ABSTRACT

Title of Document: MODELING AND EMPIRICAL ANALYSIS OF TAILGATING BEHAVIOR OF DRIVERS

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This dissertation presents a microscopic study of tailgating behavior of drivers. There are very few studies focused on tailgating, although it is a serious issue for traffic safety. The reason for very few studies might be the fact that tailgating is a complex problem involving human behavior and kinematics of the vehicle and it is also equally challenging to collect naturalistic driving data relevant to tailgating.

Because this approach is empirical, we developed a sophisticated data acquisition system using an instrumented vehicle to collect naturalistic driving data. Data were collected on freeways in Maryland during times of moderate traffic flow. The instrumented vehicle was driven in a naturalistic way that was benign to the surrounding traffic. Tailgating events were detected using the empirical data and a model of safe following distance.

We tested and affirmed the hypothesis that tailgaters of short tailgating duration are more willing to follow at close following distances than those who tailgated for longer durations. We also tested and affirmed the hypothesis that following vehicle speeds are strongly influenced by lead vehicle speeds. We studied the causal relations between certain observable data from the lead vehicle and possible reactions in the following vehicle.

We contributed new estimates of driver reaction times, focusing on a subset of the population deemed to be tailgating at the time. We also conducted a new calibration of the well-known GHR car-following model that is specific to tailgating situations.

The data and method for collecting the data are contemporary and relevant to current modes of thinking in traffic flow theory. The results can contribute directly to models and parameter estimates in microscopic simulators. Many of the results would also be of use in the automotive industry, for the development of driver safety assistance systems and countermeasures. Finally, we think the results could be useful for driving instructors, to help students understand better this dangerous driving behavior. In the end, we hope that this study could help to improve traffic safety by reducing the number of crashes resulting from this behavior.

MODELING AND EMPIRICAL ANALYSIS OF TAILGATING BEHAVIOR OF DRIVERS

By

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This dissertation is dedicated to

my late father Kaji Shrestha

who taught me to be a good human being.

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TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

Chapter 1: Introduction

1.1 Background

Traffic accidents cause huge losses of life and property damages all around the world. In the United States, there were 10.4 million motor vehicle crashes in 2006, out of which 38,648 were fatal crashes killing 42,708 people (U.S. Census Bureau, 2008 and FARS, 2006) Motor vehicle crash was a leading cause of death for people aged 3 through 33 in the United States in 2002 (Subramanian, 2005). This dissertation is concerned, in a broad sense, with tailgating behavior of drivers. With that in mind, it is interesting to note that approximately 29.7% of all vehicle crashes were rear-end crashes in 2000 (NHTSA, 2003). Similarly, rear-end crashes accounted for approximately 25% of all police-reported crashes and 5% of all traffic fatalities in 1996 (NHTSA, 1999). This is relevant because rear-end crashes are the most likely accidents to result from driver errors associated with tailgating behavior.

More specifically, the rear-end crash is a common type of crash which is caused by one vehicle colliding with the rear of another vehicle when both vehicles are in the same lane and moving in the same direction. Most of these rear-end collisions happen because drivers follow the vehicle in front of them too closely, and then some combination of deceleration on the part of the lead vehicle and/or inattention on the part of the follower leads to a collision. The behavioral pattern of following too closely is colloquially known as tailgating. This is a form of aggressive driving, which is a serious concern to traffic engineers, traffic safety experts and police.

According to a NHTSA study (1999) tailgating caused 1% of all the crashes in 1996. Although 1% seems to be a low percentage rate, since there are more than 10 million traffic accidents that happen annually, even 1% of the total number becomes significantly high. This is equivalent to at least 285 crashes per day on average due to tailgating (U.S. Census Bureau, 2008). So, the losses caused by tailgating related crashes are significant. To make some contribution in the areas of tailgating, this research is focused on the study of tailgating behavior of drivers.

As stated above, more than 100,000 crashes occur per year due to tailgating. We present an approach to study this problem that can be called "microscopic" in the sense that we measured and modeled the behavior of individual vehicles in conditions where tailgating was likely to occur. The study of tailgating involves the study of human behavior as well as the kinematics of vehicles. Human behavior is complex and poorly understood and hence a careful empirical study is required. Thus, this research focused on empirical studies and modeling of the tailgating behavior of drivers. We determined the patterns and situations most prone to tailgating and attempted to measure statistically its propensity within the traffic stream. Armed with this information, one would certainly understand better the traffic conditions that give rise to tailgating. It would also be possible to use these data to help build countermeasures or warning systems into vehicles. Automobile manufacturers currently invest a lot of effort into developing driver assist systems and driver safety systems, and the results of this research could be directly beneficial to that effort. The outcome of this study would also be useful for traffic safety experts, traffic enforcement agencies, traffic engineers and driving instructors to deal with the problems of tailgating and aggressive driving. It would also be useful to those involved in development of rear-end crash avoidance system since this study provides a better understanding of driver's following behavior particularly tailgating.

1.2 Research Objectives

The goal of this research was to conduct a microscopic study of tailgating behavior of drivers by developing a mathematical model using vehicle kinematics and human behavior to distinguish tailgating from normal driver behavior, to measure its frequency and other characteristics, and to determine the conditions most likely to produce it. The models are built with the aid of a considerable amount of detailed data from field experiments with real vehicles in real traffic situations. We measured the actual distance between two consecutive vehicles with high frequency. Using a model of the minimum safe distance between the vehicles we were able to compare the measurements with the model results to determine if the following vehicle was tailgating. Then we examined various parameters such as speed, following gap, following duration, acceleration, etc. during tailgating for microscopic study of tailgating. The data necessary to identify tailgating from the model were distance between the vehicles, speeds of the lead and following vehicles, the perception and reaction time of drivers, and road friction factors. We used the values of some variables such as perception and reaction time and road friction factor from past studies. But, we collected data such as distance between vehicles, distance traveled, relative speed between two vehicles and video data by field experiments using an instrumented vehicle.

The instrumented vehicle was equipped with sensors including a Distance Measuring Instrument (DMI) with differential GPS, an infra-red radar sensor and a digital video camcorder. A laptop computer with custom-written software to connect all of the sensors and the vehicle's Controller Area Network (CAN) was used to acquire data. In the field experiments, the instrumented vehicle served as a lead vehicle, and it was driven in a naturalistic way with the flow of traffic. Data were then collected from the lead vehicle and from various anonymous vehicles following the lead vehicle. The objectives of the study were as follows:

- Develop a mathematical model to identify tailgating behavior on the part of a driver, as a function of vehicle dynamics, external factors affecting stopping distance, and elements of human behavior.
- Identify the data necessary to calibrate and validate such a model, and to conduct other detailed inquiries into microscopic driver behavior.
- Identify necessary hardware such as sensors and instruments to collect the data.
- Build an instrumented vehicle platform with all necessary sensors and instruments to collect these data. In this case, a research vehicle from Nissan was already available, and it had been used for some previous studies that involved the collection of similar data, although additional sensor measurements and software modifications were necessary.
- Develop software to acquire all of the data from the instrumented vehicle. The software was required to connect and synchronize all sensors, as well as the in-vehicle CAN. Conduct field experiments using the instrumented vehicle to collect the required data about the lead vehicle and a number of anonymous following drivers who were not aware that they were participants in the experiments.

- Analyze the empirical data: to find out the situations and patterns of tailgating and to measure its propensity within the traffic stream, to find out the causal influence and relationship between the following and the lead vehicles in tailgating situation
- Investigate the behavioral patterns of tailgating drivers and relating that to potential risk-taking willingness on the part of those drivers.

1.3 Benefits

This research explored the tailgating behavior of drivers, which will be a valuable input to develop a mitigation plan and a system for avoidance of rear-end collision of vehicles due to tailgating. Identification of situations and patterns prone to tailgating will help to effectively address at least part of the problem of aggressive driving. The findings of the study will also help to educate drivers and eventually reduce the crashes caused by tailgating. Since it is an empirical study collecting data from anonymous drivers in natural driving environment, it will give more realistic results than what might be expected from driving simulators or controlled experiments.

1.4 Organization of Dissertation

The remainder of this dissertation is organized into 6 chapters. A survey of existing literature on tailgating and related areas of traffic engineering is given in Chapter 2. The proposed research methodologies are given in Chapter 3, which include the modeling, the make-up of the instrumented vehicle used to collect data and the necessary hardware and software developments and modifications in the existing instrumented vehicle. The data collection method, calibration of the sensors of the instrumented vehicle and field experiment to collect data are described in Chapter 4. This chapter also explains the plan and procedures for data collection. Chapter 5 describes the data analysis procedures and the results of the data analysis. Chapter 6 contains the conclusions and some ideas about future research directions.

Chapter 2: Literature Review

The areas of traffic engineering, most relevant to this research include tailgating, safe following distance, driver's perception and reaction time, rear-end collision avoidance, and car-following behavior. The available literature on these subjects is summarized here, including existing limitations and opportunities for new contribution that this research proposal is intended to address. This chapter is divided into four sections. The first section presents a review of literature on safe following distance followed by a discussion on perception and reaction times of drivers. Some of the relevant contributions to the car-following literature are reviewed in section three; whereas section four presents a review on rear-end collision avoidance.

2.1 Safe Following Distance

In traffic engineering, the separation between two consecutive vehicles can be expressed in terms of the headway, which is the temporal interval between the two successive moving vehicles. In particular, the headway is defined as the elapsed time between the front of the lead vehicle passing a point on the roadway and the front of the following vehicle passing the same point (Evans et al. 1983). The safe headway is a headway which a driver should maintain to avoid rear-end collisions. Various factors such as speed, road surface condition, brake intensity, brake technology such as Antilock Brake System (ABS) and driver's perception and reaction time might affect the safe headway.

