ESTIMATION OF DYNAMIC TRAFFIC DENSITIES FOR OFFICIAL STATISTICS BASED ON COMBINED USE OF GPS AND LOOP DETECTOR DATA[1]

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ABSTRACT

Traffic density is one of the important variables to identify traffic states. Traffic management and traffic control require real-time estimation of traffic density as an input for large spatial and temporal coverage of the road network. Statistics Netherlands as a national data collection institute publishes quantified traffic data, among others to support policy makers. In this paper, we aim to validate the usage of GPS information for traffic statistics. The density definition is applied for modelling, and by combining loop detector and GPS data we take the advantages of both data sources. However, the adoption of GPS data is seriously hampered by the fact that few vehicles are equipped with GPS transponders. GPS-collected data thus represent only a limited part of the whole traffic for a delineated area and specific time slots. In our model, travel time of GPS vehicle is an essential concept to get the time boundary of density measurement. Finally, the estimated dynamic density is scaled up to the whole road network to be used for official statistics. GPS data collection has the marked advantage that traffic data are captured automatically at highly frequent rates. As such, it provides dynamic information and offers opportunities to reduce administrative burdens. Furthermore, GPS data collection opens the door to other relevant application areas.

Keywords: Traffic Density Estimation, Traffic Population Estimation, GPS Sample Data, Loop Detector Data, Official Statistics

[1] This paper is result of work in progress: the approach presented in this paper is subject to further research, will be tested with real traffic data, and may be adjusted as a result. The views expressed in this paper are those of the authors and do not necessarily reflect the views of Statistics Netherlands.

INTRODUCTION

Traffic density, defined as the number of vehicles per unit length of a road segment at a certain time period measured in vehicles/km (HCM, 2000), is one of the important characteristics of traffic states. Classical traffic flow theory defines the fundamental relation amongst flow, density and average speed as flow equals density times speed. Flow is the number of vehicles passing a given cross-section of the road per time interval and measured in vehicles/hour. In this present paper we focus on traffic density, as an ideal indicator of traffic conditions (Ni, 2007), which draws attention from both traffic management and official traffic statistics. Traffic management and traffic control use real-time estimation of traffic density as input for the spatial and temporal monitoring of the road network (Qiu et al., 2010). Statistics offices, especially Statistics Netherlands, the national data collection institutes, are interested in real-time measurement of traffic density to support policy makers with more accurate, more relevant and timely statistics about traffic states.

The quality of traffic density estimates is naturally defined by the data sources used. Currently, two collection methods are employed: traffic surveys based on in-out traffic flows or high altitude photographs; and fixed detector data (Hu and Yang, 2008). The use of loop detectors generates the main data source. Traffic surveys are used infrequently as they are relatively costly. At the same time, with the development of information and communication technology, the last decade has seen a massive increase of traffic state signals generated by GPS (Global Positioning System). A marked practical advantage of GPS data collection is that transport and traffic data are captured automatically at highly frequent rates yielding instantaneous, real-time and accurate information, including position, direction, instant speed and time. The question therefore arises whether and how this real-time captured electronic data could serve as alternative, possibly complementary, data to construct traffic statistics. This approach may provide dynamic and real-time information and offer opportunities to reduce the disadvantages of traffic surveys.

However, the adoption of GPS-based statistics is seriously hampered by the fact that relatively few vehicles are equipped with GPS. Qiu, et al. (2010) mention that the penetration rate of GPS vehicles is only 5% of the whole traffic population. GPS-collected data cover only a limited part of all transport and traffic activities for a delineated area and specific time slots. A substantial, continuously varying number of vehicles thus goes unobserved. The combination of GPS data with loop detector data might solve the GPS coverage problem to estimate traffic density and further to improve traffic statistics.

