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Measurement and Analysis of Heterogenous Vehicle Following Behavior on Urban Freeways: Time Headways and Standstill Distances

Andrew Houchin
Iowa State University

Jing Dong
Iowa State University, jingdong@iastate.edu

Neal Hawkins
Iowa State University, hawkins@iastate.edu

Skylar Knickerbocker
Iowa State University, sknick@iastate.edu

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Abstract

Microscopic traffic modelling is a popular tool in the transportation field, but using such models comes with significant data needs in order to properly calibrate them. Two important driver behavior parameters in these models are the preferred time headways and standstill distances. In this paper, an economical method for collecting headways and standstill distances is presented and applied to urban freeways in Iowa, USA. The following time headways and standstill distances were categorized into four combinations of car and truck pairs. It was found that headway values largely depend on the following vehicle type-when a car was following the average headway was around 2 seconds, compared to around 3 seconds when a truck was following. Additionally, the car-car combination leaves much less space when stopped than when a pair involves trucks. In particular, the average standstill distance of a car following a car was found to be around 9 feet, while the average standstill distances are around 12 feet when a truck is involved. However, both headways and standstill distances follow fairly disperse distributions, due to the heterogeneity in driver behavior. Thus, microsimulation software should be improved to allow these parameters to follow distributions.

Keywords

Time headway distribution, Driver behavior, Car following, Standstill distance, Heterogeneity

Disciplines

Civil Engineering | Transportation Engineering

Comments

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Measurement and Analysis of Heterogenous Vehicle Following Behavior On Urban Freeways: Time Headways and Standstill Distances

Andrew Houchin, Jing Dong*, Neal Hawkins and Skylar Knickerbocker
Institute for Transporation, Iowa State University, Ames, Iowa 50011, USA
*Corresponding author, email: jingdong@iastate.edu

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***Abstract*—Microscopic traffic modelling is a popular tool in the transportation field, but using such models comes with significant data needs in order to properly calibrate them. Two important driver behavior parameters in these models are the preferred time headways and standstill distances. In this paper, an economical method for collecting headways and standstill distances is presented and applied to urban freeways in Iowa, USA. The following time headways and standstill distances were categorized into four combinations of car and truck pairs. It was found that headway values largely depend on the following vehicle type—when a car was following the average headway was around 2 seconds, compared to around 3 seconds when a truck was following. Additionally, the car-car combination leaves much less space when stopped than when a pair involves trucks. In particular, the average standstill distance of a car following a car was found to be around 9 feet; while the average standstill distances are around 12 feet when a truck is involved. However, both headways and standstill distances follow fairly disperse distributions, due to the heterogeneity in driver behavior. Thus, microsimulation software should be improved to allow these parameters to follow distributions.**

Keywords—Time headway distribution; Driver behavior; Car following; Standstill distance; Heterogeneity

I. INTRODUCTION

Preferred time headway and standstill distance are two of the most important parameters in microscopic traffic modeling. However, the actual values of these parameters for the site being modeled are rarely collected at the individual vehicle level. This is due largely in part to individual vehicle behavioral parameters being generally difficult to collect compared to macroscopic traffic parameters, such as occupancy and flow rates.

Often, instead of collecting data on the microscopic parameters, macroscopic traffic flow parameters such as speed flow relationships are collected and microscopic modelling parameters are then changed to match the simulation output to the collected data. Various approaches have been proposed in the literature to use flow-speed relationships to calibrate microscopic driver behavior parameters (e.g. [1]). While these methods can be very effective in calibrating the models, they have their drawbacks. They can be highly computationally intensive and require complex algorithms to select the parameter values as well as recognize the similarities in speed-flow relationships. Additionally, since this process calibrates based on aggregate measures, individual vehicle interactions such as lane changes and near crashes may not be the same in models with the same speed flow relationship.