Given vehicle speeds and an assumption that (at least briefly) speeds remain constant, headways can be converted to distances between consecutive vehicles, measured at equivalent points on both vehicles. By subtracting the length of the lead vehicle, then, the bumper-to-bumper distance between the vehicles can be measured. The safe following distance can be defined as the gap or distance between the two consecutive vehicles which will allow the following vehicle to slow down or stop without colliding with the leading vehicle in case the leading vehicle slows down or stops.

Some driver-training programs (National Safety Council, 1992 and Tennessee Department of Safety, 1991) state that the recommended headway for safe following is 2 seconds. Many drivers, however, maintain headways considerably less than 2 seconds, and this behavior is an example of what might be referred to as 'tailgating.' Thus, the headway between vehicles is sometimes used as a simplistic definition of tailgating in many studies. In this study, we consider various factors to precisely define tailgating rather than just considering the headway. These factors are explained in the following paragraph.

The safe following distance can be said to be bounded below by the safe stopping distance. The safe stopping distance is a distance sufficient enough to allow the following vehicle to stop without colliding into the lead vehicle when the lead vehicle stops unexpectedly. Figure 1 shows the safe following distance in a time space diagram. The factors that affect the stopping distance are the speeds of the lead and following vehicles, both drivers' braking intensity, the condition of the road surface (for example, dry or wet) and the following driver's perception and reaction time. One possible definition of tailgating is whenever a following driver does not maintain the safe following distance.

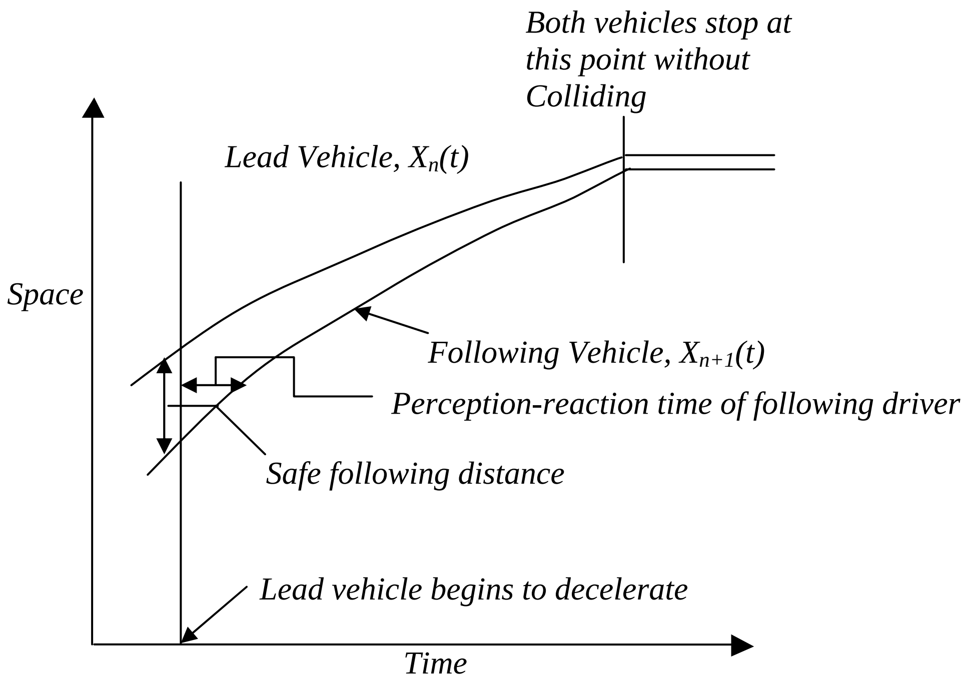


Figure 1: Safe Following Distance

Pipes (1967), in one of the earliest studies of how drivers follow each other, assumed that the vehicles moving in a line obey a postulated following rule suggested by a rule of thumb often taught in driver training, which is to allow one additional car length in front of the subject vehicle for every 16 kmph or 10 miles per hour (mph) of speed. By the application of this postulated following rule, he proposed a simple linear equation in which the car spacing is a linear function of speed of the following vehicle.

$$x_l - x_f = b + \tau \dot{x}_f + L_l \qquad (1)$$

where x_l is the position of the front of the lead vehicle, x_f is the position of the front of following vehicle, b is the minimum distance between the vehicles when stopped, τ is the time gap prescribed by the postulated traffic law, $\dot{x}_f$ is the speed of following vehicle and L_l is the length of the lead vehicle. For example, if the rule of thumb is to allow 15 feet for every 10 miles per hour, τ would be

$$\frac{15'}{10mph} \times \frac{1mile}{5280'} \times \frac{3600\sec}{hour} \cong 1.0227\sec$$

If equation (1) is differentiated with respect to time, the result is as follows:

$$\dot{x}_l - \dot{x}_f = \tau \ddot{x}_f \qquad (2)$$

In the integral form, (1) describes the desired steady state according to this law. In the differential form, equation (2) shows how the following vehicle should behave to maintain equation (1), i.e. (2) can be interpreted as a control policy. The problem is that equation (2) cannot be applied in general as a traffic law, because it only serves to keep those pairs of vehicles in equilibrium that were in equilibrium to begin with. In fact, all linear models would suffer from this same problem. Since the derivative of equation (2) is independent of the constant terms of the equilibrium spacing rule, equation (1), any initial condition would produce the same following behavior for the same speed profile of the lead vehicle, including a spacing that was far too close (after a lane change, perhaps) or too distant (in which case the interaction between the vehicles might be weak or nonexistent). Pipes did not study the drivers' behavior where the drivers, finding themselves in an "out-of-equilibrium" status, might seek to return to an equilibrium state.

In some studies, the assumed stimulus for the lead vehicle is a "brick wall stop," i.e. one where the lead vehicle comes to a stop instantaneously (carefully sidestepping the laws of physics). At this extreme, the stopping distance should vary with the square of the vehicle speed. If a more realistic model is assumed for the lead vehicle, the appropriate relationship is probably linear, although with a proportion bounded by the most significant difference in braking performance between the two vehicles. Sometimes the extreme case is adopted to avoid having to make this determination, but empirical evidence suggests that drivers are following more closely than this assumption would require. Kometani and Sasaki (1961) modified the linear model to accommodate that consideration and expressed the vehicle spacing by a quadratic relation of speeds of the lead and following vehicles. They introduced a time lag T (perception and reaction time of a driver) in the model and assumed that a driver chooses his speed at time $t+T$ based on the spacing observed at an earlier time t. Their model is given by the following equation:

$$\Delta x(t-T) = \alpha v_l^2 (t-T) + \beta_1 v_f^2 (t) + \beta v_f (t) + b_0 \qquad (3)$$

Studies on headways are good sources of information on following distances of drivers on urban freeways. Michael et al. (2000) describes a method to collect headways from video observation. They videotaped traffic flow for about an hour for four sessions in the morning and four sessions in the afternoon. They recorded 25,000 headways in free flow traffic. They found the average headway as 2.11 sec, which is higher than the recommended minimum headway in the driving manuals. They also collected headway data after using two hand-held signs warning drivers not to tailgate to see the impact of such signs on drivers' behavior. With the use of signs the average headway was 2.29 sec, which is an increase of .18 sec or 8.5%. They also found that 49.4% drivers complied with the 2 sec headway rule when the sign was not used compared to 57.5% when the sign was used, an increase of 8.1% with the use of signs. So, about 50% of the observed headways were less than 2 sec when the signs were not used. They classified drivers as tailgating if the headway was less than 2 sec. According to that criterion, however, half of the drivers were tailgating and this seems to be impractical. Thus, the 2 sec headway limit for defining tailgating seems not to be realistic. Another small limitation was that they did not account for pavement conditions (via a friction factor) in calculating the safe headway.

Taieb-Maimon and Shinar (2001) conducted a field experiment to evaluate drivers' actual spacing in car-following situations and their relationship to the drivers' perception and reaction time. The experiment was conducted during the daylight hours of clear summer days on a 20-km segment of a 4-lane divided highway near Tel-Aviv, Israel. Thirty human drivers participated in the experiments. Both the lead and following vehicles were driven by these drivers. A laser-based device was installed on the dashboard of the following vehicle to measure the distance between the lead and following vehicles and speeds of the lead and following vehicles.

The lead driver was asked to maintain a constant speed of 50, 60, 70, etc. km per hour whereas the following driver was asked to approach the lead vehicle until he reached a minimum safe gap. They obtained the time headway by dividing the gap (bumper-to-bumper distance between lead and following vehicles) by the speed of the following vehicle. This definition of headway is slightly different than what was described above, because the length of the lead vehicle is not accounted for. Using their definition, they found that the average safe headway is 0.66 second and that over 90% of the drivers maintained gaps below 1.0 second. One would have to know the lengths of the vehicles and their speeds in order to convert these results to the more typical definition of headways.

Their experiment might not have given realistic results because both the lead and following drivers were participants who were aware of the field experiment. Also, as they conducted their experiment only in clear weather, they did not have any data for wet road conditions. They also did not consider the effect of the friction factor on safe headways. They assumed that the speed difference between the lead and following vehicles were negligible.

Safe following distance may also depend on the braking behavior of a driver. The study conducted by Brunson et al. (2002) used three categorical terms: *normal*, *comfortable hard*, and *hard* for representing the application of brakes. The braking intensity is expressed as a fraction of the gravitational acceleration, *g*. The study also indicated that at speeds of 30, 45 and 60 mph or 48, 72 and 96 kmph, the actual deceleration value estimates were –0.36, -0.41 and -0.46*g*, respectively. The following driver's behavior, in anything but an extreme emergency, depends on their personal preferences for braking deceleration, as well as their driving skill. In extreme situations, however, physics probably does all the work.