The aim of this paper is to validate the use of GPS information for official traffic statistics. We explore the following research questions: (1) how can we integrate GPS data and loop detector data; and (2) how can the combined data be used to measure dynamic traffic density for official statistics? The paper proceeds as follows. First, we review the related literature about traffic density estimation and traffic statistics to show the current developments in both areas and further explain the contribution of this paper. Next, we develop the core model of dynamic density population on the basis of different scenarios. Finally, the conclusion and discussion finalize the paper.

STATE OF THE ART

Faced with highly dynamic traffic situations, decision makers find that the current statistics insufficiently support policy making. Current traffic statistics are of a highly aggregate nature and hide much important traffic phenomena. Increasing the relevance of these traffic statistics, in terms of detail, coverage and timely availability, requires the use of adequate raw traffic data, but also of suitable models to process these data. The latter has been the subject of various studies in traffic engineering. In this section, we review the related literature on density estimation and traffic statistics, with specific emphasis on density estimation based on loop detectors and GPS. Additionally, we discuss studies on traffic statistics to outline the current development of applied methods in statistics offices.

Density Estimation

From traffic model point of view, there are two main approaches to estimate traffic density: one is direct method which determines the characteristics by definition, and the other is indirect method that estimates characterises from other parameters or use surrogates (Ni, 2007). Most of the researches are based on the relation among flow, density and speed and then considering the characterises of traffic movement on the highways, they set up other models to estimate density. For instance, Daganzo (1994) introduced the cell transmission model (CTM) to detect changes in traffic density on motorways with an open-loop density estimator. The cell transmission model is extended to the load network level in Daganzo (1995). Additionally, Munoz et al. (2005) apply a macroscopic traffic flow model, the switching-mode Model (SMM) which is based on the cell transmission model, to estimate traffic densities at unmonitored locations along a highway. However, few researches of density estimation are really definition-based, using the direct method, except Qiu, et al (2010). Their proposed method derives from the definition of density and count the number of vehicles within specific freeway segments though loop detectors.

Furthermore, density estimation requires not only analytical modelling but also simulation to represent the current traffic situation. Using loop detector data, density measurement models have been proposed by Coifman (2003), Gazis and Knapp (1971), and Nahi and Trivedi (1973). Coifman (2003) applies re-identification techniques to estimate lane densities instead of a dynamic traffic model, which is a general tool for simulating traffic situation. Gazis and Knapp (1971) estimate the number of vehicles on a freeway section based on speed and flow measurements at the entrance and exit points of the section. An estimation of vehicle travel times is needed from time-series speed data, and subsequently a rough estimate of vehicle counts is obtained from the inventory of car arrivals at the entrance of the section and the travel times of existing cars. Thus, this method relies on the accuracy of travel time estimation.

With the development of vehicle telematics, information about individual vehicles is a potentially valuable source to compensate for the deficiencies of point sensors. In Qiu et al. (2010), GPS vehicle information is applied to estimate density. They use a moving window over distance for speed and position, combined with loop data to obtain traffic speed and flow. Furthermore, Di and Liu (2010) estimate traffic density by means of a hybrid extended Kalman filter that integrates the approximated Markov transitions with detector and GPS measurements to set up a state-space model. Though elegant, this approach involves many assumptions, which may limit the widespread application.

Various approaches to estimating traffic density have been suggested adopting machine learning or system control, but of these take the initial definition of traffic density into account when modelling time-dependent density, combined with loop detector and GPS information. Only Qiu, et al (2010) tests two data sources to estimate density. Although they do not have on ramp and off ramp data in this system, they still pave the way to combine different data sources for estimating traffic density. Meanwhile, modelling traffic density on the basis of its definition offers the opportunity to link with traffic population estimation.

Traffic Statistics

Few studies discuss the use of electronically captured data for traffic statistics. Most of these studies are about testing the effects of various missing data patterns on existing statistical calculation procedures.