High-resolution vehicle trajectory data can capture the interactions among drivers in the traffic stream and are better suited for estimating driving behavior parameters. For example, one study used the Next Generation SIMulation (NGSIM) datasets to calibrate car following parameters [2]. The vehicle trajectory data can be collected by a series of cameras mounted on tall structures along a stretch of roadway (e.g. NGSIM), or by helicopter flying over the highway (e.g. [3]). Extracting vehicle trajectories from these video data usually requires great effort. Furthermore, naturalistic driving studies, primarily for safety analyses, can provide valuable and accurate information at individual driver level, and have been used to study car following [4] and lane change behavior [5]. However, naturalistic driving data are usually expensive to collect and require tremendous effort to process. Therefore, it is generally not practical to deploy and collect instrumented vehicle data for the calibration of driver behavior parameters to local conditions.

This study uses a more economical method to directly collect data on two vehicle following parameters, that is, preferred time headway and standstill distance. Specifically, by using roadside radar detectors capable of recording individual vehicle data, it is possible to determine time headways between two vehicles, vehicle classification, as well as traditional macroscopic parameters. Through the use of the video of stop and go traffic and photo editing software, standstill distances could be determined.

II. LITERATURE REVIEW

There have been many papers and projects investigating different methods of calibration for microsimulation software. Reference [6] laid out a foundation in the form of a basic outline of calibration steps and applied them to a case study.

The next year, the FHWA released its *Traffic Analysis Toolbox Volume III: Guidelines for Applying Traffic Microsimulation Modeling Software* [7] which included a chapter about calibration and an outline of its steps similar to the one presented by [6]. The Oregon DOT later created a *Protocol for VISSIM Simulation* [8] which applied the FHWA's toolbox to provide more specific guidance for VISSIM in particular.

In general, there have been two main approaches used to select values of parameters and evaluate the model for each iteration of the calibration process—manual and automated. In the manual method (e.g. [9]), the most important modeling parameters affecting the selected measure(s) of effectiveness are identified and various values for those parameters are selected using engineering judgement. Measures of effectiveness used can include quantitative values such as speed, flow, travel, or delay or qualitative characteristics of the flow such as locations of bottlenecks, time of day bottlenecks occur, or lane utilization. In the automated method, the values of the parameters being calibrated in the current iteration are selected by an algorithm based on the performance of the model in the previous iteration. The measures of effectiveness in automated calibration are limited to quantitative values in order for the algorithm to evaluate their performance and select new parameters. Overall, automated calibration appears to be favored in the literature with numerous algorithms being used to evaluate measures of effectiveness including genetic algorithms (e.g. [1] and [10]) and simultaneous perturbation stochastic approximation algorithms [11].

Whether a manual or automated process is used to calibrate the parameters, there is a common theme that the parameters are adjusted in order to match measures of effectiveness between the simulation and the observed values. Very few studies attempted to calibrate microsimulation models by collecting the data on any of the actual parameters themselves.

However, separate studies which were not focused on microsimulation calibration have proposed many distributions to model time headway on freeways including single models, mixed models, and combined models (e.g. [12] and [13]). Most of these models fairly accurately predict the actual headway distributions when properly calibrated.

III. DATA COLLECTION

In order to collect the time between vehicles, side-fired radar detectors were installed temporarily with video cameras at several locations along freeways in Des Moines, Iowa. The camera and the radar sensor were mounted behind a road sign where possible, as illustrated in Figure 1, so as to minimize driver distraction. The locations were both eastbound and westbound directions of Interstate 235 near 73rd Street and both northbound and southbound directions of Interstate 80/35 between University Avenue and Hickman Road (see Figure 2). The speed limits were 55 mph at the I-235 location and 65 mph at the I-80/35 location. The radar detectors collected the length, speed, lane detected, and time detected for each vehicle. Vehicle classification can be determined based on vehicle length. The time headway can be calculated as the time difference between two vehicle arrivals.