2.2 Perception and Reaction Time

When a driver sees a stopping or slowing lead vehicle, he will either decelerate his vehicle by pressing the brake pedal or he will change lanes. This proposal is concerned primarily with the behavior of vehicles that choose to, or are forced to remain in their lane, even under these circumstances. The time elapsed from the moment the driver sees the slowing lead vehicle or the onset of the brake lights of the lead vehicle, to the moment he begins to press the brake pedal is known as the perception and reaction time. The perception and reaction time does not include vehicle response time, which is the time from application of the brakes to its result, i.e. slowing down or stopping of the vehicle. This time is small but not zero, as it includes the time necessary for brake pressure to build up and be transmitted to the brakes, time for the calipers to engage, etc. In studies of automated driving in tight platoons, for example, this time is not negligible, but for human drivers it is much smaller than the other components of delay involving the brakes.

The perception and reaction time varies for drivers of different age groups. Summala and Koivisto (1990) found that older drivers' (56+ years) perception and reaction times were 0.3 sec longer than those of younger drivers (18-30 years). They conducted experiments with controlled urgency where a police officer forced un-alerted drivers to stop. Distractions such as using a cell phone or talking to passengers may also cause some delay in perception and reaction of a driver.

The perception and reaction time is expected to be shorter for expected events than that for unexpected events (Summala, H., 2000). Drivers may be more attentive in high-density traffic flow with smaller headways than in low-density traffic flow with longer headways. Hence, it will be interesting to observe the variation of the perception and reaction time with traffic density. The average driver's perception and reaction time was assumed to be 1.5 seconds according to Brunson S. J. et al. (2002).

Taieb-Maimon and Shinar (2001) found the average perception and reaction time 0.47 seconds measured under optimal laboratory conditions. They conducted the experiments in a laboratory simulator, which consisted of a mockup of the rear of a vehicle with original rear brake lights and a center high-mounted stop lamp. The test driver was seated in a vehicle console with accelerator and brake pedals about 3.5 m (11.5 ft) from the mockup vehicle. In this experiment, the participants knew they were in a timed experiment and they knew ahead of time what the stimulus would be. This would highly alert the drivers and hence would enable them to hit the brake more quickly than in the naturalistic driving situation. As a result, one might consider that this experiment captured only a single component of the normal perception and reaction chain of events. Hence, these results cannot be compared directly to measurements from experiments designed to replicate real-life situations with unknown and unexpected braking stimuli.

Green (2000) found that when fully aware of the time and location of the brake signal, drivers could detect a signal and move the foot from the accelerator to the brake pedal in about 0.70 to 0.75 sec. Response to unexpected but common signals, such as a lead car's brake lights, was about 1.25 sec, whereas reaction times for surprise events, such as an object suddenly moving into the driver's path, were roughly 1.5 sec. However, these times are varied somewhat by other factors, including driver age and gender. Summala (2000) suggested that un-alerted drivers were able to react to an obstacle by braking at an average range of 1.0 to 1.3 sec, depending on the site. In their functional definitions for a Forward Collision Warning System (FCWS), the National Highway Traffic Safety Administration assumed (NHTSA 1999) that the driver perception and reaction time prior to a crash alert should be 1.52 sec, based on the 95th percentile driver perception and reaction time from a surprise braking event study.

From the above literature, we observed that the perception and reaction time was found in a range from 0.5 sec to 1.52 sec by various researchers. There are many factors that affect the perception and reaction time such as the age of the driver, traffic density, visibility of vehicles ahead and other distractions such as talking to passengers or use of cell phones. However, there are no studies which specifically describe the impact of such distractions on the perception and reaction time.

All of the studies cited here tried to collect perception and reaction time data in a controlled environment such as a simulator or from experiments where drivers knew they were participants of the experiment. Such data cannot represent naturalistic behavior since drivers would be in high alert in such an environment. In this study, we obtained data from anonymous drivers who should have been driving in a naturalistic manner rather than in a controlled environment. These data may be useful to form more realistic estimates of the distribution of perception and reaction time across drivers, as well as variations that might exist within the same driver.

2.3 Rear-end Collision Avoidance

This study on tailgating behavior of drivers is aimed at shedding light on important issues to mitigate rear-end collisions. Tailgating is one of the main causes of rear-end collisions. The auto industries and research institutes have conducted a number of studies in development of rear-end collision avoidance systems, which are summarized below.

Brunson et al. (2002) at the Johns Hopkins University Applied Physics Laboratory developed an algorithm to issue collision alerts that allow the driver of a following vehicle to stop or approach no closer than a designated distance behind a stopped or decelerating lead vehicle. They considered 3 scenarios: 1) stopped lead vehicle, 2) slower lead vehicle and 3) braking lead vehicle. A Field Operational Test (FOT) was conducted with the algorithm installed in a test vehicle equipped with the Automotive Collision Avoidance System (ACAS), a prototype collision warning system developed by General Motors. The primary input parameters were test vehicle speed and acceleration, relative acceleration, distance and relative speed. The decision to issue an alert is made every 100msec upon parameter updates by the collision warning system. The tailgating mode provides cautionary alerts based on distance to advise the driver that deceleration by the lead vehicle would require a quick braking response.

NHTSA (1999) evaluated Forward Collision Warning (FCW) systems, based on algorithm developed by Brunson et al. explained above, that provide alerts to drivers to avoid rear-end collisions. Tests were executed with off-the-shelf laser- and radar-based FCW systems at the General Motors (GM) Proving Ground in Milford, Michigan and at the

Transportation Research Center in East Liberty, Ohio. The FCW systems were designed for light vehicles (passenger cars, light trucks and vans). The two fundamental driver behavior parameters considered were: 1) how hard the driver will apply brake in response to the alert (i.e. driver deceleration behavior) and 2) driver's reaction time to the crash alert. They obtained a wide variety of deceleration-based and time-based (e.g. time-to-collision) driver performance measures from over 3,800 last-second braking trials. Drivers were asked to wait to brake until the last possible moment in order to avoid collision with the surrogate target. These last-second braking judgments were made while approaching the surrogate target under a wide range of speed (30 to 60 mph) and lead vehicle deceleration conditions (0 to –0.39*g*). The deceleration values were estimated to be –0.36, -0.41 and –0.46*g* at speeds of 30, 45 and 60 mph or 48, 72 and 96 kmph, respectively.

Zheng and McDonald (2004) studied the collision warning timing, which can be used to create an alert in collision warning systems to enable drivers to take evasive actions compatible with normal driving behavior. Such an alert would help drivers to react without using an emergency braking maneuver, which likely jeopardizes driving safety and comfort. The driving behavior data were collected using an instrumented vehicle equipped with a brake movement sensor and a laser speedometer. Thirteen drivers were involved in the experiments and they collected 8000 datasets for braking events. The collision warning timing was determined based on necessary deceleration rates. They found that not all collisions could be avoided even using maximum braking capacity when warning timing is based on an intended deceleration of 0.3g. They found that the collision warning timing could be significantly affected by the assumption of the behavior of the leading driver. Hence, they would not be able to generate reasonably accurate collision warning, as it is hard to assume the behavior of the leading driver. They considered only braking behavior of driver for collision warning but did not consider the tailgating scenario.

Kim (2005) identified similar distribution issues both across and within drivers, and conducted instrumented vehicle tests with anonymous subjects to quantify these parameters. This implies that collision warning timing can be configured for specific traffic conditions and individual drivers, either by an adaptive mechanism or through user interfaces.

Many rear-end collisions are caused by tailgating behavior. However, the above studies did not extensively study the tailgating behavior of drivers. Brunson et al. (2002) mentioned that the following vehicle should maintain a designated distance behind a decelerating lead vehicle, which is a factor of tailgating, but they did not elaborate on it. The other authors focused on braking behavior in response to collision warning but did not study the tailgating behavior of drivers.

2.4 Car-following Behavior

Tailgating is one of the aggressive car-following behaviors of a driver. However, most past car-following studies have been concerned with quantifying parameters of various normal driving rules, without regard to this exceptional behavior. Many drivers tend to keep a comfortable gap from the vehicle in front of them. The following driver's acceleration or deceleration action depends upon the proximity to the lead vehicle and its speed. Chandler et al. (1958) put forward the first prototype of a mathematical car-following model in 1958 at the General Motors research labs. This was based on an intuitive hypothesis that a driver's acceleration was proportional to the relative speed or deviation from a fixed following distance, which could itself be speed-dependent. The Gazis-Herman-Rothery (GHR) model is perhaps the most well known model and dates from the late fifties and early sixties (Gazis et al., 1961). Their formulation was as follows:

$$a_f(t) = c[v_f(t)]^m \frac{\Delta v(t-T)}{[\Delta x(t-T)]^l} \qquad (4)$$

where a_f is the acceleration of the following vehicle implemented at time *t* by its driver, and it is proportional to v_f**,** the speed of the *following vehicle*, and Δx and Δv, the relative spacing and speeds, respectively, between following and lead vehicles, assessed at an earlier time *t*-*T***,** where *T* is the driver reaction time. The constants *m*, *l* and *c* are calibration parameters. The analysis of the resulting data showed that the results were not as sensitive to the relative distance Δx as might have been expected.

Gazis, Herman and Potts (1959) attempted to derive a macroscopic relationship describing speed and flow using the microscopic equation as a starting point. The mismatch between the macroscopic relationship they obtained from the microscopic equation, and other macroscopic relationship in use at the time, led to the hypothesis that the algorithm should be amended by the introduction of a $1/\Delta x$ term into the sensitivity constant $(c \to c/\Delta x)$, in order to minimize the discrepancy between the two approaches. This gave a model with *m*=0 and *l*=1.