Turner and Park (2008) examine the effects of missing data patterns on existing and modified procedures to calculate annual average statistics of traffic counts. They simulate these missing data patterns by randomly or systematically removing data. For urban locations, where commuter traffic dampens seasonality patterns, they find that a significant amount of missing data can be tolerated with little or no effect on annual traffic statistics. For rural locations, a month of missing data still results in a tolerable error for most procedures, whereas two months of missing data is close to or exceeds tolerable error levels for most procedures. They conclude that modifications of conventional calculation procedures (that account for small gaps in data on a daily basis) are suited to archive ITS data.

Statistics offices have their own approach to produce traffic statistics, which requires specific tools to fuse survey information gathered from different perspectives. Ressen and Van Delden (2009) review the tools based on these criteria: acknowledged business functions in the production of a statistic and the current set of tools. They build an organizational architecture to show the relation among each actor in the whole process. With these statistics methods, traffic states and travel survey can be represented for the official statistics.

CORE MODEL OF DYNAMIC TRAFFIC POPULATION

The estimation of dynamic traffic density requires information about road networks and vehicle characteristics. Road network information is basically concerned with the number of vehicles in a specific road segment at a particular point in time or during a certain time interval, while vehicle information consists of vehicle characteristics, such as length, weight, engine power and so on. Loop detector and GPS data are the main data sources to capture the traffic information in the network. In this section, we demonstrate the mechanism of data capture through loop detectors and GPS, and discuss why these two data sources are suitable for density measurement. Next, we present the methodology for estimating dynamic traffic population based on these two data sources.

Working Mechanism of Loop Detector and GPS

The most popular approach to capturing traffic data on roads is through inductive loop detectors embedded in the pavement. Technically, the loop detector system includes one or more turns of insulated loop wire wound in a shallow slot in the pavement of a road or highway. The loop system forms a tuned electrical circuit in which the loop wire is the inductive element (Ki and Baik, 2006). When a vehicle passes over the loop or stops within the loop, the inductance of the loop is decreased, which is observed by a sensor. Based on these observations, information about traffic flows is generated, such as vehicles counts per hour and time-mean speed of vehicles passing the loop detectors during a time interval.

The main detector types are single loop and double loop, which share the same mechanism to count traffic volumes per time period, but involve different speed calculations. In the case of single-loop detectors, the speed of passing vehicle is calculated as the effective length -- vehicle length plus detector length -- divided by the time elapsed between the on and off switching of the detector (Ki and Baik, 2006). Since loop detectors cannot observe the actual length of individual vehicles, the speed calculation makes use of a mean vehicle length. This may lead to inaccurate speed measurements: longer trucks will produce underestimated speed, and shorter passenger cars will produce overestimated speeds (Sun and Ritchie, 1999). In the case of the double-loop system, speed is measured as the distance between the two detectors divided by the time elapsed between the turning on of the first and the second detector. This approach avoids the requirement of knowing the length of vehicles, and consequently is more accurate.

GPS is a spaced-based global navigation satellite system, which consists of 24 to 32 satellites, an extensive control system and many users. Currently, the USA controls the military GPS system, while Europe is developing a civil system named Galileo. GPS provides reliable positioning, navigation, and timing services to worldwide users on a continuous basis in all weather conditions, day and night. For traffic, GPS provides location data (latitude, longitude and elevation) in minimum time intervals of 0.3 seconds, together with speed and number of satellites that identify the source.

Speed measurement with GPS is based on a series of ‘track points’ of position estimates at regular time intervals. The difference between the known satellites carrier frequency and the frequency determined at the receiver, known as a Doppler shift, is directly proportional to the velocity of the receiver along the direction to the satellite, regardless of the distance to this satellite. The vehicle speed thus obtained is very accurate. However, the measurement accuracy is not constant (Chalko, 2002), but depends on the number of tracked satellites and their geometrical distribution above the horizon. If the number of measured satellites is three or four, then the observations are generally regarded as reliable.

Both loop detector and GPS-based data capturing methods produce different types of traffic data. Loop detectors offer relatively reliable and stable data but are location dependent, while GPS data represent instant traffic states with detailed information. Exploiting the advantages of each capturing method, the following section considers the estimation of traffic density.