Figure 1 Camera and side-fired radar sensor installation

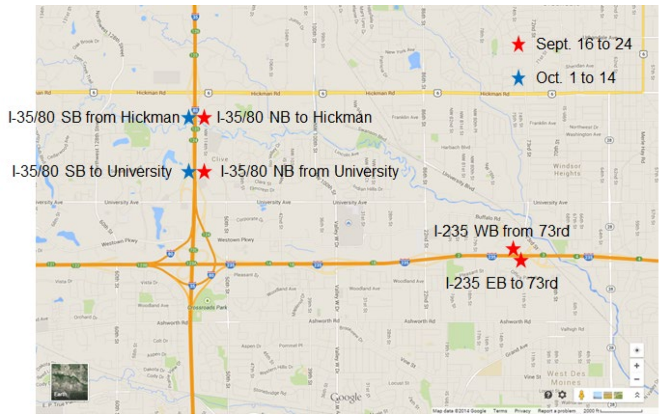

Figure 2 Data collection sites in Des Moines, IA in 2004

The data collected from those detectors were checked for accuracy against manual counts from video as well as similar sensors the Iowa Department of Transportation (DOT) had permanently installed nearby. From watching 30 minutes of peak hour traffic at each location, both directions of I-235 were excluded because the radar counted less than half as many vehicles as were manually counted (see Table 1). This was likely the result of an error in the installation of the temporary radar detectors at those sites. However, for both directions of the I-80/35 locations, the average total vehicle count error was +3 percent (i.e. the radar counted 3% more vehicles than were counted manually). Additionally, 30 minutes of the off peak was observed to have a +1 percent error. In addition, the vehicle class frequencies, lane detection frequencies, and average vehicle speeds in 5 minute intervals were compared. These accuracy results are summarized in Table 1. The accuracy of the headway values were not directly measured, because it was not possible to match the vehicles detected with those observed in the video.

Table 1 Relative Error of Radar Detector

		Location				
		I-235 EB	**I-235 WB**	**I-80/35 SB**	**I-80/35 NB**	**I-80/35 NB**
	Time Observed	9/19/14 7:15-7:45	9/19/14 17:00-17:30	10/8/14 17:00-17:30	9/18/14 17:00-17:30	9/18/14 12:00-12:30
Error (in %)	**Count**	-50.71	-54.26	1.01	2.99	1.06
	Lane 1 %	-0.41	1.85	1.86	-0.23	-0.2

	Lane 2 %	0.6	-0.35	-3.1	0.04	0.33
	Lane 3 %	-0.5	-0.44	1.05	-0.09	-0.44
	Lane 4 %	0.3	-1.06	0.18	0.29	0.31
	Car %	0.7	9.4	1	1.9	3.3
	Truck %	-0.4	-9.2	-0.6	-1.6	-3.2

IV. METHODS

A. *Preferred time headway*

Once the data from the I-80/35 location were deemed accurate enough for analysis, the lane and time detected information were combined to calculate individual headways for each vehicle. In order to limit the analysis to mainly following headways, only vehicles which were detected during periods of 15 min flow rates above free flow (1000 vehicles per hour [14]) and had headways rounded to the nearest second of 6 seconds or less were used to build the following headway distribution. The 6 second threshold was determined by following a procedure outlined in [15]. This process involved grouping time headways by rounding them to the nearest second (or any other interval) and finding the correlation between the leading vehicle and following vehicle speeds for each group. The correlation used in this process was the Pearson correlation coefficient which is calculated with Equation 1 below. The results followed what one would expect—at small headways, the vehicle speeds are highly correlated, and as the headways increased, the correlation between the vehicle speeds decreased to near random noise. This process was repeated for both the NB and SB directions of the I-80/35 location independently. It was found for both directions that at a headway of about 6 seconds, the vehicle speeds begin to become more correlated. This is shown in Figure 3 below for the NB direction. Therefore, observations of time headways that are greater than 6 seconds were excluded in the subsequent analysis, as well as the observations collected under free flow conditions.