Edie (1960) attempted to match the m=0, l=1 model to new macroscopic data in a manner similar to Gazis et al., finding that another amendment should be made to the sensitivity constant, the introduction of the velocity dependent term. This produced a new model with m=1 and l=1. Edie's formulation was found to be better at low flow due to its ability to predict a finite speed as density approaches zero. This suggested that two separate relationships could be used in the description of traffic flow, one for congested and other for non-congested traffic.

Several investigations occurred during the following 15 years, in the attempt to define the 'best' combination of m and l. May and Keller (1967) found optimal integer solutions of m=1 and l=3, (or assuming non-integer values, m=0.8 and l=2.8 with scaling constant of approximately 1.33×10^{-4}). Heyes and Ashworth (1972) used as stimulus $\Delta v^2 / \Delta x^2$ and the sensitivity constant as the time headway Δt^P. This constant was evaluated using data from the Mersey tunnel in the UK, corresponding to m=-0.8 and l=1.2. Cedar and May (1976) found optimum values of m=0.6 and l=2.4. They acknowledged the "two regime" approach; for the uncongested regime m=0 and l=3 and for the congested regime m=0 and l=-1. Treiterer and Myers (1974) used airborne film footage of a flow breakdown to monitor the paths of a large number of vehicles, from which they determined v and Δx. They used separate analysis for acceleration and deceleration phases of car-following, the acceleration phase with m=0.2 and l=1.6 and the deceleration phase with m=0.7 and l=2.5. Hoefs (1972) similarly found m=1.5 and l=0.9 for accelerating vehicles, m=0.2 and l=0.9 for decelerating vehicles without braking, and m=0.6 and l=3.2 for decelerating using brakes. Since the late 70's the GHR model has seen less and less investigation because of the large number of contradictory findings for the values of m and l; however, two studies by Aron and Ozaki are notable. Aron (1988) used an instrumented vehicle to collect car-following data in various conditions in Paris. The 60 min data was collected at an average speed of only 25 kmph and a spacing of 14m. He found m=0.655 and l=0.676 for deceleration, m=0.26 and l=0.5 for the steady state, and m=0.14 and l=0.18 for acceleration. Ozaki (1993) used 90 min of data extracted from video film taken of a motorway from the 32nd floor of a city office building. He got a 160m field of view and data were obtained on the passage of a total of 2000 vehicles. He found the optimum values as m=0.9 and l=1 for deceleration and $m = -0.2$ and l=0.2 for acceleration.

The GHR model is not used these days because of the following two main reasons. Firstly, following behavior is likely to vary with traffic and flow conditions and secondly, many of the empirical investigations have taken place at low speeds or in extreme stop- and-go conditions, which may not reflect more general car-following behavior. All the car-following studies mentioned above tried to establish a car-following model to present following behavior of drivers. These studies considered macroscopic as well as microscopic car-following behavior and studied the relevant parameters trying to find out optimum values for them.

Del Castillo et al. (1994) modified Payne's car-following model by including reaction time. They found that the perception and reaction time is a decreasing function of the density. They found the perception and reaction time remains almost constant at a low value of the order of 0.6 sec at high densities. At low densities, driving becomes looser and the reaction time becomes larger than at high densities tending to infinity as density decreases, which means there is almost no interaction between drivers.

One possible explanation for the variance in calibrated values of the model parameters is that while only one model form is postulated, perhaps there are multiple car-following regimes that vehicles might find themselves in. While some of the studies differentiated between acceleration, steady flow, and deceleration, there may be even more strata than that to consider, particularly dealing with the overall congestion level that the vehicles find themselves in. Tailgating might be thought of as one of these car-following behaviors; however, it is not studied extensively in any of these studies. It is our belief that it is a key behavior of drivers concerning car following and traffic safety.

2.5 Summary

Past studies have not focused extensively on tailgating behavior of drivers. Some studies considered such factors as headway, stopping distance and driver's perception and reaction time that influence tailgating. Some car-following studies mentioned the possibility of a tailgating situation while explaining the car-following behavior of a driver. However, these studies could not illustrate tailgating behavior in a naturalistic manner as it happens in the real world. Minimum headway is not the most effective measurement of tailgating, because other confounding behaviors such as lane changing (or preparation to do so) can corrupt the understanding. So, it is not appropriate to judge whether the driver is tailgating or not based solely on headway. Safe following or stopping distance would be a better parameter to describe tailgating. Some studies derived the safe following distance based on the speed of the following vehicle and driver perception and reaction time whereas some considered the relative speed between the lead and following vehicles. To define tailgating precisely, it is important to determine the safe following distance very accurately and in an empirical setting. It is deemed necessary to consider various parameters such as speeds of lead and following vehicles, the friction factor, driver's braking behavior and perception and reaction time of driver to find out safe following distance accurately.

Chapter 3: Research Methodologies

Having hypothesized that tailgating exists and is an important component of some drivers' car-following behavior, one of the next logical steps is to investigate detailed data on car trajectories to look for this behavior and to study it. It is important to determine whether a following vehicle is tailgating or not in order to study the tailgating behavior, because tailgating might be one of those maneuvers that need to be distinguished from other car-following activities in order to properly calibrate multi-regime models. How then to determine if a vehicle is tailgating or not? In general terms, tailgating may be described as following too closely. But how close is too close? Some convention wisdom suggests that there should be one car length distance for every 10 miles per hour of speed. But this is not an accurate method of measuring safe distance as there are also other factors which affect the safe following distance in addition to speed. Tailgating may be an on-and-off activity rather than a continuous one-time activity. So we should be able to detect when the driver starts and ends tailgating. We developed a mathematical model to detect tailgating. We considered vehicle dynamics, external factors which affect the stopping distance and driver's behavior to develop our model.

The various tasks performed in this study including formulation of the mathematical model for detecting tailgating are given in Figure 2.

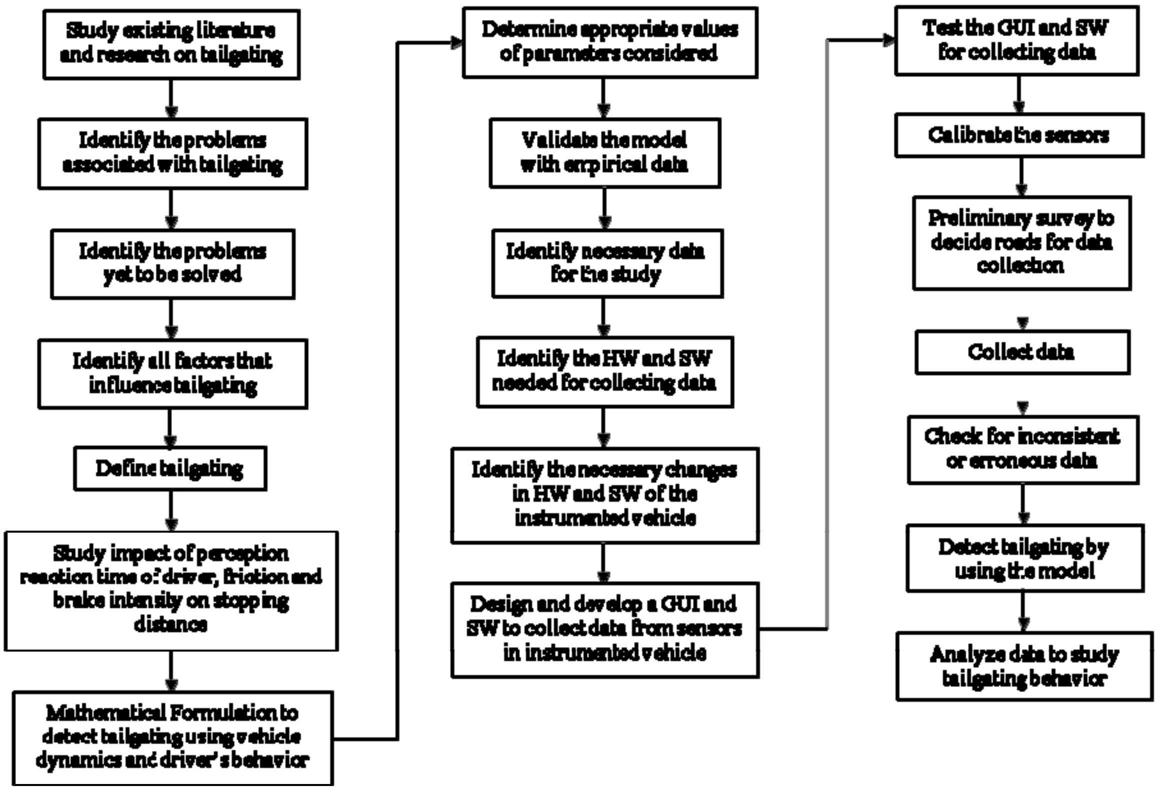


Figure 2: Flow Chart of Research Tasks

3.1 Modeling

It is colloquially understood among drivers that if a driver follows another vehicle too closely, that driver is said to be tailgating. Tailgating is one of the aggressive driving behaviors. For our purposes, however, a more precise definition is required. In this research, the following definition of tailgating is proposed.

When the stopping distance of the following vehicle becomes equal to or greater than the sum of the stopping distance of the lead vehicle and the spacing between the following and lead vehicle, the following vehicle is said to be tailgating. The stopping distance of the *following vehicle includes the distance traveled by the following vehicle during perception and reaction time*.

The most subjective part of this definition is the stopping distance. We considered stopping distance to be a function of speed, perception and reaction time of the driver, brake intensity, and friction between the vehicle and the road surface.