Traffic Density Estimation

Our method of traffic density estimation is based on the definition of traffic density proposed in Qiu, et al (2010). The number of vehicles is counted directly by the loop detectors. This information is matched with the characteristics of passing GPS vehicles, making use of the GPS location estimates. The travel time of GPS vehicles can be easily obtained, and so the time interval during which the GPS vehicle passes the two loop detectors can be determined. We adopt ‘Method 2’ proposed by Qiu, et al (2010) to measure traffic density on the road segments. We extend their method to handle road segments with on- and off-ramps having no loop detectors installed.

Estimating traffic density is challenging, because it depends on time as well as space. We therefore consider its estimation for road segments of increasing complexity; beginning with typical road segments between two loop detectors on a highway without on- and off-ramps, and then discussing a road segment with on- and off-ramps between two detectors. For both cases, the objective is to estimate the traffic density on the main lane.

Main Lane without on/off-ramps

Consider a road segment that begins and ends with two detectors at locations x_i and x_{i+1}. The loop detectors count the number of passing vehicles. Between the detectors there is neither on-ramp nor off-ramp, as in Figure 1.

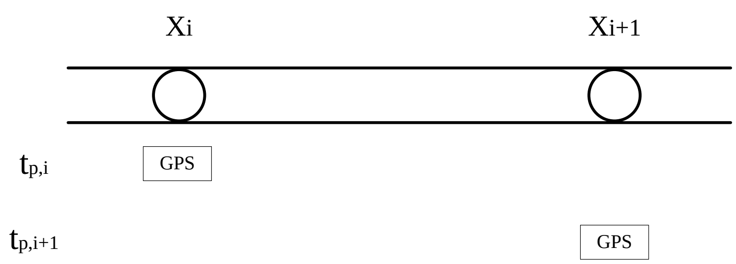

Figure 1 Main lane without on/off-ramps

When a GPS-vehicle *p* passes a loop detector, it is counted by the detector as one of the passing vehicles. At the same time, this vehicle generates GPS-data on location, instant speed and so on. When the location estimate from GPS matches with the location of the first loop detector x_i, the GPS vehicle enters the road segment $[x_i, x_{i+1}]$. Similarly, when the GPS vehicle passes the other loop detector x_{i+1}, it exits the highway section $[x_i, x_{i+1}]$. The information systems attached to GPS and loop detectors generate matching data. Therefore, the travel time of the GPS vehicle between the two loop detectors, and the number of vehicles passing the loop detectors within the GPS travel time can be obtained. Dividing this number of vehicles by the section length gives the traffic density between the two loop detectors during the GPS travel time period.

The main lane vehicle counts between two detectors during a certain travel time of a GPS-vehicle takes the first traffic count from loop detector x_i. A GPS vehicle p passes this loop detector x_i at time $t_{p,i}$, and arrives at loop detector x_{i+1} at the time $t_{p,i+1}$. Let $N(x_i, t_{p,i})$ be the traffic count at loop detector x_i from a certain starting time when no vehicles were in the high way section, to time $t_{p,i}$ when the GPS vehicle passes loop detector x_i. Assuming that the GPS vehicle is driving at average speed, the number of vehicles on the main lane during the time interval $(t_{p,i}, t_{p.i+1})$ can be estimated as (see Qiu, et al, 2010):

$$V(t_{p,i}, t_{p,i+1}) = N(x_i, t_{p,i+1}) - N(x_i, t_{p,i}) \tag{1}$$

Denoting the distance between the two detectors as $L(x_i, x_{i+1})$, we obtain the traffic density on the main lane at the GPS running time as:

$$k(t_{p,i}, t_{p,i+1}) = \frac{V(t_{p,i}, t_{p,i+1})}{L(x_i, x_{i+1})} = \frac{N(x_i, t_{p,i+1}) - N(x_i, t_{p,i})}{L(x_i, x_{i+1})} \tag{2}$$

Main Lane with on/off-ramps

The measurement of traffic density will be more uncertain when the road segment $[x_i, x_{i+1}]$ includes on- and off- ramps, as illustrated in Figure 2. In this case, the road segment is an open system as vehicles can enter and leave the main lane through on- and off-ramps. The target is still on the traffic counts in the main lane.

