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Microscopic Estimation of Freeway Vehicle Positions Using Mobile Sensors

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ABSTRACT

The introduction of mobile sensors, i.e. probe vehicles with GPS-enabled smart phones or connected vehicle technology, will potentially provide more comprehensive information on roadway conditions than conventional point detection alone. Several mobility applications have been proposed that utilize this new vehicle-specific data rather than aggregated speed, density, and flow. Because of bandwidth limitations of cellular and an expected slow deployment of connected vehicles, only a portion of vehicles on the roadway will be able to report their positions at any given time. This paper proposes a novel technique to analyze the behavior of freeway vehicles equipped with GPS receivers and accelerometers to estimate the quantity, locations, and speeds of those vehicles that do not have similar equipment. If an equipped vehicle deviates significantly from a car-following model's expected behavior, the deviation is assumed to be the result of an interaction with an unequipped vehicle (i.e. an undetectable "ghost" vehicle). This unequipped vehicle is then inserted into a rolling estimation of individual vehicle movements. Because this technique is dependent on vehicles interacting during congestion, a second scenario uses an upstream detector to detect and insert unequipped vehicles at the point of detection, essentially "seeding" the network. An evaluation using the NGSIM US-101 dataset shows realistic vehicle density estimations during and immediately after congestion. Introducing an upstream detector to supply initial locations of unequipped vehicles improves accuracy in free flow conditions, thereby improving the root mean squared error of the number of vehicles within a 120-foot cell from 3.8 vehicles without a detector, to 2.4 vehicles with a detector, as compared to ground truth.

INTRODUCTION

Each year, American drivers waste 4.2 billion hours and 2.9 billion gallons of fuel due to traffic congestion (*1*). Several strategies have been proposed to reduce congestion, including dynamic signal timing, ramp metering, and dynamic speed limits. These strategies often rely on historical data supplemented with real-time point detection such as in-pavement loop or video detectors. Because point detection cannot cover the entire roadway, this data is often aggregated over time and space. The high installation and maintenance costs of point detection also prevent wide-scale deployment. Even when detectors are deployed, they are often spread far apart and the conditions between detectors must be estimated.

There are several new technologies that allow the (previously impossible) tracking of probe vehicles through a corridor and measure traffic conditions between detectors. The most prevalent example of this technology is a smart phone equipped with a GPS receiver. A smart phone traveling in a vehicle can compute its own geographic location, heading, and speed. Research suggests GPS may achieve lane-level accuracy in the near future (*2,3*). Many smart phones also have built-in accelerometers with sensitivities as small as 0.6 ft/s^2 (*4*). When a smart phone traveling in a vehicle reports its position and acceleration over time, the phone is acting as a mobile sensor. A similar system is under development in the United States, referred to as "connected vehicles." This system would facilitate wireless communications among vehicles and between vehicles and infrastructure (*5*). Using data collected from the vehicles' own diagnostic system, this information can be wirelessly transmitted through a variety of mediums including Dedicated Short Range Communications (DSRC).

As methods for collecting mobile vehicle data are defined and implemented, researchers have proposed mobility applications that utilize these new mobile data to improve traffic flow and reduce congestion. Several new algorithms have been developed that, rather than estimate vehicle trajectories from loop detectors or historical data, rely on the locations and speeds of individual vehicles. A ramp metering scheme that is based on detecting platoons of vehicles in the mainline rather than aggregated density measurements is an example of an application that requires the locations of individual vehicles (*6*). Many of these applications function most effectively when all, or the majority of vehicles are equipped with sensing technology (*6,7,8*). Simply put, these applications are not designed for detector or historical data only, but instead require the precision of mobile sensors. Some proposed applications include adaptive traffic signal control (*7,9*) and ramp metering (*6*), with others in development.

