EXPLOITING EMERGING DATA COLLECTION TECHNOLOGIES FOR DYNAMIC TRAFFIC MANAGEMENT APPLICATIONS

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ABSTRACT

Several existing and emerging surveillance technologies are being used for traffic data collection. Each of these technologies has different technical characteristics and operating principles, which determine the types of data collected, accuracy of the measurements, levels of maturity, feasibility and cost, and network coverage. This paper reviews the different sources of traffic surveillance data currently employed, and the types of traffic management applications they may support. The current state-of-the-art of traffic modeling is also discussed, in the context of using emerging data sources for better planning, operations and dynamic management of road networks.

Keywords: traffic data collection, automated vehicle identification, traffic management applications

1. INTRODUCTION

Growing traffic levels and their related externalities have prompted research into methods to alleviate urban traffic congestion. Intelligent transportation systems (ITS) are being widely deployed to better manage and operate existing transportation infrastructure. The broad objectives of advanced traffic management systems (ATMS), advanced traveler information systems (ATIS) and advanced public transportation systems (APTS) are the use of sophisticated technologies to improve the efficiency of current transportation modes, maximize capacity, minimize delays and improve system reliability. Several software programs have been developed to support these initiatives. Such systems simulate road network performance at various levels of detail, optimize signal cycles, estimate and predict real-time conditions and generate consistent, anticipatory route guidance (Yang and Koutsopoulos, 1996, Ben-Akiva et al., 2002, Mahmassani, 2001).

The development of advanced traffic optimization software has been motivated by the large-scale deployment of traffic surveillance technologies. Towns and cities are increasingly installing sophisticated sensor networks to automatically and routinely collect and archive time-varying traffic data. Such sensors vary widely in their operating principles, resulting in a diverse array of potential data. Each type of data possesses strengths that may be exploited by certain types of traffic management applications. In this paper, we review current and emerging data collection technologies, and classify them according to (a) the type(s) of data they collect and (b) their primary applications. This discussion is intended as a synthesis of the current state-of-the-practice of traffic data collection, as well as the state-of-the-art of traffic modeling and systems management. Therefore, the emphasis is not on the technologies themselves, but specifically on the use of the collected data for traffic management purposes.

The remainder of the paper is organized as follows. The following section provides a classification of traffic sensor technologies based on their operating principles and the traffic metrics they can potentially collect. The subsequent section outlines the emerging dynamic traffic assignment models, followed by a section highlighting the aspects of these models that can benefit from richer data. The next section details a number of opportunities provided in light of the new traffic data collection technologies, while the concluding section includes a summary of the current state-of-the-art.

2. TRAFFIC SENSOR TECHNOLOGIES

Based on their functionality traffic sensors can be categorized as point, point-to-point and area-wide.

2.1 Point sensors

Point sensors are the most widely used type of detector in use today. (Inductive) loop detectors have been in use for decades, while other technologies, including radar, infrared, acoustic, and video sensors have also been developed. This category includes:

- Inductive loop detectors: By far the most widely deployed sensor technology, loop detectors are typically low cost sensors but installation and maintenance are disruptive to traffic, and there are potentially serious reliability/accuracy issues. Due to their ubiquity, researchers have developed ways to use them for vehicle classification (Oh et al., 2002) and vehicle re-identification (Oh et al., 2004, Coifman and Krishnamurthy, 2007, Ndoye et al., 2008). Recently, devices that can perform similar functions with higher accuracy and reliability, easier installation, lower maintenance and longer life span have been introduced (e.g. sensysnetworks.com).
- Radar/Infrared/Microwave/Acoustic/Ultrasonic sensors: These non-intrusive roadside technologies cause minimal disruption to normal traffic operations and do not need to

be installed in or on the pavement. They are generally mounted overhead or to the side of the pavement, often on pre-existing structures. Most of these sensors are cost competitive with inductive loop detectors, if not cheaper (Nooralahiyan et al., 1998).

- Video image detection systems: Closed-circuit television (CCTV) cameras record traffic images, which are in turn analyzed by machine vision software to monitor freeway conditions, collect data at intersections for traffic control purposes, detect incidents and classify vehicles. These systems may have high initial costs, but require little maintenance (which minimizes traffic disruptions). They also do not suffer from the reliability issues associated with loop detectors (Pack et al, 2003). However, the performance of video image detection systems are affected by adverse weather conditions (such as rain, fog) and limited visibility (e.g. night) (Minami et al., 2008).
- Weigh-in-motion (WIM) systems: WIM systems allow for the unobtrusive and continuous collection of vehicle weight information (Yannis and Antoniou, 2005).

