

Predicting the Locations of Many Vehicles from the Behaviors of a Few

Engineering, Biosciences, & Health
School of Engineering and Applied Science

Department of Civil and Environmental Engineering

Goodall, N.J. (Ph.D. Candidate), Smith, B.L. (Faculty), and Park, B.B. (Faculty)

Introduction

Modern passenger vehicles are incredibly complex machines, with electronic control of virtually every component, and running more lines of code than a Boeing 787. Similarly, many smart phones are able to provide detailed vehicular data similar to internal automotive sensors. Recent advances in wireless communication will soon allow vehicles to transmit their speeds, locations, and headings to nearby vehicles and roadside infrastructure. This advance has the potential to drastically alter transportation – traffic signals can become much more responsive, authorities can quickly detect incidents, and many more applications, some yet to be developed, may be forthcoming. The applications that use data from individual vehicles generally don't experience benefits until 20-40% of all vehicles are equipped with communication devices. It will be several years before this is possible, and even then bandwidth limitations may limit the number of vehicles that can participate at any given time.

Predicting Vehicle Locations

Fortunately, the behavior of a few monitored vehicles can be analyzed to estimate the quantity and locations of nearby vehicles. For example, consider two vehicles on a freeway in Figure 1. Vehicle A is traveling slower than Vehicle B, yet it is decelerating. A widely accepted model for car behavior, the Wiedemann model, predicts that Vehicle A should accelerate at 7 ft/s². The maximum difference between the expected and actual acceleration is 0.25g or 8 ft/s². We can then conclude that Vehicle A is reacting to an unseen vehicle.

The speed of the unseen vehicle, "Vehicle C" is assigned based on an empirically observed linear relationship with the speed and acceleration of Vehicle A. The distance ahead, Δx , is determined from the Wiedemann model. The assigned speeds and headway are shown in Figure 2. The inserted vehicle drives according to the Wiedemann model, never switching lanes, until it is "run over" by an equipped vehicle, thereby deleting it, as shown in Figure 3.

Figure 1



Figure 2

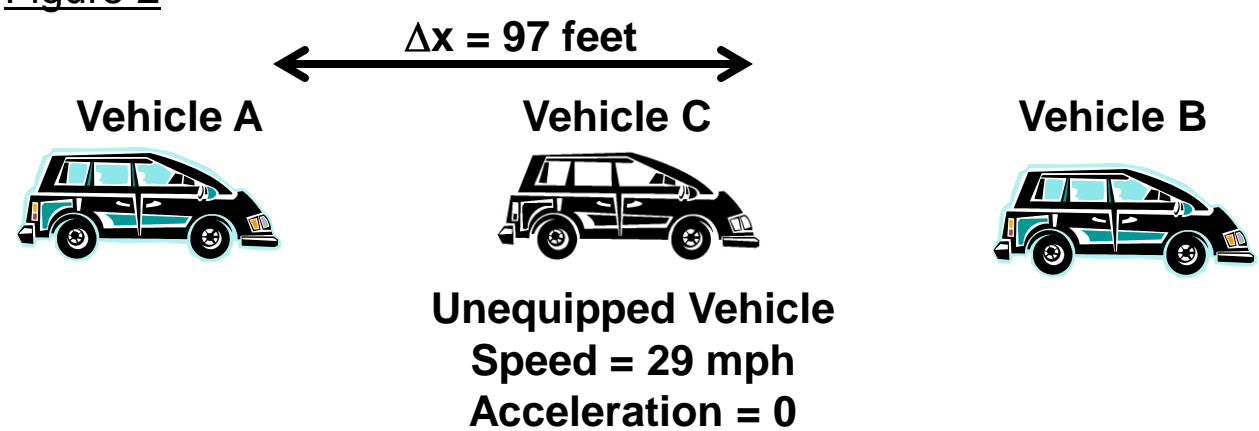
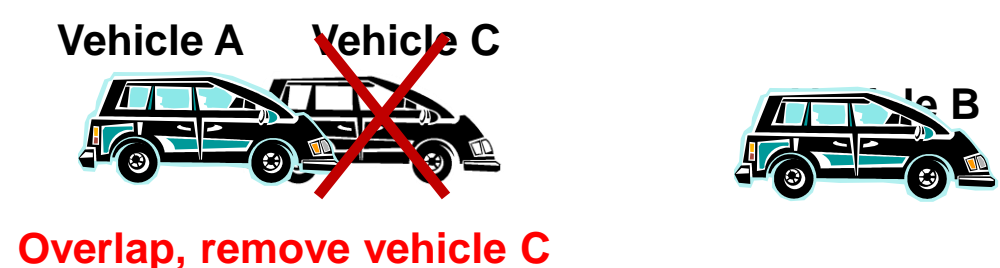