The full adoption of mobile sensors by roadway users will not be instantaneous. Bandwidth shortages and battery life restrict the use of smart phones, and the John A. Volpe National Transportation Systems Center estimated that only 50% of vehicles will have connected vehicle communications capabilities nine years after the program's initiation (*10*). In any scenario, there will likely be transition period where only a portion of vehicles are equipped. The developers of mobility applications have been careful to study the effect of low mobile sensor penetration rates on the application's performance, testing their applications across a wide range of penetration rates. The locations of vehicles that are not participating as mobile sensors are referred to as unequipped vehicles and are ignored in most applications. Unsurprisingly, mobility applications produce greater benefits with higher mobile sensor penetration rates (*6,7,8*).

One can assume that with a reasonable approximation of the locations and speeds of unequipped vehicles, the performance of mobility applications will be significantly improved. This paper proposes a method to estimate the quantity, locations, and speeds of unequipped vehicles on a freeway with a portion of vehicles acting as mobile sensors, based on the detection of unexpected behavior of the equipped vehicles. By estimating the locations of these unequipped vehicles, a mobility application that relies on mobile sensors can use these estimates to improve its performance, thereby increasing the effective penetration rate of mobile sensors.

BACKGROUND

Predicting the locations of individual vehicles based on mobile sensor data is a recent area of interest. Preliminary work focused on estimating freeway travel states rather than individual vehicle locations. The earliest work was based on vehicle location and travel time information as determined from cell tower signal triangulation (*11*,*12*,*13*). Later work focused on the much more accurate, although sparsely collected, GPS data *(14)*. Mobile sensor data was eventually integrated with point detection data, and used to estimate vehicle travel time by Nanthawichit et al. (*15*). Herrera and Bayen used Kalman filtering techniques and Newtonian relaxation to integrate point detection and mobile sensor data into a high resolution traffic state estimation of a freeway (*16*). Their algorithms were evaluated with both empirical ground truth freeway data (*17*) and actual in-vehicle cell phones with GPS receivers (*18*).

One technique has been proposed to estimate vehicle locations based on their travel times through a section. Ban et al. used the reported travel times of a portion of vehicles traveling through an intersection to calculate their individual delays (*19*). This information was then used to determine the amount of time each vehicle was in the signal's queue. Using this information, Ban et al. could estimate the arrival rate at the intersection, and by assuming uniform flow rate and constant discharge rate, could estimate the total length of the queue with only 30% of vehicles reporting their locations.

Building on this technique, Sun and Ban attempted to estimate the precise trajectories of the unequipped vehicles that make up the total queue, whose length was estimated using the technique described above (*20*). However, the number of unequipped vehicles arriving between equipped vehicles is known, implying the use of an upstream detector. The behavior of these unequipped vehicles did not follow a car-following model, but instead showed immediate speed changes from free flow to stopped and back again. No techniques have yet been proposed to estimate individual vehicle locations based on the behavior of equipped vehicles beyond queuing analysis.

DESCRIPTION OF THE ALGORITHMS

To develop a microscopic estimation of vehicle locations and speeds, the proposed algorithms determine when an equipped vehicle is behaving differently than would be expected based on the locations and speeds of vehicles directly ahead. This requires a definition of expected vehicle behavior. Car-following models, which attempt to predict the behavior of individual vehicles, are used here as an approximation of a vehicle's expected behavior. For this study, the Wiedemann model is used as the car-following model. The Wiedemann model is a psychophysical model which estimates the thresholds for a driver's decision to accelerate or decelerate based on drivers' perceptions of changes in relative velocity (*21*). The model uses four stages: free driving, following, approaching, and braking/emergency (*22*). A vehicle's current stage is based its change in headway and relative velocity to the leading vehicle. The Wiedemann model has gained acceptance as the basis for the microscopic simulation software VISSIM (*22*).

Originally introduced in 1974 (*23*), the Wiedemann model was later refined, calibrated, and validated by Wiedemann and Reiter in 1992 based on empirical freeway traffic data (*24*). To avoid overfitting the Wiedemann model to the evaluation data set (discussed later), the model as applied here uses the calibration parameters proposed by Wiedemann and Reiter in 1992, and based on the empirical data they collected at the time. While Wiedemann and Reiter defined some parameters explicitly, others were estimated from their charts and graphs by Olstam and Tapani (*25*). For the proposed algorithm, the Wiedemann model is also limited to in-lane car-following; lane changing decisions are not modeled.