2.2 Point-to-point sensors

These emerging technologies detect vehicles at multiple locations as they traverse the network. This supports re-identification and tracking, which may (under certain conditions) provide point-to-point travel times, route choice fractions, paths, and OD flows. Examples of technologies in this category include:

- Automated Vehicle Identification (AVI) systems: The underlying principle is based on the identification of individual (probe) vehicles equipped with an appropriate device, at various locations in the network (Antoniou et al., 2004, 2006).
- Vehicle identification without driver "cooperation": One disadvantage of the AVI approach is that it requires that the vehicles be equipped with special electronic tags (e.g. those used for electronic tolling). Recently, approaches that leverage the Bluetooth and Wi-Fi radios on cell-phones carried by drivers in passing vehicles have been developed (e.g. bitcarrier.com). The advantage of these approaches is that they merely "ping" the Bluetooth or Wi-Fi adapters for their MAC hardware address, thus only relying that a phone with an activated Bluetooth or Wi-Fi adapter is within range. Since the vehicle-to-device correspondence is not necessarily one-to-one (drivers may not carry a Bluetooth-equipped device, or a vehicle may contain more than one Bluetooth device), such data collection methods are more appropriate for measuring quantities such as speeds and route choice fractions, but not counts.
- License plate recognition: CCTV cameras record license plates, which are recognized through special Optical Character Recognition (OCR) software, and transferred to a central system that matches subsequent detections of particular vehicles (FHWA, 1998). These technologies are also limited by the susceptibility of cameras to weather and lighting conditions (Minami et al., 2008).

2.3 Area-wide sensors

While the examples listed above are sensors mainly dedicated to traffic applications a number of opportunistic sensors are receiving attention for their potential to provide traffic data for real time traffic monitoring, traffic information, and traffic prediction. Cell phones, smart-phones, and Global Positioning Systems (GPS) are typical examples of such sensors. Furthermore, this category includes promising technologies that are still under research and include airborne sensors such as unmanned aircraft continuously flying over and surveying a traffic network. The traffic information (collected e.g. using photogrammetry, video-recording, and Light Detection and Ranging (LIDAR) techniques), is communicated to the TMC via wireless communication networks (Srinivasan et al., 2004).

GPS devices in the vehicle collect location information, which is transmitted to a central facility for processing. A downside to this technology is that a wireless telecommunication connection (e.g. through a cell phone) is required for the transfer of information from the vehicle to the TMC (Quiroga et al., 2002).

Wireless service providers can automatically collect geo-location data of wireless phones, which can be used to extract flow and speed information. The concept is still at an experimental stage, but applications are emerging, e.g. for the measurement of traffic speeds and travel times (Bar-Gera, 2007) and the identification of spatial and temporal congestion characteristics (Bekhor et al., 2008). The accuracy of the technology is limited by several parameters (including the size and density of the GSM cells) (Laborczi et al., 2004).

Technologies such as Automated Vehicle Location (AVL) are in use in the transit industry. Modern AVL systems are based on GPS or differential GPS, often augmented by dead reckoning, for collection of data on vehicle location, speed and other information (Furth et al. 2003, Gomez and Shen, 1998, Okunieff, 1997).

The Mobile Century project aimed at a proof of concept for using smartphones with GPS capabilities to collect traffic data and use them for real time traffic estimation and prediction. The field test involved 100 cars. It is to be followed by Mobile Millenium, a large scale freeway experiment with the same objectives. The study will focus on commuters in the San Francisco Bay Area (Work and Baye, 2008)

2.4 Summary

Table 1 summarizes the data collection capabilities of each sensor technology.

Table 1. Main types of data collected by each sensor type

		Data collection technologies							
		Point sensors			Point-to-point		areawide		
		Loop detectors	Radar/infrared/ acoustic sensors	CCTV cameras	License plate recognition	GPS/cell-phone tracking	transponder-based (1)	Airborne sensors	AVL
Data collection capabilities	(Point) flows	√	√	√			√#		
	(Point) speeds	√	√	√		(3)			
	Occupancies	√		√					
	Subpath flows				√*	√	√*#	√	√**
	Route choice fractions				√*	√	√*#	√	
	OD flows				√*	√	√*#	√	
	Travel times				√*	√	√*#	√	√**
	Vehicle classification	√	√	√			√	√	
	Paths				(2)	√	(2)	√	√*

(1) This technology could be used to collect practically any type of information from the vehicle (including speed profiles, origin, destination, and path). In this table, only the information that can be collected by "dumb" transponders, that simply report a unique vehicle signature, is reported.
(2) Possible with a dense network of detectors
(3) When combined with GPS
* Data limited by network design
** Data limited by market penetration
\# indirect; for the sample of equipped vehicles only

Emerging data collection technologies provide a multitude of rich data from diverse data sources. This data creates new opportunities in dynamic traffic management, as well as other aspects of traffic simulation and prediction.