Figure 3



Results

The algorithm was tested against empirical vehicle location data collected for the Next Generation Simulation (NGSIM) dataset. A percentage of vehicles was designated as unequipped, and was removed from the dataset before testing. To discourage over-guessing, each estimate outside the required accuracy range negated an estimate within the accuracy range. Figure 4 shows the new "effective" market penetration, based on the original market penetration and the desired accuracy. The algorithm is able to replicate a rate of 30% market penetration at much lower actual market penetrations, as summarized in Figure 5.

The performance of the model varies over space and time. Because the estimation is populated by the behaviors of equipped vehicles, it performs best after observing vehicles for a few seconds. Figure 6 shows the density of vehicles along the test site. Notice how the accuracy of the algorithm improves, i.e. there's less difference between Figure 6a and 6b farther down the roadway.

Figure 6: Densities Along I-80 at 25% Market Penetration

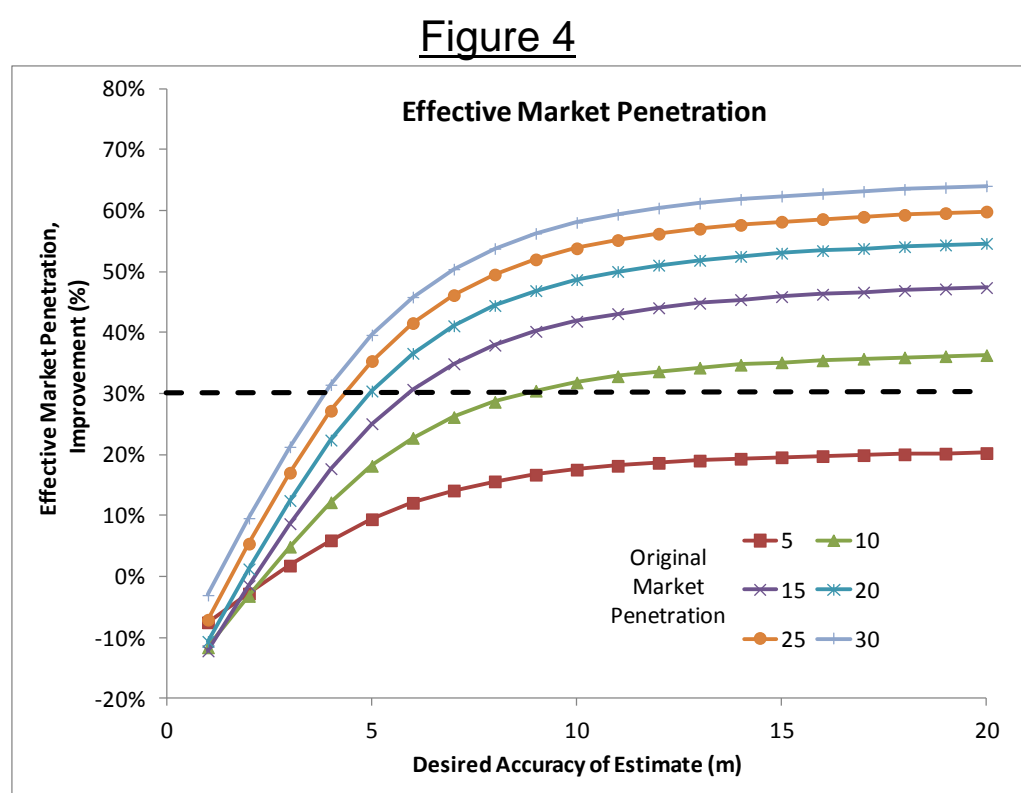
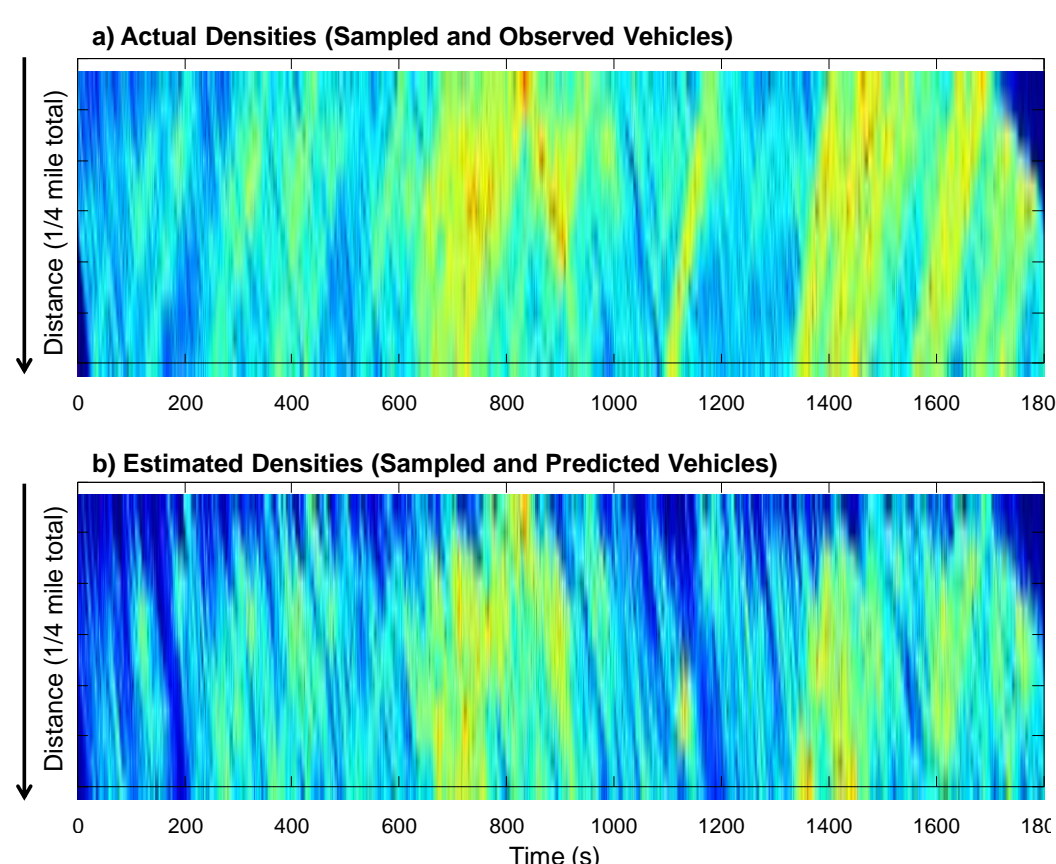


Figure 5

Original Market Penetration	Minimum Accuracy Level to Reach 30% Effective Market Penetration
5%	N/A
10%	9 meters
15%	6 meters
20%	5 meters
25%	5 meters
30%	4 meters

Conclusions

By post-processing wireless vehicle data as demonstrated through this research, current and future transportation systems that use wireless vehicle data will experience greater benefits, and sooner than without. This has the potential to reduce emissions, travel time, and fuel consumption, particularly in nations with good wireless networks and poor static sensor networks.

The wireless transmission of a vehicle's location, speed, and heading to nearby roadside equipment has the potential to drastically improve the efficiency of the transportation network, save time, and reduce emissions. The improvements are expected to be especially dramatic in developing nations with broad wireless coverage and few existing roadway sensors. Most research suggests that benefits from these new data begin when the locations of at least 30% of vehicles are known.

This research proposes an algorithm to predict the location of non-communicating vehicles based on the behaviors of nearby communicating vehicles. By employing driver behavior models and rolling estimation techniques, the algorithm is able to predict the locations of 30% of vehicles with 9-meter accuracy when only 10% of vehicles are communicating, theoretically leading to improvements in traffic signal timing, ramp metering and incident detection, among others.