Mobile Sensor Only Scenario

To predict the location of unequipped vehicles, first the locations, speeds, and accelerations of all vehicles at a given time t are used to populate a virtual roadway. The expected position of all vehicles are updated to time t+1 based on the Wiedemann model considering all known equipped vehicles as well as the estimated positions of unequipped vehicles at time t. The positions of all vehicles, equipped and unequipped, are checked against two criteria. First, if an unequipped vehicle is found to overlap with an equipped vehicle, the unequipped vehicle is erased from the rolling estimation. Second, if an equipped vehicle is found to have an acceleration that is less than expected by a predetermined threshold, it is assumed that the sample vehicle is reacting to an unseen unequipped vehicle. The equipped vehicle is expected to be in the closing stage of the Wiedemann model, whose acceleration b_n is determined by Equation 1.

$$b_n = \frac{1}{2} \cdot \frac{(\Delta v)^2}{ABX - (\Delta x - L_{n-1})} + b_{n-1} \tag{1}$$

In Equation 1, *ABX* is the desired minimum following distance at low speed differences, Δv is the difference in speed between the n-1 lead vehicle and vehicle n, Δx is the space headway from vehicle n and vehicle n-1, L_{n-1} is the length of vehicle n-1, and b_{n-1} is the deceleration of the n-1 lead vehicle. A more detailed description of the model can be found in (*24*) and (*25*).

Because the actual acceleration b_n of vehicle n is known, Equation 1 can be rearranged to determine the space headway, thereby predicting the location of the leading vehicle n-1. The speed of the leading vehicle must be assumed as equal to some fraction q of vehicle n's speed. By making this assumption, the difference in speed between the leading and following vehicles can be calculated using Equation 2.

$$\Delta v = v_n - q v_n = (1 - q) v_n \tag{2}$$

The leading vehicle is assumed to have zero acceleration, and a standard vehicle length of 15.6 feet. Equation 3 demonstrates this rearrangement of Wiedemann and Reiter's closing acceleration equation with the new assumptions.

$$\Delta x = ABX - \frac{1}{2} \cdot \frac{\left[(1-q)v_n\right]^2}{b_n} + L_{n-1} \tag{3}$$

By assuming the lead vehicle (i.e. the unseen, unequipped vehicle) has 90% of the speed of the following vehicle (q = 0.9) and has an acceleration of zero, the headway of the two vehicles is quickly calculated, and the lead vehicle is inserted at the appropriate location and speed. The new vehicle's location and speed can be found from Equations 4 and 5.

$$x_{n-1} = x_n + \Delta x \tag{4}$$

$$v_{n-1} = q \cdot v_n \tag{5}$$

The inserted vehicle now exists in the rolling estimation of the traffic network, and continues to move forward and interact with other equipped and unequipped vehicles according to the Wiedemann car-following model, although it never changes lanes. The inserted vehicle is only removed from the simulation when an equipped vehicle no longer reacts to it and overlaps positions, essentially running over the unequipped vehicle.

This algorithm does not require conventional point detection such as loop detectors. When it is used without point detection, the scenario is referred to as *mobile sensor only*.

Detector-Supplemented Scenario

The proposed algorithm is limited in that it can only predict the presence of unequipped vehicles once an equipped vehicle shows a reaction. This generally doesn't happen in free flow traffic, but only during congestion. Although the predicted locations of unequipped vehicles are updated each time step, i.e. they move forward as though simulated vehicles and can therefore predict densities downstream of congestion, the algorithm cannot predict vehicle locations upstream of congestion during free flow. To improve these predictions, the use of an upstream detector can be utilized. When the vehicle presence is detected, vehicles can be inserted at the correct lane and the correct speed. In this way, the rolling estimation is seeded with correct vehicle locations, and is updated throughout the length of the freeway corridor based on vehicle behaviors and interactions. The scenario using the upstream detector is referred to as *detector supplemented*.