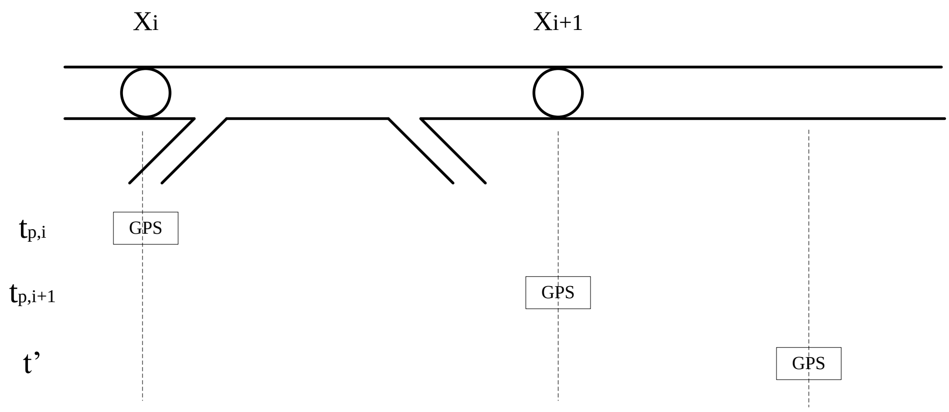

Figure 2 Main lane with on/off-ramps

Considering the general layout of loop detectors in the highway, two cases are discussed. One is with loop detectors at on- and off-ramps, and the other is without loop detectors at on- and off-ramps. Modelling the former one is relatively straightforward, while modelling the latter is more challenging.

- *The Situation With loop detectors at on/off-ramps*

If the road segment contains on- and or off-ramps, traffic enters the road segment via either the on-ramp or x_i and leaves the road segment via either the off-ramp or x_{i+1}. With loop detectors installed at the on- and off-ramps, the traffic count at the on-ramp can be obtained as C_{on} and that at the off-ramp as C_{off}. The travel time of the GPS vehicle between the loop detector x_i and x_{i+1} is the time interval used to determine the counts of entering vehicles via the on-ramp. Thus, the number of vehicles entering the main lane section during this travel time can be formulated as:

$$N_{on}(t_{p,i},t_{p,i+1}) = C_{on}(t_{p,i+1}) - C_{on}(t_{p,i}) \quad (3)$$

The number of vehicles counted at the off-ramp (C_{off}) is similarly obtained as:

$$N_{off}(t_{p,i},t_{p,i+1}) = C_{off}(t_{p,i+1}) - C_{off}(t_{p,i}) \quad (4)$$

In the general situation of a main lane with on- and off-ramps with loop detectors, the traffic count during the time when a GPS-vehicle moves from x_i to x_{i+1} is:

$$\begin{aligned} &V(t_{p,i},t_{p,i+1}) \\ &= N_{mainlane}(t_{p,i},t_{p,i+1}) + N_{on}(t_{p,i},t_{p,i+1}) - N_{off}(t_{p,i},t_{p,i+1}) \\ &= [N(x_i,t_{p,i+1}) - N(x_i,t_{p,i})] + [C_{on}(t_{p,i+1}) - C_{on}(t_{p,i})] - [C_{off}(t_{p,i+1}) - C_{off}(t_{p,i})] \end{aligned} \quad (5)$$