The activation of the brake light of the leading vehicle acts as a stimulus to the driver of the following vehicle. A slowing lead vehicle can also be a stimulus for the following driver to slow down or stop his vehicle, even if brake lights are not visible, provided the deceleration can be detected by the following driver. The expected response of the following driver is to decelerate, which can be done either by removing the foot from the accelerator, whereby allowing it to decelerate by gravitational (if on a hill) and frictional force, or by applying the brakes. Since deceleration by brake is more severe, it is more likely to play an influential role in tailgating and collision avoidance behavior.

We assume that the following driver is reacting to the brake lights immediately ahead, although in reality drivers sometimes have a sequence of brake indications from the vehicles ahead of them to provide stimulus. This type of stimulus is known as multi-anticipation in car-following theory. In any event, the time elapsed from the moment the driver perceives the stimulus to the moment he slows down his vehicle either by applying the brake or decelerating by other means is known as the perception and reaction time of the driver.

The perception and reaction time used for highway design standards by the American Association of State Highways and Transportation Officials, AASHTO (2001) is 2.5 sec, with 1.5 sec for perception and 1.0 sec for making the response. According to a NHTSA Technical Report (NHTSA, 1999), the perception and reaction time of drivers to apply the brake is 1.52 sec, based on the 95th percentile of drivers' brake reaction time. Researchers came up with various perception and reaction times of drivers. Sivak et al. (1982) found the median perception and reaction time as 1.38 sec out of 277 sample data where drivers applied the brake in response to the brake light. Summala and Koivisto (1990) found the perception and reaction time for young drivers (18-30 years) as 1.65 sec and for old drivers (56+ years) as 1.95 sec. Lerner (1993) found the mean perception and reaction time as 1.5 sec out of 116 sample data where drivers applied the brake in response to a surprise rolling of a trash barrel on a chain into the road. Hankey (1996) observed 1.55 sec as the perception and reaction time from his road experiments. Van Winsum and Brouwer (1997) carried out experiments using a simulator to find perception and reaction time to pressing the brake pedal in response to the brake light. They found the perception and reaction time to be 1.35 sec. The perception and reaction time of 1.52 sec proposed by NHTSA seems to be in line with the results from various studies.

I. Stopping Distance

How to find the stopping distance using vehicle kinematics is explained here. When a driver applies brake to stop his vehicle, a frictional force develops due to friction between the tires and road surface. This frictional force must work to reduce the vehicle's kinetic energy to zero in order to stop the vehicle. If the wheels of the vehicle continue to turn while braking, then static friction is working, but if the wheels are locked and sliding over the road surface, then the braking force is a kinetic friction force only.

Condition to stop the vehicle: Work due to friction = Kinetic energy

The above condition can be written as following in a mathematical expression. We introduce k coefficient of deceleration to take account of the intensity of braking and μ coefficient of friction in deriving work due to friction.

$$m\mu kgd = \frac{1}{2}mV^2 \qquad (5)$$

Rearranging (5) we get, $$d = \frac{V^2}{2\mu kg} \qquad (6)$$

Where,

V is speed

m is mass of the vehicle and

g is acceleration/deceleration due to gravity

In equation (6), d is the stopping distance of a vehicle. But we also need to consider the distance traveled by the vehicle in perception reaction time of the driver and this is given as follows:

$$d_{PR} = VT_{PR} \qquad (7)$$

Thus the stopping distance of the vehicle is given by combining (6) and (7).

$$D = VT_{PR} + \frac{V^2}{2\mu kg} \qquad (8)$$

II. Stopping distance of the following vehicle:

We derive the stopping distance following the above concept. The stopping distance of the following vehicle is the sum of the distance traveled during the perception and reaction time of the driver and the distance traveled from the time the brake is applied to the time the vehicle comes to a complete stop. Deceleration is expressed as a fraction of *g*, which is the acceleration due to gravity, since only frictional braking is possible with automobiles. Some drivers might apply the brake hard and some might apply it in a more moderate manner. We expect that the intensity of braking varies from person to person and is different in different situations. In our model, the brake intensity is represented by $\boldsymbol{k_f}$ which also can be thought of as the coefficient of deceleration. Since no driver would be able to apply the brake to stop immediately with 100% brake performance, the value of $\boldsymbol{k_f}$ should be less than 1. The deceleration rate is obtained by multiplying *g* by $\boldsymbol{k_f}$, which is a coefficient of deceleration. Friction between tires of a vehicle and road surface provides some resistance to the motion of vehicle. Coefficient of friction, μ is used to take into account of this frictional resistance. The stopping distance for the following vehicle can be expressed mathematically as follows:

$$D_f = V_f T_{PR} + \frac{V_f^2}{2\mu_f k_f g} \qquad (9)$$

where,

V_f - speed of the following vehicle at the time of the hypothetical stimulus

T_{PR} – perception & reaction time of the following driver to apply brake

k_f – coefficient for deceleration for the following vehicle ($k_f <= 1$)

μ_f – coefficient of friction between the tires and road surface

g – acceleration due to gravity

III. Stopping distance of lead vehicle**:**

In this research, the stopping distance of the lead vehicle is the distance that would be traveled by the lead vehicle from the time the brake is applied until the vehicle stops. The perception and reaction time of the lead driver is not considered here since the reaction mechanism of a following driver is initiated when the brake lights of the lead vehicle are perceived. Mathematically, the lead vehicle's stopping distance can be expressed as:

$$D_l = \frac{V_l^2}{2\mu_l k_l g} \qquad (10)$$

where,

V_l - speed of the lead vehicle at the time of the hypothetical stimulus

μ_l - coefficient of friction between the tires and road surface based on vehicle type and road surface condition

k_l – coefficient for deceleration for the lead vehicle ($k_l <= 1$)

g – acceleration due to gravity

III. Condition for tailgating**:**

A vehicle will be considered tailgating when its stopping distance is larger than or equal to the sum of the stopping distance of the lead vehicle and the spacing between the two vehicles. This can be expressed mathematically as follows:

$$V_f T_{PR} + \frac{{V_f}^2}{2\mu_f k_f g} \geq \frac{V_l^2}{2\mu_l k_l g} + d \qquad (11)$$

subject to

$i)\ t \geq X$

$ii)\ V_f \geq Y$

where,

d – spacing between the two vehicles

t – duration of following

X and *Y* are thresholds for following duration and speed

We expect equations (11) to be satisfied occasionally for inadvertent and/or temporary situations such as immediately following a lane change. In many of these situations, it is not the intent of the following vehicle to remain at such close spacing, as evidenced by a subsequent decision to increase the following distance. Thus, a threshold *X* will be established empirically to limit our consideration to only those situations where the tailgating criterion (11) has been satisfied continuously for long enough to rule out these spurious events. From our empirical studies, we found that 2 seconds was a threshold that was sufficient to exclude such extemporaneous events but short enough that incidents of actual tailgating were not filtered from the data.

The tailgating condition cannot be implied when there is severe traffic congestion because vehicles pack themselves so densely in these situations that the model would predict them all to be tailgating. While this may be physically true, it is due to a different behavioral incentive, and is not consistent with the primary type of activity we are interested in this research. Thus we introduced a speed threshold *Y* to the tailgating criterion (11). The speed of the following vehicles should be greater than the speed threshold. The value of the speed threshold was set as 25 kmph for this study.

By re-arranging the terms in equation (11), the condition for tailgating can be written as in equation 12 below. The term on right hand side is considered as the safe following distance.

$$\boxed{d \le V_f T_{PR} + \frac{V_f^2}{2\mu_f k_f g} - \frac{V_l^2}{2\mu_l k_l g} \qquad (12)}$$

subject to

$i)\ t \ge X,\ Time\,threshold$

$ii)\ V_f, V_l \ge Y,\ Speed\,threshold$

IV. Values of Model Parameters

We have to determine the values of various parameters such as perception and reaction time, coefficient of friction and coefficient of decceleration to use in our model for the analyses. Since it was impossible to measure the values of these parameters for anonymous drivers and vehicles in our experiment, we considered past studies to determine values of these parameters for this study. The NHTSA study (NHTSA Technical Report, August 1999) assumed driver brake reaction time to the crash alert of 1.52 seconds based on the 95th percentile driver brake reaction time from a surprise braking event study. So, we assumed the perception and reaction time T_{PR} of following driver as 1.52 seconds to use in our study.

The coefficient of friction depends upon the road surface and surface of tires. We considered the value of coefficient of friction μ as 0.5 for both lead as well as following vehicle.

The coefficient of deceleration tells how hard the brake is applied. Brunson et al., (2002) in a rear-end collision alert algorithm used the deceleration rate ranging from 0.27g to 0.55g, which implies the deceleration coefficient values ranging from 0.2 to 0.55. They assumed 0.55g as the maximum deceleration rate considering driver and passenger comfort. The value of the deceleration coefficient will always be a fraction of "g" because a vehicle cannot stop instantaneously by applying brake. NHTSA study (1999) estimated the 85th percentile actual deceleration value for the "hard" braking instruction as a function of speed.

The study estimated deceleration values of -0.36, -0.41 and -0.46g's at speeds of 48, 72 and 96 kmph, respectively. It may be on safe side to assume a larger value of coefficient of deceleration for lead vehicle than for the following vehicle when determining a safe following distance. By doing so, one may consider of the worst-case scenario in which the lead vehicle is likely to stop quicker than the following vehicle. Since we are studying the tailgating situation with aggressive drivers and the urgency of stopping is high in order to avoid collision, we considered a high value of coefficient of deceleration k at 0.75 for both lead and tailgating vehicle.

V. Study Parameters:

We will examine the following parameters to study their influence on the tailgating behavior of a driver.

1. Speed

Generally, aggressive drivers drive at high speeds, or they would like to, and they also follow too closely with high chances of tailgating. We hypothesize a high degree of correlation between speeding and tailgating behavior.