3 OPPORTUNITIES FOR DYNAMIC TRAFFIC MODELING

The use of emerging data collection technologies in transport can lead to two broad categories of benefits: (i) facilitating direct applications, such as congestion pricing, automatic incident detection (AID), travel time/speed measurements and (ii) enhancement of existing modeling capabilities through improved support for model development, calibration, and validation. While the first type of impacts has been well discussed, e.g. the new congestion pricing applications in London, Stockholm and elsewhere, the main focus of this section is on the second type of impact.

Ma and Koutsopoulos (2008) use data collected from a plate matching system (i.e. point-to-point data) in Stockholm, Sweden for the on-line estimation and prediction of travel times in urban areas. The system is based on video cameras placed at various intersections and software with image processing capabilities to match the plate numbers of vehicles as they cross equipped intersections. The data are collected in an urban area, and hence exhibit very high noise. The proposed approach emphasizes the need to properly identify outliers (for example, cars temporarily parked on an urban street).

Park et al. (1999) use real-time AVI data for the prediction of link travel times for one to five (5-min) time periods ahead. The authors employed a spectra basis artificial neural network that utilizes a sinusoidal transformation technique to increase the linear separability of the input features.

The integration of diverse sources of data, which can improve the performance of the various algorithms, is a great opportunity. For example, the calibration of new, emerging model systems, can benefit from data fusion from diverse sources, as each measurement may be more suitable to the calibration of some subset of parameters. Point-to-point travel times are valuable for assessing and validating travel times (which is an important expected output of the simulation model), but do not directly provide information on traffic volumes. On the other hand, point flow measurements may not provide particularly rich point-to-point information, but may provide accurate flow data.

In recent years a number of advanced model systems, using simulation-based dynamic traffic assignment (DTA) concepts, have emerged to support network state estimation and prediction. This capability in turn, enables a number of traffic management applications, such as traffic information generation, dynamic congestion pricing, etc.

DTA systems are typically designed to reside in TMCs and support real-time applications such as the on-line evaluation and implementation of guidance and control strategies, incident management and control, and the support of emergency response operations. DTA models can also be used for short-term planning applications. A DTA system integrates historical data and information from multiple sensor sources to perform two main functions (Ben-Akiva et al., 2002):

- State estimation, during which real-time surveillance information is combined with historical data and a priori parameter values to capture current traffic conditions, using detailed traffic information from instrumented portions of the network to infer the conditions in the parts for which no real-time information is available, and
- Prediction-based information generation, aimed at generating unbiased and consistent traffic information for dissemination to travelers.

In order to provide the above functionality, DTA systems are a synthesis of a number of models and algorithms. DTA systems use detailed travel demand and network supply simulators to synthesize multiple sources of information and perform state estimation and prediction. The demand simulator simulates network-wide demand patterns through time-dependent origin-destination (OD) matrices, and captures the travel choices of individual motorists (e.g. route choice). The supply simulator is usually based on mesoscopic or macroscopic models that represent traffic dynamics using speed-density relationships and queuing theory. (e.g. Ben-Akiva et al., 2002, Mahmassani, 2001). Speed-density relationships depend on location-specific parameters, such as type of facility, number of lanes, lane width, slope, surroundings, as well as weather and time of day factors, reflecting different driving behaviors (e.g. experienced drivers during commute periods). In a DTA model, the complex demand-supply interactions are represented by detailed algorithms that estimate current network state, predict future conditions, and generate anticipatory route guidance and control strategies.

DTA systems combine individual models into a complex system with many inputs and parameters. The proper calibration of these models and inputs is essential to improving their ability to accurately predict future conditions and generate consistent route guidance. Calibration can take place off-line and on-line.

3.1 Off-line calibration of dynamic traffic models

Off-line calibration involves the estimation of variables such as time-varying OD flows, route choice model parameters, other parameters used by the OD estimation and prediction modules and, depending on the nature of the supply simulator, segment capacities and speed-density functions. The variables must be determined such that the model's outputs match the ground reality reflected in archived measurements such as time-varying traffic counts observed across several days. The estimated model inputs and parameters represent average or expected traffic conditions, encapsulating the conditions encountered in the archived data over several prior days. For this reason, they may be viewed as a database of historical estimates.