EVALUATION

The proposed algorithms are tested using data from the Next-Generation Simulation (NGSIM) project. NGSIM is a field-collected dataset of vehicle movements along several corridors in the United States. Vehicle movements were collected from video recordings, and then extracted via specialized software. This study used the dataset collected from a 0.4 mile stretch of US101 in Los Angeles, California between 7:50 AM and 8:35 AM on June 15, 2005. The roadway has five lanes in the southbound direction, along with a one on-ramp and one off-ramp. The activity on the ramps and merge lanes are not analyzed, only the behavior of vehicles traveling in the main lanes. Figure 1 shows an overview of the network. Because the NGSIM data records the position of every vehicle ten times per second, it can be treated as ground truth data. To develop a test data set of mobile sensors, a portion of vehicles are randomly assigned as mobile sensors and their movements are pulled from the full data set. For both scenarios, 25% of vehicles were designated as sample vehicles that report their locations once per second.

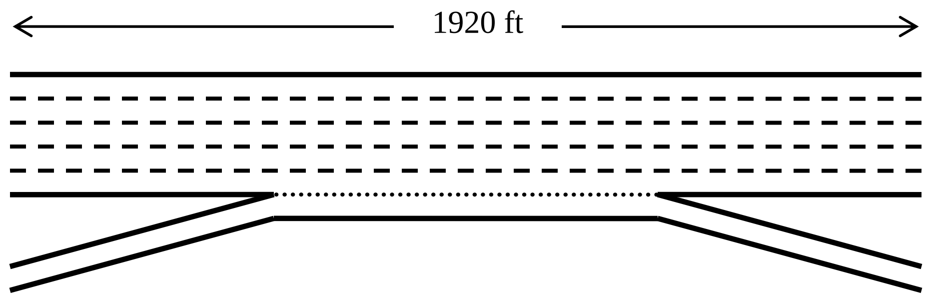

Figure 1 Section of US 101 highway used in the NGSIM dataset.

To test the algorithm, several assumptions and thresholds were set. First, the maximum speed of a vehicle, and therefore the free flow speed of the corridor, was assigned as 68 miles per hour based on field observations. Second, the threshold difference in acceleration between a vehicle's expected and actual accelerations to trigger an inserted vehicle was set to 0.2g (6.43 ft/s^2). This amount seemed reasonable, as the threshold for determining a potential incident in naturalistic driving studies is a 0.5g deceleration (*26*). Also, the car-following model used here has a maximum acceleration of 0.36g (11.5 ft/s^2) when a vehicle is at standstill, which decreases as the vehicle's speed increases, so that a vehicle that should be accelerating, but is not acceleration, will trigger an insertion.

Furthermore, if a vehicle is inserted into the roadway, its initial speed is 90% (q = 0.9) of the initiating equipped vehicle, and its initial placement assumes that the vehicle has zero acceleration. Finally, the algorithm assumes that equipped vehicles report their lane, location, speed (which if not reported directly can be determined from the difference in location since the last transmission), and instantaneous acceleration. The vehicles are assumed to report once per second.

The algorithm was evaluated under two scenarios. In the mobile sensor only scenario, the algorithm does not use any detectors in the roadway, and simply bases its results on data reported from the mobile sensors. In the detector supplemented scenario, a detector at the beginning of the corridor is used to insert a vehicle in the correct lane immediately after it is detected, to ensure that the corridor is properly seeded with vehicles, even during free flow. Each scenario was evaluated over twenty repetitions, with each repetition designating a different set of randomly selected vehicles as the equipped vehicles.

RESULTS

The two scenarios, mobile sensor only and detector supplemented, were implemented as described previously. For a high-level view of the behavior of the algorithm, Figure 2 shows a time-space diagram of the predicted locations of unequipped vehicles at 25% market penetration. Equipped vehicles are not shown.