Equation 1. Pearson correlation coefficient

$$r_{xy} = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2 \sum_{i=1}^{n}(y_i - \bar{y})^2}}$$

Where:

r_{xy} = Pearson correlation coefficient

x_i = the ith value of variable x

y_i = the ith value of variable y

$\bar{x}$ = the mean value of variable x

$\bar{y}$ = the mean value of variable y

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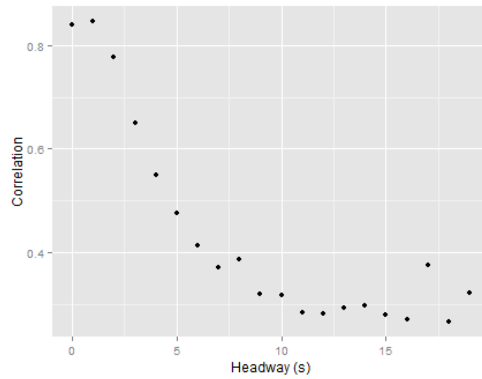

Figure 3 Leading and Following Vehicle Speed Correlations vs. Headway

Time headway was analyzed separately for the different combinations of car and truck following (i.e. car following car, car following truck, truck following car, and truck following truck). Trucks were defined as vehicles longer than 35 feet for the purpose of this analysis. This value was selected to match the vehicle class lengths specified in the DOT's permanent radar detectors. The summary statistics and histograms of time headway were observed for each group and the differences between the groups were noted. This analysis was performed separately for the northbound and southbound directions of the I-80/35 location to provide a basis for comparison and ensure that the calculated values are consistent for a similar driver population.

B. *Standstill distance*

Due to the unpredictability of stop-and-go traffic condition (there is little to no reoccurring heavy congestion in Des Moines area), no stop-and-go traffic was observed during the data collection period at the location where the temporary cameras were set up with the radar. Instead, video from Iowa DOT cameras during incidents which caused stop-and-go traffic in Des Moines were accessed and downloaded after the fact to be processed. Screen captures of the video were taken when vehicles were stopped within the frame. Those stopped vehicles were identified and the distances between them measured using a photo editing software capable of measuring distances on plane distorted by perspective. Painted lane lines (10 feet long) were used as a control measurement on which the software based the rest of its measurements. The length of the lane lines was confirmed using the measuring capabilities of Google Earth. Figure 4 shows an example of the screen capture. The vehicles marked with a green cross were moving vehicles and were excluded from the analysis. The distances between every pair of stopped vehicles were measured.

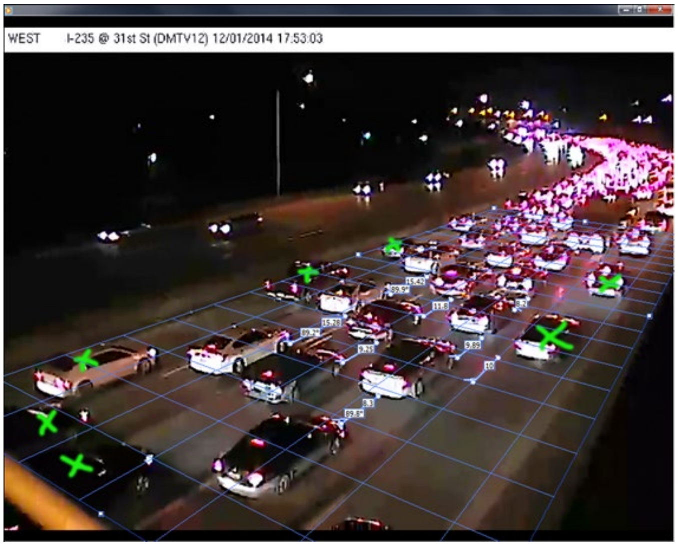

Figure 4 Standstill distance measurement

The accuracy of the measuring in this software was tested by taking photos of a grid with known dimensions from several angles and comparing the measurements of the software to the actual dimensions. The average of the absolute relative error of these measurements was 1.2 percent. Additionally, the primary source of error appeared to be in determining the exact end points to be measured, which is limited by the picture quality rather than the software.

Histograms and the summary statistics of the standstill distances were used to investigate the shape of the distribution and its measures of central tendency and dispersion.