The traffic density on the main lane at the GPS running time is defined as:

$$\begin{aligned} &k(t_{p,i},t_{p,i+1}) \\ &= \frac{N_{mainlane}(t_{p,i},t_{p,i+1}) + N_{on}(t_{p,i},t_{p,i+1}) - N_{off}(t_{p,i},t_{p,i+1})}{L(x_i,x_{i+1})} \\ &= \frac{[N(x_i,t_{p,i+1}) - N(x_i,t_{p,i})] + [C_{on}(t_{p,i+1}) - C_{on}(t_{p,i})] - [C_{off}(t_{p,i+1}) - C_{off}(t_{p,i})]}{L(x_i,x_{i+1})} \end{aligned} \quad (6)$$

- *The situation without loop detectors at on/off-ramp:*

In the situation without loop detectors at on/off-ramps, the number of the vehicles that enter or leave the main lane cannot be observed. However, it is possible to measure the change of traffic counts based on the two loop detectors. Here, we introduce time instant t' to represent the point in time after $t_{p,i+1}$ equal to the elapsed time between $t_{p,i}$ and $t_{p,i+1}$, that is $t' - t_{p,i+1} = t_{p,i+1} - t_{p,i}$ or, similarly, $t' = t_{p,i+1} + (t_{p,i+1} - t_{p,i})$. Further, the traffic count at loop detector x_{i+1} at t' is denoted as $N(x_{i+1}, t')$. So, the number of vehicles passing loop detector x_{i+1} between $t_{p,i+1}$ and t' can be computed as $N(x_{i+1}, t') - N(x_{i+1}, t_{p,i+1})$. Assuming constant traffic flow and speed between $t_{p,i}$ and t', the change of the number of vehicles in the main lane as a result of on- and off-ramp traffic, is obtained as:

$$\Delta V(t_{p,i}, t_{p,i+1}) = [N(x_{i+1}, t') - N(x_{i+1}, t_{p,i+1})] - [N(x_i, t_{p,i+1}) - N(x_i, t_{p,i})] \tag{7}$$

When ΔV is negative, the number of vehicles leaving the system through the off-ramp is larger than the number of vehicles entering the system through the on-ramp. When ΔV is positive, then the number of vehicles entering the main lane is larger than the number of vehicles leaving the main lane.

The traffic volume between the two loop detectors during time period of $(t_{p,i}, t_{p,i+1})$ is equal to the traffic counts at loop detector x_i plus the change because of on/off-ramp traffic:

$$V(t_{p,i}, t_{p,i+1}) = \Delta V(t_{p,i}, t_{p,i+1}) + [N(x_i, t_{p,i+1}) - N(x_i, t_{p,i})] = N(x_{i+1}, t') - N(x_{i+1}, t_{p,i+1}) \tag{8}$$

Thus, traffic volume between loop detectors with on- and off-ramps is measured with only the second loop detector x_{i+1}; the influence of the first detector is hidden in time t', defined as $t' = t_{p,i+1} + (t_{p,i+1} - t_{p,i})$. Finally, traffic density is estimated as:

$$k(t_{p,i}, t_{p,i+1}) = \frac{V(t_{p,i}, t_{p,i+1})}{L(x_i, x_{i+1})} = \frac{N(x_{i+1}, t') - N(x_{i+1}, t_{p,i+1})}{L(x_i, x_{i+1})} \tag{9}$$

Dynamic Traffic Population Estimation

In the preceding cases, we determined traffic density in a specific lane segment with the help of GPS-installed vehicles. In practice, this method can only be applied for a subset of road segments and time intervals. The next step is therefore to scale up the estimation results for the observed road segments to the whole road network. This step is particularly relevant for the potential use of traffic data for official traffic statistics.

So, traffic density, as one of the important variables of traffic state, needs to be scaled up to the whole road network and time horizon. Traffic flow, as the other of the essential variables of traffic state has a close relation with traffic density and can be generated by loop detectors. Therefore, the ratio of traffic flow in a road segment without density information and traffic flow in a reference road segment is used for scaling up.