Stratification of the historical database could allow the off-line calibration of multiple sets of parameters, each corresponding to different prevailing conditions observed in the data. For example, a different set of model inputs and parameters may be created for various combinations of weather conditions, days of the week, seasons and special events. It is assumed that the archived traffic data contain at least a few days of measurements for each combination of factors that is deemed necessary for the modeling exercise. Given a particular combination of factors, the parameters from the closest matching category in the historical database can be quickly selected to accurately assess expected traffic patterns. The historical database has the added advantage of conveniently and efficiently incorporating several days of prior data into the model. If the conditions on a given day are found to deviate from these historical estimates, on-line adjustments may be executed, as explained next.

Complex traffic simulation and assignment models have been developed for various transportation planning and traffic management applications. The state of the art of such models includes simulation-based approaches such as MITSIMLab (Yang and Koutsopoulos, 1996, Yang et al., 2000), TransModeler (Yang and Morgan, 2006), DynaMIT (Ben-Akiva et al., 2002) and DYNASMART (Mahmassani, 2001). The importance and complexity of model calibration has been recognized and documented. However, existing approaches often rely on simplifications and heuristics that limit the accuracy and efficiency of calibration (e.g. sub-problems are solved sequentially, the complex relationships between model parameters and data are approximated, or the use of approximations restricts the data that can be used.

Recent research (Balakrishna, 2006; Balakrishna et al., 2007b) has developed calibration methods that simultaneously estimate all model inputs and parameters, while using the outputs of the model directly (instead of approximating the linkage between the calibration variables and the data). Methodologies to incorporate and efficiently exploit newer data sources are already being developed. For example, state-of-the-art traffic simulation models have been calibrated using speed data in addition to loop detector counts (Balakrishna, 2006; Balakrishna et al., 2007a). The resulting estimates are shown to be more accurate in replicating the observed data due to the use of additional speed information and are of particular interest in applications of route guidance and ATIS, since a greater accuracy in speed estimation is expected to translate to better estimates of travel times.

The discussion above has focused on improving the quality of off-line calibration *for a given day of traffic measurements*. Since traffic conditions can vary significantly across days, the off-line calibration process can be used to create a *historical database*. For example, parameter sets may be calibrated by day of the week, weather conditions and season, or for specific special events such as concerts, trade shows or sporting events. The process of creating a historical database can benefit significantly from the availability of more advanced sources of traffic measurements. For example, point-to-point speeds or travel times from AVL technology are better reflections of congestion along a link than measurements at a single location. Airborne sensors can also provide data on queue lengths and traffic density, which can improve a dynamic model's ability to estimate and predict congestion. Similarly, route choice model parameters may be fine-tuned using sub-path flow data that contains valuable information about drivers' choices along an entire stretch of roadway. Classification counts can be used to calibrate OD tables by vehicle class (e.g. cars, trucks, buses) and vehicle type (e.g. single occupancy, high occupancy), while weather data collected simultaneously with traffic data can aid in stratifying the historical database accordingly.

3.2 On-Line Calibration of Dynamic Traffic Models

On-line calibration exploits the continuous flow of surveillance information to allow the real-time, dynamic adjustment of model inputs and parameters for each time interval. Using the off-line calibration as a starting point, on-line calibration fine-tunes the model parameters so that they capture the prevailing traffic conditions more accurately, and can therefore lead to better predictions.

The new data sources provide unique opportunities to enhance models for decision support in Dynamic Traffic Management, such as the emerging models presented in the previous section. Richer information can enhance this framework in multiple ways. First, the off-line calibration algorithms will have richer data on which to build the historical database. The supply simulator may use data-driven traffic dynamics models to replicate the movement of vehicles in the network, since more and richer data will be available. The on-line calibration will also benefit from the richer and more reliable surveillance data available over the short horizon that it uses for refinement of a priori parameter values. These aspects are discussed in more detail below.

The problem of OD estimation and prediction has been well studied over the last two decades (e.g. Cascetta 1984, Okutani, 1987, Ben-Akiva, 1987, Ben-Akiva and Morikawa, 1989, Cascetta et al., 1993, Ashok and Ben-Akiva, 1993, 2000, 2002). A majority of the relevant literature is based on historical demand information and link count data. Ashok (1996) introduced the notion of direct measurements for the incorporation of probe vehicle information for the solution of the OD estimation and prediction problem. By definition, a direct measurement provides a preliminary estimate of an OD flow. Van der Zijpp (1996, 1997) combined volume counts with trajectory information obtained from automated license-plate surveys for the estimation of OD flows.