2. Spacing

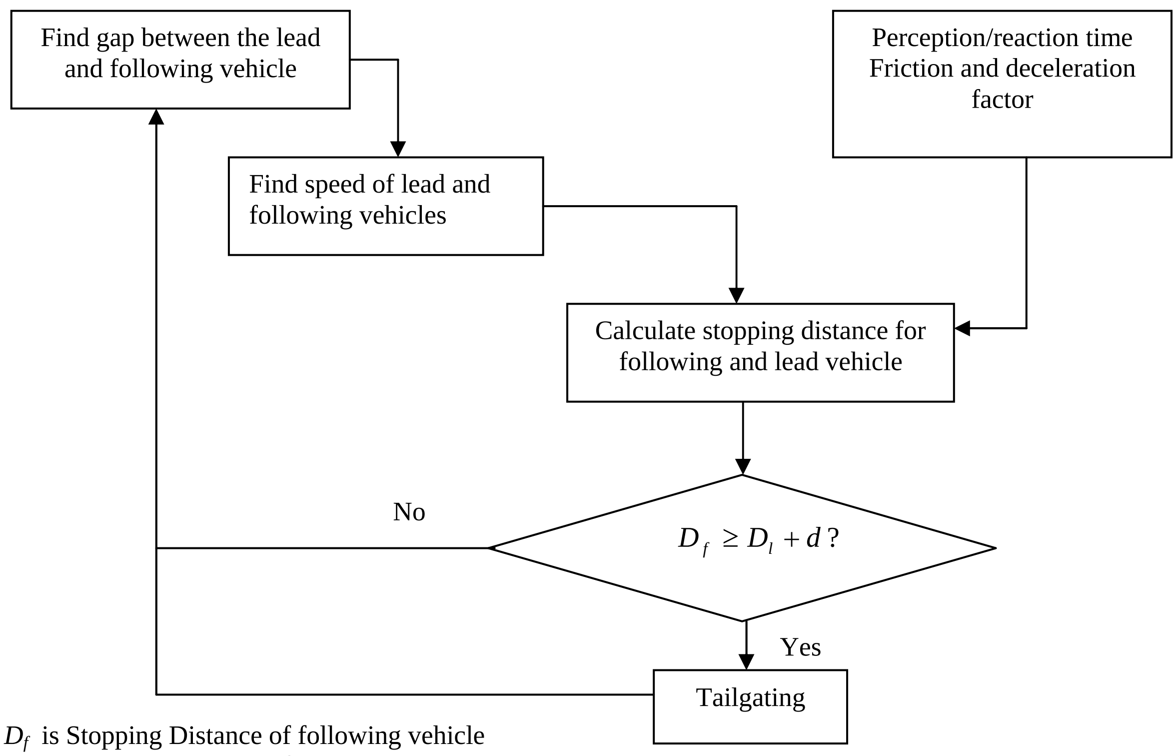
Spacing which can also be called as following distance is a clear distance or gap between the two vehicles. Lesser the spacing between the two vehicles, higher the chances of a collision between them. Since the tailgating threshold is defined in terms of spacing, a correlation here is not informative. However, we were interested to determine how spacing could be correlated with speed and tailgating duration.

3. Tailgating Duration

In the data, we found tailgating incidents that lasted for different periods of time. Without knowing precisely the driver behavior giving rise to those times, it would be interesting to examine if there is any correlation between tailgating duration and other parameters such as speed and spacing.

3.2 Process to Determine Tailgating

Whether a driver is tailgating or not can be determined by using the model developed in Section 3.1. The data required to use the model are the spacing or distance between the lead and following vehicles, the speeds of the lead and following vehicles, a friction factor, and the perception and reaction time of the following driver. The spacing and speeds were measured using appropriate sensors that will be discussed in the next section. Required data were collected from the field experiment. Using these data, stopping distances of the lead and following vehicles were calculated. Figure 3 shows the process how we determined tailgating in this study.



D_f is Stopping Distance of following vehicle
D_l is Stopping Distance of lead vehicle
d is gap between lead and following vehicle

Figure 3: Process to Determine Tailgating

3.3 Instrumented Vehicle

An instrumented vehicle is a vehicle with necessary sensors installed in it, which can be used for data collection. The data necessary from field experiments for the study are the speeds of the following and lead vehicles the spacing between them, and some time derivatives of these quantities. We needed to measure the distance between the test and subject vehicles, at a frequency of at least 10 times in a 10 second period. We did this with an infrared radar sensor adapted from its normal role to support adaptive cruise control. We used the video from a digital video camera to determine traffic and surrounding condition as well as to verify the following vehicle data from the sensor whenever that was necessary. The speed of the test vehicle at desired time intervals was measured by using a distance-measuring instrument, which records the distance traveled and time lapsed.

The vehicle used for this study was provided by Nissan Technical Center North America, Inc. with some necessary modifications. The vehicle is an Infiniti Q45, which contains a Controller Area Network (CAN) mechanism for communication between modules in the vehicle, which can also be tapped for use as a sensor device. The vehicle had to be modified by the University of Maryland team. Additional instruments and sensors which were added included an Infrared Radar Sensor (normally used for Automatic Cruise Control), a vehicle computer, a differential GPS Distance Measuring Instrument (DMI), and a digital camcorder (video camera). We developed a software tool to connect to all of the sensors, the vehicle CAN, and the digital camcorder. This software synchronizes the time of all sensors with the GPS clock of the DMI and acquires necessary data from these sensors as well as the vehicle CAN and stores them in the laptop. A schematic diagram of the instrumented vehicle is shown in Figure 4. Figure 5 shows the instrumented vehicle and its cockpit.

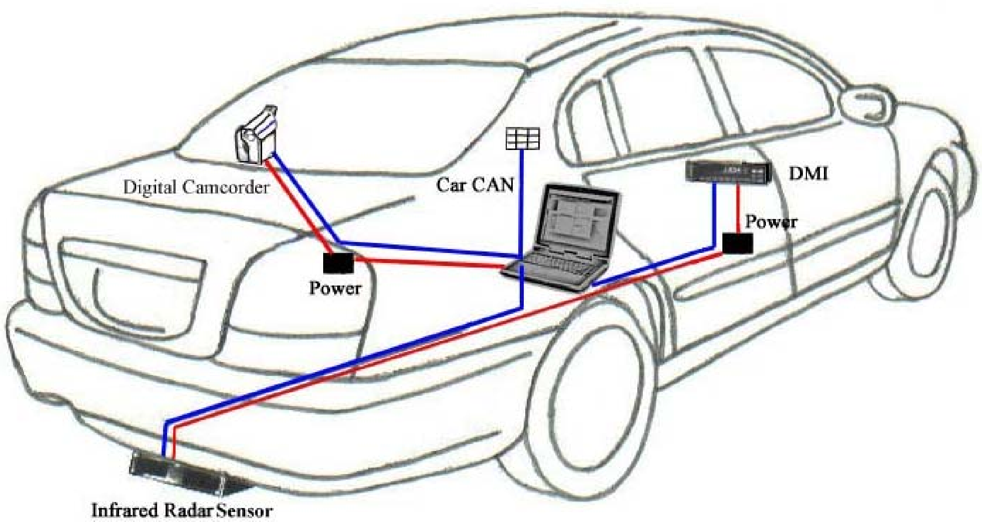


Figure 4: Schematic Diagram of Instrumented Vehicle

Figure 5: Instrumented Vehicle

The Infrared Radar Sensor (IRS) is used to measure the spacing between the vehicles and the speed of the following vehicle. The IRS receives tangential velocity information from the vehicle CAN, and has its own yaw rate sensor. Integrating these pieces of information, it is able to determine the instantaneous curvature of the roadway it is currently on, and the radar beam is bended to accommodate this curvature. Thus, the radar is able to maintain a longer lock on radar tracks on curves than would have been possible otherwise. Because the instrument is normally intended to be mounted on the front of the vehicle, the direction at which the beam should be bent when using it in a rear-facing manner is opposite; however, the sensor includes an option to mount it upside-down. Rather than doing so, the sensor was mounted in a right-side-up configuration but was told via the CAN interface that it was upside-down, thereby “tricking” it into bending the beam in the proper direction for a rear-facing device. The Distance Measuring Instrument is used to measure the speed and position of the instrumented vehicle.

A digital camcorder was used to capture video of the following vehicle and surrounding traffic conditions.

3.4 Hardware Configuration

The hardware consists of various sensors, vehicle computer, digital camcorder and a laptop computer as mentioned in the above section. The sensors are connected to the laptop through various connecting media as shown in Figure 6.