V. RESULTS

A. *Preferred time headway*

The summary statistics of time headways are listed in Table 2. It was found that the values of headway differed substantially between the different groups of following but were fairly consistent between the two directions. Unsurprisingly, it was found that the average preferred following headway was smallest when a car was the following vehicle, as cars have better acceleration and deceleration characteristics than trucks and can thus follow more closely. The average value of headway when cars were following was a little over 2 seconds compared to almost 3 seconds when trucks were following. Additionally, as illustrated in Figure 5, cars most frequently follow at between 1 and 1.5 seconds, whereas trucks most frequently follow from 1.5 to 2.5 seconds. It was somewhat surprising that there was a slightly lower average for a car following a truck (i.e. the Truck-Car pair in Table 2) than a car following a car, as the latter leads to an obstructed view for the following car. However, that could reflect a subset of the population who are more aggressive when following trucks, because they know that they can stop more quickly than the truck. It is interesting to note that the leading vehicles have little to no impact on the average headways compared to the following vehicles. The difference between the respective mean and median headway values for car-car and truck-car following combinations were 0.1 seconds at most, and between the car-truck and truck-truck combinations the biggest difference was less than 0.05 seconds. This suggests that, at least when only considering traffic as a stream of passenger cars and trucks, the vast majority of a driver's selection of a headway time to maintain comes from his or her behavior rather than what type of vehicle he or she is following.

Accordingly, Figure 5 plots the histograms of headway distributions when cars are following, trucks are following, and the entire dataset. It is worth noting that the median headway values were consistently less than their corresponding mean values. The headway distributions are heavily skewed to the right (i.e. long tail to the right) even when limiting the sample to only vehicles in the range of potential following effects. Thus, when selecting a headway value to use in a microsimulation program, for example, the median of the distribution or the mode of a more finely binned histogram is a more appropriate representation of the center than the arithmetic mean. However, when estimating headways based on measured flow rates, the average headway equals the reciprocal of the flow rate, so the arithmetic mean of headways is generally used.

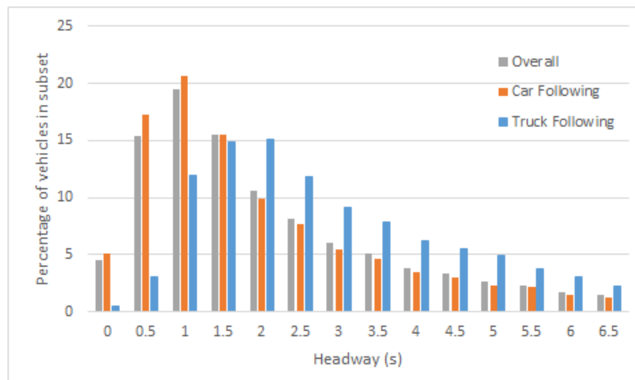

Figure 5 Histogram of Time Headways

B. *Standstill distance*

The results in this section reflect values from 26 stop-and-go incidents in cities throughout Iowa, which resulted in 803 standstill distance measurements. As more incidents are processed they can be compared to the results presented here and to each other to investigate the consistency among different driver populations and incidents. In particular, there are relatively few measurements which involved trucks so far.

There were some unusually high values (greater than 30 feet) which were measured; these were assumed to be the result of vehicles trying to perform a maneuver and not exhibiting following behavior. After the measurements greater than 30 feet were removed from the data, the mean standstill distance was 9.5 feet with a standard deviation of 5.0 feet and a median value of 8.6 feet. This indicates a right skewed distribution similar to the headway distribution, as shown in Figure 6. This makes sense intuitively because there is a physical limit to how close a vehicle can be to the vehicle in front of them, whereas there is no physical limit preventing vehicles from leaving much more space between them (e.g. as far as 28 feet as observed in the dataset).