Dixon and Rilett (2000) propose a method for using sample link choice proportions and sample OD matrix information derived from AVI data sampled from a portion of vehicles to estimate population OD matrices with the AVI data collection points acting as the origins and destinations. Dixon and Rilett (2005) extend this approach to estimate ramp-to-ramp freeway OD volumes, and demonstrate the approach using a large urban freeway network equipped with an AVI system.

Kwon and Varaiya (2005) develop a statistical OD estimation model using partially observed vehicle trajectories obtained with vehicle re-identification or automatic vehicle identification (AVI) techniques such as electronic tags.

Antoniou et al. (2004) present a methodology for the incorporation of AVI information into the OD estimation and prediction framework, which –however- was limited with respect to the type of data that could be considered. In Antoniou et al. (2006) the approach is generalized into a flexible formulation that can incorporate a large range of additional surveillance information.

Zhou and Mahmassani (2006) propose a dynamic origin-destination (OD) estimation method to extract valuable point-to-point split-fraction information from automatic vehicle identification (AVI) counts without estimating market-penetration rates and identification rates of AVI tags.

Balakrishna et al. (2006) present a general methodology that can use any surveillance data (including counts, speeds, densities, queue lengths and travel times) to estimate dynamic OD flows across many time intervals simultaneously. The approach moves away from the traditional assignment matrix formulation, and directly uses the output of a network-loading model. The complex relationships between the data and the OD flows are thus captured accurately and without linear approximations.

The additional data are useful not only on their own merit, but also as used in the above applications to improve the accuracy of the estimation and prediction of OD flows. For example, Antoniou et al. (2006) report improvements in terms of normalized root mean square error (RMSN) of more than 40 percent for OD estimation and up to three-step prediction (i.e. looking up to three time intervals ahead), and 37 percent for four-step prediction, when AVI data are added to count data. Besides only relying on link point counts for the OD estimation, in this case study it is assumed that AVI detectors are located at three fixed locations on the network. Subsequent detections of the transponders of the equipped vehicles by these detectors provide two subpath flow measurements. For more details on the assumptions, the network geometry and the formulation, the reader is referred to Antoniou et al. (2006). Antoniou et al. (2007) present a methodology for the generalization of this concept to all inputs and parameters of traffic simulation models.

4. CONCLUSION

Clearly, the applications of advanced information for traffic management applications are numerous, and more than can be included in a single paper. We now briefly outline some other emerging applications beyond those discussed earlier.
While considerable advances have taken place in methodological aspects of transportation management applications, data surveillance and collection was until recently revolving around conventional loop detectors. From the review presented in this paper, it becomes apparent that numerous emerging technologies are becoming increasingly available. These technologies provide additional types of data that were previously impossible, or too difficult, to collect, with practical advantages over conventional data collection mechanisms (e.g. lower cost, higher reliability and accuracy). Hellinga and Fu (1999) provide an assessment of the expected accuracy of probe vehicle travel time reports, including the various sources of bias that can affect AVI-based travel time collection.

The additional data are useful not only on their own merit, but also as used in applications to improve the accuracy of the estimation and prediction of OD flows. In this paper, several applications that can benefit from such data are considered, and indicative results are presented. The experiences are not only useful in demonstrating the potential benefits of such emerging data collection techniques, but can also be used to fine-tune and improve their deployments. For example, the configuration of the ETC sensors forming an automatic vehicle identification network may have considerable impact on system performance. Chen et al. (2004) formulate the problem of optimal location of AVI sensors as a multi-objective integer-optimization problem with the following objectives: minimize the number of AVI readers, maximize the OD coverage and maximize the number of trips covered by the system. The authors apply a distance-based genetic algorithm to solve the problem by explicitly generating the non-dominated solutions. Mirchandani and He (2008) formulate a 0-1 mathematical program to determine the routes on which to locate AVI sensors to minimize the variance of the predicted distribution of network travel time.

As data collection technologies become more commonplace and accessible, further applications are expected to emerge. For example, recent research investigates the applicability of AVI technologies for measuring border delay and crossing times at the U.S./Mexico border (Villa and Solari, 2008) and for congestion pricing at border crossings (Baker et al., 2008). Distance-based user charging (Zhang and McMullen, 2008) and pay-as-you-go insurance are other applications that rely on the proliferation of innovative data collection methods.

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