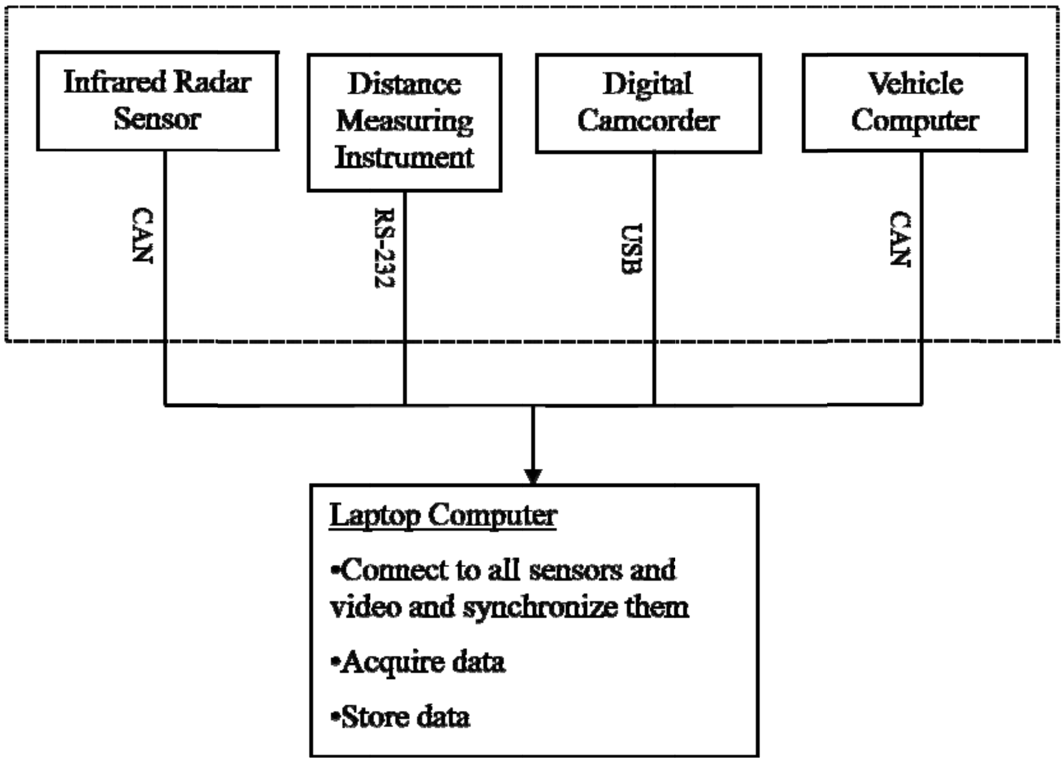


Figure 6: Hardware Configuration

Table 1 shows the functions of different instruments used in the instrumented vehicle.

Table 1: Functions of Instruments in the Instrumented Vehicle

Name	Function
Infrared Radar Sensor (AR211, Omron)	It measures distance and relative speed between the lead and the following vehicles. When combined with DMI information, this produces position, speed, and acceleration of the following vehicle. It also measures road curvature.
Distance Measuring Instrument (SL3000DX, Sun-Lab)	It measures the position, speed and acceleration of the lead vehicle. It uses a combination of Differential Global Positioning System (DGPS) and inertial navigation. The inertial navigation system relies on a calibrated version of the digital transmission speed signal captured from within the vehicle, and accelerometers.

Name	Function
Digital Camcorder (DCR-TRV33, Sony)	It records video of the following vehicle and surrounding traffic conditions.
Vehicle Computer	Various data such as speed and brake pressure can be acquired from the vehicle computer through CAN connection.
Laptop Computer	It synchronizes all the instruments on board used for data collection and stores time-synchronized data from each of them.

Kim (2005) used the same instrumented vehicle for field experiments in his car-following study, with the same sensors installed. For this study, the sensors were re-calibrated and the software was re-written.

3.4.1 Infrared Radar Sensor

The infrared radar sensor is used to measure distance and relative velocity between the leading and the following vehicle. The device itself is identical to what is used in adaptive cruise control (ACC) equipped vehicles. The infrared radar sensor is a Controller-Area-Network (CAN) device, which means it is designed to operate as a node in the internal communications network common in newer cars that use the CAN protocol. We used a commercially available PCMCIA CAN interface (CANcardX) and CAN connection cable (CANcab251opto) to interface between the infrared radar sensor and the laptop computer. The connection cable is opto-isolated to prevent any hardware malfunctions on the sensor side from damaging the PCMCIA interface card or the laptop computer. The infrared radar sensor is normally installed in a car facing forward for automated cruise control purpose but in our instrumented vehicle it is installed facing backwards. The reason for doing so is to be able to get data of anonymous drivers following the instrumented vehicle. If the infrared radar sensor had been used facing forward, then the following vehicle would have been the instrumented vehicle, in which case the driver of the instrumented vehicle would have been the subject of the experiment. This has the possibility of inducing experimental error on the part of the subject, and removes the opportunity to collect data from a much wider population of drivers.

Vehicles tend to be designed to have an aerodynamic profile on the front of the vehicle, and a flatter profile on the rear. Hence, the ability of a forward-facing radar to get a strong radar return from the vehicle in front of it is quite good. In our case, we had to rely on radar returns from vehicles behind the instrumented vehicle, which would have to reflect off of a vehicle surface that was frequently not close to orthogonal with the incident radar beam. The sensing distance and reliability of the sensor, therefore, are greatly reduced in this configuration, but this is an unavoidable consequence of desiring to collect data from anonymous followers.

The infrared radar sensor has 5 beams, transmitting with a typical wavelength of 850 nm. The sensor can detect relevant targets in the range of 2 to 150m in distance and -20m/s to 60m/s in relative velocity, with a measured accuracy of ±1.0m for distance and ±0.3m/s for speed. It operates with a power supply of 10 to 16V direct current (DC). The sensor has been mounted on the metal frame of the back bumper, and is disguised to the extent possible by integrating it with the plastic bumper housing. This and all other sensors were disguised to the extent possible to prevent following drivers from noticing anything unusual about the instrumented vehicle and perhaps driving differently as a result. Figure 7 shows the IR Sensor installed in the back bumper of the instrumented vehicle. The bumper was cut to house the sensor in a casing as shown in the picture at left and the picture at right shows the whole back bumper with the sensor at the center.

Figure 7: IR Sensor at the Center of Back Bumper

3.4.2 Distance Measuring Instrument (DMI)

The Distance Measuring Instrument (DMI) determines distance and positions of the instrumented vehicle. The DMI we used finds distance and position at the time interval of every second. The DMI uses a combination of inertial navigation and Differential GPS technologies to predict the position and speed. We used the DMI model number SL3000DX made by Sun-Lab Technologies which is shown in Figure 8. The DMI also gives us an accurate time standard from its GPS clock, based on which we synchronized the time of all sensors and devices. The DMI has a distance accuracy calibrated to ±1.0 ft/mile and the DGPS accuracy is less than 1 meter (Circular Error Probable).

The device connects to the laptop computer via the serial port and “speaks” the standard NMEA protocol common to GPS receivers, but it augments this vocabulary with proprietary sentences. These sentences were reverse-engineered in our software to provide the best real-time information on vehicles speeds and accelerations. The DMI operates with power supply from 10V to 15V DC @ 1.0 Amp and will connect to the power supply of 12V of the instrumented vehicle. Figure 8 shows the DMI installed in the instrumented vehicle.

Figure 8: Distance Measuring Instrument

3.4.3 Digital Camcorder

A digital camcorder is mounted on the back of the car to capture video of the following car and its surroundings. It can be used as a visual aid to clarify situations that might seem ambiguous when focusing solely on the numerical data gathered from the other sensors. It will also give information on weather, visibility, dry or wet pavement (to some extent in daytime) and traffic conditions such as congested or free flow. The camcorder was disguised and placed in the back just inside the rear windshield as shown in Figure 9.

Figure 9: Disguised Digital Camcorder behind the Rear Windshield

3.4.4 Laptop Computer

A laptop computer is used as the central controller of the system. We used a Dell Latitude D630 with a built-in PCMCIA slot and a serial port. The laptop has 4 GB of RAM and 110 GB of hard disk space. The C++ software we developed to acquire data from the sensors and vehicle computer was installed in it. All of the sensors, the vehicle computer and the video camcorder were connected to it while collecting data. The CANcard (CANcardX) was inserted in the PCMCIA slot and the IR Sensor and vehicle CAN bus were connected to the laptop through the CANcard. The digital camcorder was connected to the laptop through the USB port. The DMI was connected to the serial port at the back.

The software allows the laptop to communicate with all sensors and devices, synchronizes their time with the GPS clock. It acquires and stores all necessary data in it. Figure 10 shows the laptop computer we used in this study. On the left were the IR Sensor and vehicle CAN connected to the the two slots of CANcardX, the digital camera was connected to the USB port at right and DMI was connected to the serial port at the back.

Figure 10: Laptop Computer with all Sensors Connected

3.5 Hardware Connectivity

The Infrared Radar Sensor is connected to the laptop through Controller-Area Network (CAN). The sensor is designed to operate as a node in the internal communication network common to certain brands of newer cars. While it would have been possible to connect the radar directly to the in-vehicle CAN, and then to connect the laptop to that same CAN by a single connection, we decided not to do so for two reasons, both predicated on the fact that the IR sensor “expects” that it is being used for Automated Cruise Control (ACC) in a vehicle so equipped. First, the radar sensor relies on certain CAN messages being transmitted from the vehicle in order to perform necessary functions, and it will shut down if those messages fail to appear. Because our vehicle is not ACC-equipped, some of those messages are not being transmitted over the in-vehicle CAN. Second, the vehicle itself is not “expecting” to see the messages from the radar on the CAN. The introduction of an unexpected set of frequent messages (sometimes as often as 100 Hz), might disrupt the priority structure established in the vehicle CAN and lead to its malfunction.

Instead, we deployed two independent CAN connections in the laptop, one connecting to the vehicle and the other to the infrared radar sensor. A commercially available PCMCIA CAN interface card, CANcardX, and CAN connection cable, CANcab251opto are being used (Kim, 2005). Figure 11 shows a CAN card with two I/O ports and CANcab with transceiver, I/O connector and D-sub CAN connector. The laptop was configured only to “listen” to the in-vehicle CAN, hence no new messages were added to that stream that might disrupt normal vehicle operations. On the CAN bus connected to the IR sensor, the laptop fabricated the necessary update messages at the appropriate frequencies, so the sensor would remain in a functional state, and it recorded the output messages from the IR sensor. While the specific CAN sentences required by the IR sensor were not provided by the in-vehicle CAN, the lower level information (such as brake pressure) was available in a differently formatted sentence. Thus, the software was programmed to fuse necessary information from CAN messages on the in-vehicle CAN and create appropriate messages for the IR sensor. From the perspective of the IR sensor, therefore, it appeared as if it were installed in a perfectly functioning ACC-equipped vehicle, even though it was only connected to a laptop computer.