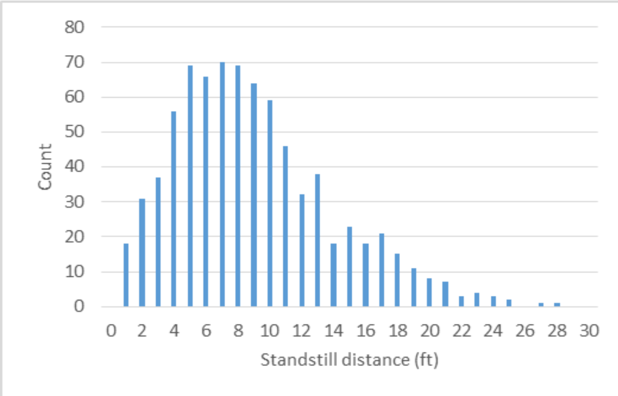

Figure 6 Histogram of Standstill Distance

When examining how the standstill distance compares among the different combinations of car and truck following, it can be seen that there is a marked difference between the car-car pair versus any pair involving a truck (Table 2). The car-car combination seems to leave much less space when stopped than when a pair involves trucks. The differences between car-car and car-truck/truck-car following are statistically significant at the 0.001 level using a two-sample t-test for unequal sample sizes. However, due to a small sample size of the truck-truck following, the difference between car-car and truck-truck following cannot be shown to be statistically significant at this time. There were no statistically significant differences between any other pair types,

Table 2 Summary statistics by following type for standstill distance

Pair Type: Lead-Follow	Count	Mean (ft)	Median (ft)	Std. Dev. (ft)
CC	737	9.22	8.51	4.78
CT	27	12.89	12.80	6.09
TC	32	12.40	9.99	6.94
TT	7	11.47	10.88	4.44

VI. CONCLUSION

With the increasing use of microscopic simulation software in traffic studies, it is important to collect accurate information regarding the driver behavior parameters used to calibrate such software. Two of the most important parameters for modelling freeways are the standstill distance and preferred time headway. In order to collect data on these parameters, instrumented vehicles or trajectory data have been used in the past. These methods provide a robust data set for analysis, but are costly and resource intensive to collect. This paper investigated an alternative method of collecting data on standstill distance and preferred time headway. For standstill distance, the process involved manually measuring the distance between vehicles in still images from video of stop-and-go traffic. For preferred headway time, roadside radar detectors were installed for one to two weeks to collect individual vehicle data. Overall, these methods are more economical alternatives to collect vehicle following behavior data.

The average standstill distance measured at 26 locations across Iowa (9.5 feet) differed dramatically from the default provided by the microsimulation software, VISSIM (i.e. 4.9 feet). This finding confirms the importance of calibrating the parameters at the study site and not simply using default values.

The average preferred headways were quite different depending on the type of vehicle which was following. When a car was following, the average was approximately 2 seconds, compared to around 3 seconds for when a truck was following. The leading vehicle type, however, did not have a noticeable effect on the calculated headways. The differences in headways based on the type of following vehicles are not always considered in microsimulation software, but could have a noticeable impact on traffic, especially in areas with high truck volumes.

Additionally, the standstill distance and headway distributions were fairly disperse with standard deviations in the range of one third to more than one half of the mean. This shows the importance of microsimulation software allowing such values to be supplied as distributions rather than applying them as constants to all vehicles in the simulation. The distributions of both standstill distances and headways are heavily skewed to the right, suggesting that the median of the distribution or the mode of the histogram is a more appropriate representation of the center than the arithmetic mean.

The methodology presented in this paper is limited to measuring only two driver behavior parameters, that is, the standstill distance and preferred time headway. If data regarding other parameters are desired, particularly those involving acceleration, instrumented vehicles or trajectory data are still likely required. Additionally, collecting data on standstill distance is still a time- and labor- intensive process. In future research, it is intended to apply image processing techniques to automate the process. Future research will repeat this process in different urban centers in Iowa to test the consistency of these parameters between different driver populations within the same state. The values from those locations will then be used as the basis of a procedure for calibrating the microsimulation software, VISSIM.

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