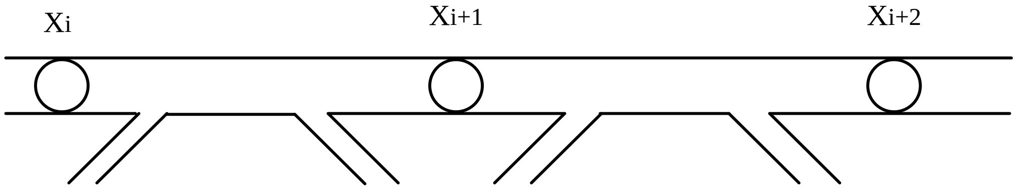

Figure 3 Traffic Network Example

We denote the estimated density and the flow of road segment s at time t by $k_{s,t}$ and $q_{s,t}$, respectively. For each segment s and time interval t, the appropriate reference segment is denoted by $r(s,t)$. If there is a GPS measurement for time t in segment s, then $r(s,t) = s$. Finally, the density in a road network of S segments at time t is approximated by:

$$k_{network}(t) = \sum_{s=1}^{S} \frac{q_{s,t}}{q_{r(s,t),t}} k_{s,t} \tag{10}$$

The proposed method of estimating dynamic traffic density population combines traffic theory and a method for scaling up. Traffic density is estimated for three different cases: a main lane section between loop detectors without on- and off-ramps; a main lane section between loop detectors with on- and off-ramps having detectors installed; and a main lane section between loop detectors with on- and off-ramps having no detectors installed. The information from a limited number of GPS vehicles provides the travel time of GPS vehicles for a certain time window. Finally, the use of reference road segments is applied to scale up the traffic densities to the whole road network. This approach fuses the data from both loop detector and GPS, and further takes the advantages of these two data sources.

CONCLUSIONS AND DISCUSSION

This paper discussed the estimation of dynamic traffic densities with the help of GPS-equipped vehicles for a road network with loop detectors. Based on the definition of traffic density, the model of traffic density estimation is set up for three different cases:

1. between the loop detectors there is only a main lane;
2. between the loop detectors on the main lane there are on/off-ramps without loop detectors, and
3. between the loop detectors on the main lane there are on/off-ramps with loop detectors.

Using the advantages of both loop detector and GPS data and taking into account that the number of GPS vehicles is limited, the combination of the two types of data is used to estimate dynamic traffic density. The idea of reference road segments is used to scale up the traffic density estimates to the whole road network.

In the future, the methods decribed in this paper will be improved in several ways. First, the information from loop detectors will be used more intensively. In that way, a stronger link to current methods of density estimation can be made. Second, the calculation of density for road segment including on- and off-ramps will be refined to better take into account the larger variability in this situation. Third, the method for scaling up density estimation to the whole road network will be worked out in more detail. When GPS measured road segments can be considered as a sample of the whole population of road segments, statistical weighing and scaling-up methods are applicable. Fourth, different types of vehicles have a different contribution to traffic density, and the identification of vehicle types could help to estimate traffic density. GPS data cannot identify vehicles directly, but the average speed of the vehicle can be used to obtain a rough indication of whether the GPS vehicle is a truck or a car.

There are several application areas where the combination of GPS and loop detector data is of use. First, once the type of vehicles is determined, the contribution to density by different types of road users can be calculated. From the perspective of official statistics, this is a relevant result in itself, but it will also help to improve the estimations of traffic emission models. Second, other breakdowns of traffic could be made, for example, by short and long journeys and by regions of origin or destination. This would help traffic policy makers to combat congestion more effectively. Third, dynamic traffic state estimates combined with GPS information can be applied to identify road types and determine the road maintenance period. As GPS information offers insight into the exact journeys through network, road usage patterns of the limited number of GPS vehicles may be used to represent the road usage of the same types of vehicles not equipped with GPS. Dynamic traffic state estimation may then provide the information required to predict the road maintenance period.

This description of applications of dynamic traffic state information is not complete. It can be linked to many traffic and transport fields. As such, the design of dynamic traffic state statistics will create several ways to improve the support of decision-making. With these methods, official traffic statistics can be made more accurate, more extensive, more detailed and presented more timely.

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