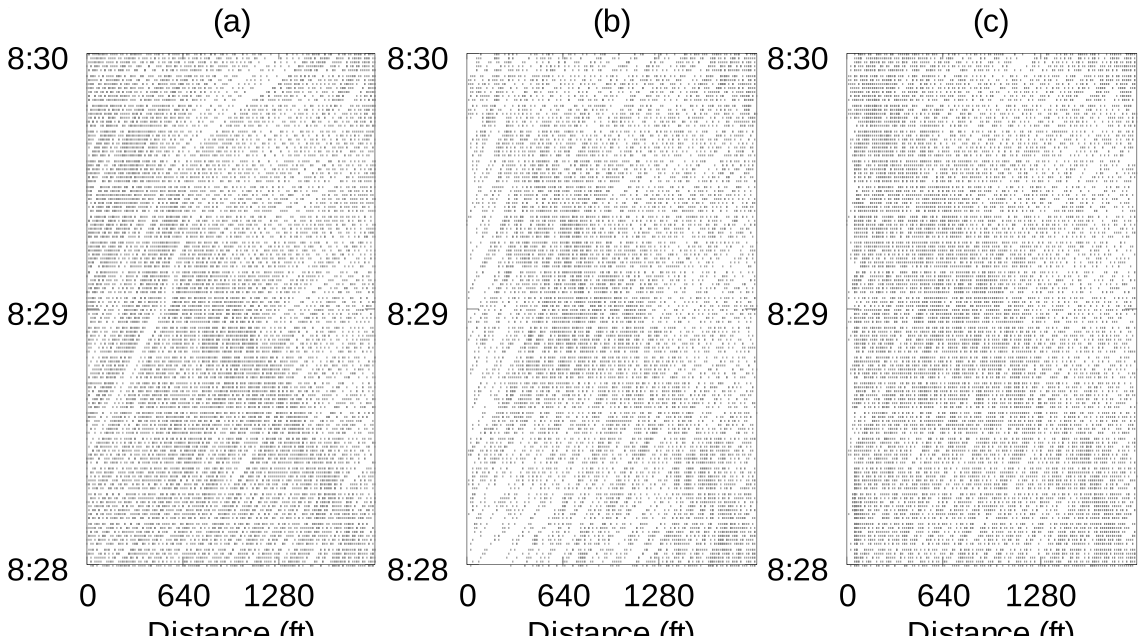

Figure 2 A time-space diagram showing the positions of unequipped vehicles for (a) ground truth and estimated vehicle locations for (b) mobile sensor only and (c) detector supplemented. Equipped vehicles, comprising 25% of the total volume, are not shown.

Figure 2 shows that without an upstream detector to seed vehicle locations, the mobile sensor only scenario (b) is inaccurate in free flow conditions, especially in free flow conditions prior to congestion. This is particularly noticeable in the early part of the corridor, near zero distance. During congestion, vehicles begin to interact more often, producing improved estimates of vehicle location estimates. In the area immediately downstream of the congestion, many of the vehicles "created" during the congestion survive, providing a good approximation of vehicle density. Using the detector supplemented scenario (c), accuracy of vehicle density and locations upstream of congestion was substantially improved. Vehicle trajectories are not as continuous in the mobile sensor only and detector supplemented scenarios. This is likely because the algorithm is continually creating and deleting vehicles as positions are updated and unequipped vehicles change lanes.

To evaluate the performance of the algorithm quantitatively, the ideal metric is the root mean square error (RMSE) of the location and speed of each individual vehicle. Unfortunately, because there is not a one-to-one ratio between number of observed vehicles (the ground truth) and the number of estimated vehicles (the result of the algorithm), this type of comparison is impossible. Instead, the network is subdivided by segment length and time, and the estimated total number of vehicles within a cell at a given time is compared to the observed number of vehicles. The evaluation used here is based on the method used by Herrera and Bayen, with some modification (*16*). The roadway is segmented into 16 cells of size 120 feet each. Densities are evaluated once per second, for a total of 2700 time steps. In total, for each of the 20 simulation repetitions for each scenario, 43200 measurements were taken. All lanes are combined in these measurements, although lane-specific measurements are possible.

For the mobile sensor only scenario, the RMSE of the number of vehicles present in each cell at each time step over twenty repetitions is 3.8 vehicles. For the detector supplemented scenario, the RMSE is 2.4 vehicles. For comparison, the RMSE of a system assuming a linear average using only values measured at upstream and downstream detectors is 2.6 vehicles as determined by Herrera and Bayen (*16*).

