the quality of traffic data being collected and how well traffic data reflects the actual situations that are occurring (Turner et al., 2010). There is no doubt that the decisions on traffic management and transportation planning would be compromised without accurate and reliable data collected from traffic flow sensors (Middleton et al., 2002).

Traffic flow sensors have been used to collect traffic data for nearly a century. As early as 1928, Charles Adler, Jr. invented the first traffic sensor (Klein et al., 2006). After that, a number of vehicle detection technologies have been developed, such as inductive loops, magnetic sensors, video image processors and laser radar sensors. For all vehicle detection technologies,

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information concerning vehicle passage and presence can be generated from vehicle-detector actuation/de-actuation events. However, conventional traffic data collection system aggregates the vehicle-detector actuation events to fixed time period of vehicle flow, velocity, and occupancy. This relatively coarse aggregation obscures features of interest and is vulnerable to noise (Coifman and Dhoorjaty, 2004; Zhang et al., 2005; Lu et al., 2008). Therefore individual vehicle actuation event data has become a topic of interests for a number of researchers (Zhang et al., 2003; Coifman and Dhoorjaty, 2004; Liu et al., 2009b; Day et al., 2010).

Interestingly, applying high-resolution traffic event data (simplified as ''event data'' for the rest of the paper) for traffic control is not a new concept. In 1928 when the first semi-actuated signal control was installed in Baltimore, event data (i.e. traffic actuations generated by vehicle horns) was used to initiate signal switches (Klein et al., 2006). However, almost a century has passed, direct application of event data is still limited to vehicle-actuated signal control and other applications are rare in practice. Although event data can be easily collected from many traffic controller cabinets (for example, through contact closures), traffic engineers are hesitant to save and use event data, partly because of the requirement of large storage space and partly due to the difficulty of real-time transmission. But with today's technologies, these limitations do not exist anymore. For example, considering that the size of one event data is no more than 32 bytes, for a busy intersection with 2 lanes in every approach, the data requirement for collecting and transmitting event data would be less than 1.2 kbps (i.e. 4 mb/h). Even dial-up connection (with a transmission speed of 50-kbps) or satellite connection (384-kbps) offers enough bandwidth for data transmission (Chen et al., 2005). With the removal of technical barriers, it is time to re-visit how event data can be used for traffic modeling and control and what benefits event data could bring to current practices in traffic engineering.

Compared to conventional aggregate traffic data, event data is much more informative (see Fig. 1 for the comparison of event data and aggregate data). By aggregating data into a fixed period of time, such as 1-min, traffic state changes within these time intervals are lost. Some critical ''turning points'', which lead to the significant changes of traffic conditions, cannot be identified. By contrast, event data records each vehicle-detector actuation. Such data accurately records the time when a vehicle arrives at and the time when a vehicle departs from detectors, from which, accurate vehicle on-detector-time, i.e. the time that the detector is occupied by a vehicle (also called ''on-time'' by Chen and May, 1987), and time gaps between two consecutive vehicles can be measured. Based on the information of on-detector-times and time gaps, traffic flow variables such as flow, occupancy, velocity, and density, and performance measures such as queue, travel time, delay and number of stops. can be estimated more accurately. Also, by continuously collecting vehicle events, variations of traffic condition can be measured. This provides very valuable information for traffic engineering applications including incident detection, vehicle classification, congestion identification, etc. More importantly, event data also describes individual vehicles' behaviors. By analyzing a large amount of these data, deeper understanding of traffic behaviors could be achieved. The discussions above clearly indicate that event data could significantly benefit current practices in traffic engineering and ultimately help relieve traffic congestion. In addition, event data can be easily collected at a low cost. They can be directly collected from the output of the detector card or the input to the controller, without any changes to the infrastructure. Since a significant number of loop detectors have been installed all over the country and the world, the cost of event data collection is very low compared to other new data collection technologies. Also, event data can be continuously collected from loop detectors on a 24/7 mode. Such massive archived data is of great importance for transportation practices and research.

Recently a number of research studies have developed event-based data collection systems and explored different applications using event data. The findings from these studies have encouraged us to prepare this review to demonstrate

Detector ID	Event Start Time	On-Detector-Time	Time Gap
1	7:10:00	0.5	0.453
1	7:10:01	0.563	0.703
1	7:10:15	0.454	13.265
1	7:10:17	0.313	2.015
1	7:10:18	0.187	0.453
1	7:10:19	0.375	0.375
1	7:10:22	0.188	3.047
1	7:10:27	0.25	4.547
1	7:10:29	0.313	1.968
1	7:10:31	0.313	1.515
1	7:10:32	0.313	0.953
1	7:10:35	0.312	3.031
1	7:10:40	0.312	4.813
1	7:10:41	0.328	0.25
1	7:10:44	0.187	2.329
1	7:10:45	0.312	1.141
1	7:10:50	0.438	4.5
1	7:10:50	0.375	0.187
1	7:10:52	0.375	0.828

(a): Event-Based Data

	Detector 1		Detector 2		Detector 3	
Timestamp	Occupancy	Volume	Occupancy	Volume	Occupancy	Volume
7:10:00	9	780	9	720	2	60
7:11:00	19	1560	13	1320	11	120
7:12:00	10	1020	7	660	98	60
7:13:00	6	540	9	780	27	180
7:14:00	21	2040	13	1260	100	0
7:15:00	10	1080	8	900	100	0
7:16:00	11	780	10	900	9	180
7:17:00	15	1560	14	1440	61	120
7:18:00	7	720	6	720	98	60
7:19:00	7	600	9	780	1	0
7:20:00	14	1380	14	1380	2	60
7:21:00	12	1080	9	960	3	120
7:22:00	8	660	10	840	5	120
7:23:00	20	1500	15	1260	9	60
7:24:00	15	1200	15	1320	100	0
7:25:00	8	660	4	360	9	180
7:26:00	20	1680	17	1560	98	60
7:27:00	19	1560	13	1200	98	60

(b): 1-min Aggregated Data

Fig. 1. Examples of event-based data and aggregated data.