Figure 3 shows the number of vehicles within a cell at any given time. For the mobile sensor only scenario, the algorithm is able to detect the shockwaves with a reasonable degree of accuracy, but is unable to estimate realistic densities during uncongested periods. For the detector supplemented scenario, the estimates are accurate near the upstream detector, as is expected. The accuracy during uncongested conditions is also substantially improved. Although this discussion refers to the average measured densities over 20 runs, the variation of estimated values is also important. For comparison, subfigures (c) and (e) show the results of a single repetition of each scenario. The single repetitions are still able to identify the periods of congestion, although the estimated densities tend to fluctuate rapidly from second to second, as groups of vehicles are rapidly added or deleted as congestion begins and dissipates. Some smoothing of the estimates over time (e.g. five seconds) may improve visualization.

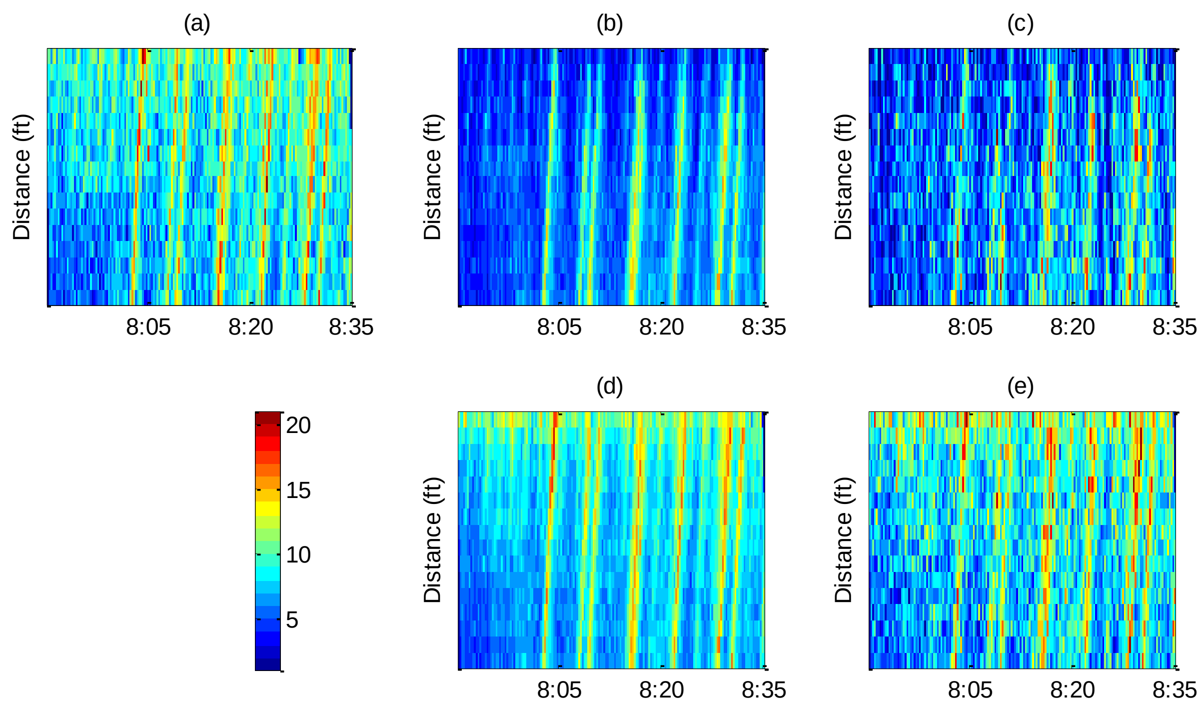

Figure 3 Number of vehicles in each of 16 cells during each second of the NGSIM data set for (a) ground truth, (b) mobile sensors only averaged over twenty repetitions, (c) mobile sensors only for a single repetition, (d), detector supplemented averaged over twenty repetitions, and (e) detector supplemented for a single repetition.

To better demonstrate the performance of the algorithm during both scenarios, Figure 4 shows the total number of vehicles in the network over the 45 minute evaluation period for the ground truth, mobile sensor only, and detector supplement scenarios. The detector supplemented scenario is able to match the ground truth volumes throughout the test period. The mobile sensor only scenario experiences similar peaks and valleys, but provides low estimates of vehicles present. The mobile sensor only scenario has greater accuracy when vehicle volumes are high, suggesting improved performance during congestion.

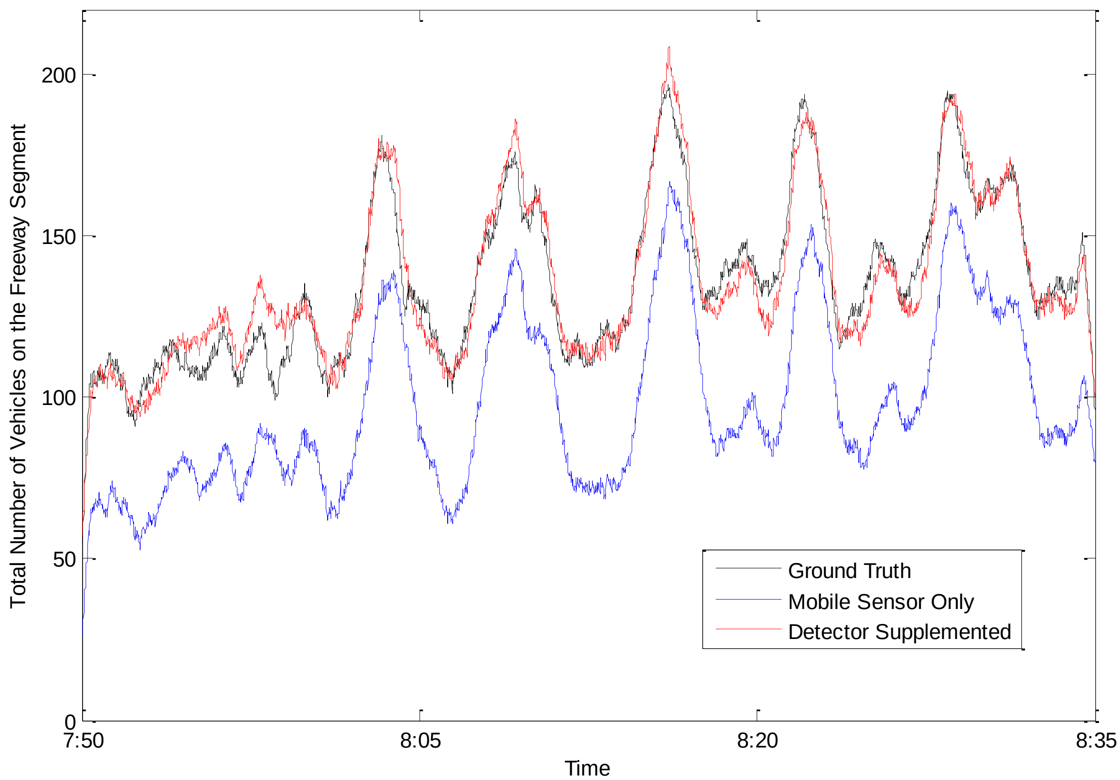

Figure 4 Total number of vehicles in the network at any given time.

The algorithm is designed not just to detect vehicle densities, but the approximate locations of these vehicles. Because there is not a one-to-one ratio of estimated and observed vehicles, a direct comparison between actual and estimated location is impossible. However, it is possible to measure the geometric center of all vehicles within a cell, by finding the average location both longitudinally (i.e. the distance along the roadway) and the laterally (i.e. a vehicle's lane). Table 1 shows the RMSE between several methods for calculating the geometric center and the ground truth data. The detector supplemented scenario was able to outperform the mobile sensor only scenario. Both scenarios were more accurate than using only the positions of equipped vehicles without applying the algorithm. However, the most accurate technique was to assume the true center of the cell (in this case, 60 feet longitudinally and 30 feet laterally) as the geometric center. This technique benefitted from the generally uniform distribution of vehicles within a cell.

Table 1 The root mean squared error of the geometric center of all vehicles as compared to ground truth. The results are separated by the method of estimation, and the longitudinal (along the roadway), latitudinal (lane position across the roadway), and absolute distance. Lanes are twelve feet wide.

	Root Mean Squared Error (ft)		
Method	Longitudinal Distance	Latitudinal Distance	Absolute Distance
Mobile sensor only	15.9	8.2	17.9
Detector supplemented	12.6	5.2	13.6
Equipped vehicles only, algorithm not applied	23.2	11.6	25.9
True center of the cell (assumes uniform distribution of vehicles)	8.8	3.8	9.6

CONCLUSIONS

An algorithm for predicting the number and locations of individual vehicles, both with and without an upstream detector, have been proposed. The algorithm uses speed, location, and acceleration data collected once per second from a portion of vehicles acting as mobile sensors. In a deployment, this data could be collected with GPS and accelerometers on smart phones, or in a connected vehicle environment using DSRC. The algorithm shows that analyzing the behavior of 25% of vehicles on the roadway to identify likely interactions with unequipped vehicles is able to accurately estimate most densities during congestion. The algorithm is also able to predict the densities of vehicles immediately after a congestion period, by assuming that invented vehicles drive as predicted by the Wiedemann car-following model. Using this method, with no point detection present, the algorithm was able to estimate the number of vehicles within each 120-foot cell every second with an RMSE of 3.8 vehicles. However when using the mobile sensor data only without any conventional point detection, performance is poor in areas with free flow traffic (and therefore few vehicle interactions), especially in areas that are not immediately downstream of congestion. This shortcoming can be remedied by the integration of point detection data. With an upstream detector, the initial speed and location of vehicles passing the detector are known, and these estimated vehicles can be seeded into the network, drastically improving algorithm performance during free flow conditions. Using an upstream detector, the algorithm was able to estimate the number of vehicles with each 120-foot cell every second with an RMSE of 2.4 vehicles.

Although the Wiedemann model was used to determine expected vehicle behavior, the model itself was chosen because of its versatility and lack of reliance on calibration factors. The model itself was not calibrated to fit the observed traffic in order to prevent overfit, and instead used default values. It is realistic to assume that any other model that is space continuous and outputs expected vehicle accelerations would work just as well. Improvements in car-following models may be imminent, as more data on individual vehicle behaviors is collected through mobile sensors, connected vehicles, or naturalistic driving studies (*27*).

The algorithm differs significantly from Herrera and Bayen's work, which relies heavily on a correct formulation of the fundamental diagram (*16*). In their algorithms, vehicle speeds from mobile sensors are directly converted to the corresponding densities based on the fundamental diagram, and these new values are used to adjust the sensor data. The algorithm proposed here may be better suited for situations where reconstruction of the fundamental diagram may be excessively difficult, e.g. few or no conventional point detectors present, or during incidents where flow on a single lane is dramatically affected. Future research will investigate the algorithm's effectiveness in these situations.

As more mobility applications are developed that require vehicle locations and speeds as inputs, the greater the need for algorithms that can predict the locations of vehicles that are unequipped with sensing technology, thereby improving the performance of these applications. The algorithm proposed in this paper is a first step towards a microscopic level view of traffic using mobile sensors, and may yet generate new applications that have yet to be determined.

This algorithm also serves as a first step towards the integration of vehicles with more advanced detections systems. For example, autonomous vehicles use laser scanners to detect nearby vehicles. These measurements could be used as estimates of actual vehicle locations, and the algorithm proposed here could quickly integrate these new measurements to improve its performance. Furthermore, with human drivers, a distinct limitation is the car-following model, where a vehicle's observed behavior will not fit the model perfectly, resulting in incorrect estimations of unequipped vehicle presence and locations. Autonomous vehicles, by contrast, would likely follow some fixed predetermined logic when encountering an unequipped vehicle. Therefore, by knowing the speed and deceleration rate of the autonomous vehicle, the lead vehicle's speed and location could be determined with much greater accuracy.

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