Figure 11: CANcardX with two I/O Ports and CANcab

Thus, the Distance Measuring Instrument was connected to the laptop through the serial port RS232, digital camcorder was connected to the laptop through the USB port and IR Sensor and vehicle CAN were connected through CANcardX to the laptop.

3.6 Development of the Software

A software system with a graphical user interface (GUI) was required to connect with all the sensors, vehicle computer and video camera installed in the vehicle, to synchronize their time with the GPS clock of the DMI, and to acquire and save necessary data. Keeping this in mind, we developed a GUI software in WIN32 platform using Visual C++. The software establishes a connection to each sensor, checks the status of each sensor, synchronizes its time with the GPS clock, acquires data from each sensor and saves them in the laptop. The data are stored in a CSV file format. We developed our own Controller-Area-Network (CAN) application consisting of two separate CAN networks. One is the CAN network of the vehicle and the other is the CAN network consisting only of the laptop computer and Infrared Radar Sensor. The complete system with the hardware and software was called Vehicle Data Acquisition System (VDAS). Figure 12 shows the user interface of VDAS. The buttons on the left top of the GUI screen are for opening and establishing connection of each sensor to the VDAS and they are labeled with the sensor names. The first one is for CANCard and the last one is for reset and the four in-between are for four sensors. After connecting all the sensors to the laptop and turning them on, the button for each sensor should be clicked and it will turn green if the connection is established and red if fail to do so. The window on the right displays the video being captured by the video camcorder in real time.

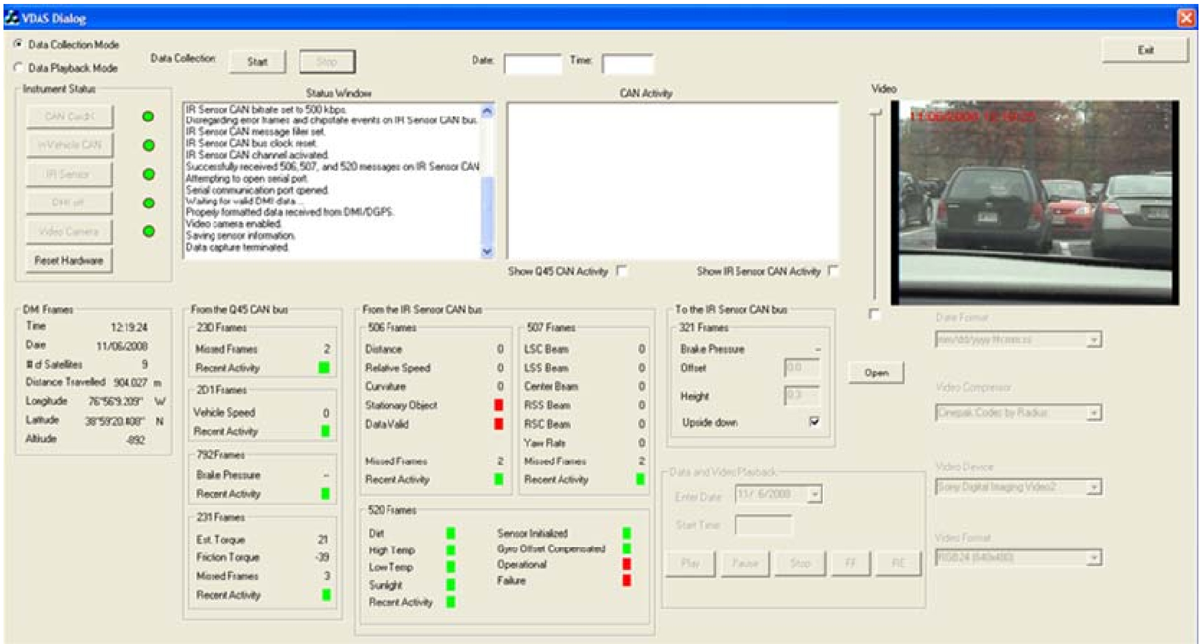


Figure 12: Graphical User Interface of VDAS

Figure 13 shows the connectivity and messages used for data transmission from each sensor. CAN messages 23D and 2D1 are retrieved from the vehicle CAN and are re-transmitted intact to the Infrared Radar Sensor. Message IDs 506, 507 and 520 are transmitted from the Infrared Radar Sensor and stored in the laptop computer. The Infrared Radar Sensor uses brake pressure information in 321 messages for calibration of yaw rate. Since the instrumented vehicle was not used for Automatic Cruise Control, the 321 messages were not available on the vehicle CAN bus. Instead, we retrieved 793 messages (which also contain brake pressure information, albeit in a different format than the 321 messages) from the instrumented vehicle CAN, reformatted them as 321 messages and transmitted to the Infrared Radar Sensor.

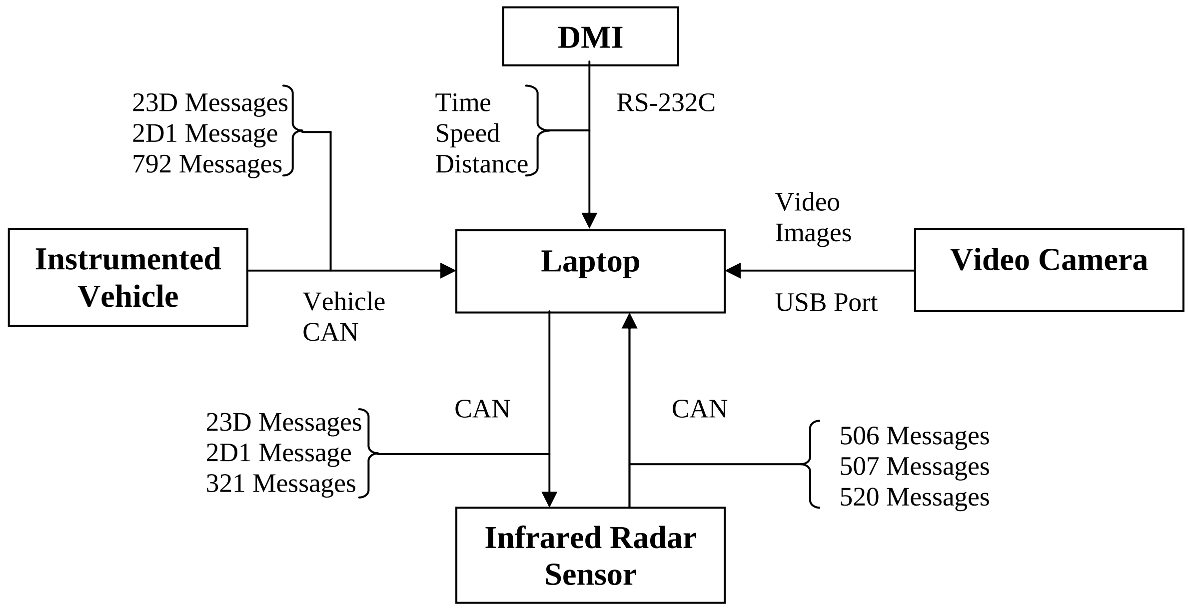


Figure 13: Messages Transmission and Connectivity

The details of CAN data such as message ID, description, transmit cycle and routing for collected data are given in Table 2.

Table 2: CAN Data Message Details

Message ID	Name	Description	Transmit Cycle	Routing
2D1	Vehicle speed Configuration	Vehicle speed Configuration of vehicle (31 hex fixed value)	10 msec	Car-Laptop-IRS
23D	Message counter	Increase by one at every transmit cycle	10 msec	Car-Laptop-IRS
321	Brake pressure Offset Height Upside-down	Brake pressure Offset distance between center of sensor and longitudinal axis through vehicle center	100 msec	Laptop-IRS
506	Distance Relative speed Curvature Stationary object Data validity Missed frame	Distance to target Relative speed of target Curvature measured by range sensor Target is a stationary object or not Target valid or not Shows missed data frame	100 msec	IRS-Laptop
507	LSC beam LSS beam Center beam RSS beam RSC beam Yaw rate Missed frame	Distance of target detected by left-side cut-in beam Distance of target detected by left-side support beam Distance of target detected by center beam Distance of target detected by right-side support beam Distance of target detected by right-side cut-in beam Yaw rate measured by range sensor Shows missed data frame	100 msec	IRS-Laptop
520	Dirt High temperature Low temperature Sun light Initialization Gyro offset Operational Failure	Performance degradation due to dirt is detected Abnormal temperature rise is detected Abnormal temperature fall is detected Performance degradation due to sunlight is detected Sensor initialization is done Gyro offset available or not Sensor is operating normally or not Failure of range sensor is detected	100 msec	IRS-Laptop
792	Brake pressure	Brake pressure from vehicle CAN	100 msec	Car-laptop

Chapter 4: Data Collection

To gain an empirical understanding of the behavioral phenomena of interest in this dissertation, it was necessary to collect detailed field data from vehicles driving in a naturalistic environment. This is not a trivial task, and for decades the inability to collect such data has led to the development and calibration of numerous models from the perspective of a limited number of drivers who were aware of the experimental premises at the time of the study. One of the first studies to attempt to eliminate these experimental biases was the Ph.D. dissertation of Kim (2005). In collected his data, Kim used the same vehicle and a very similar sensor setup as we have used in this study. He is recognized as having pioneered some of the techniques that now allow for a better representation of naturalistic driving behavior, and for capturing the magnitude of the variance in driver behavior both across and within drivers.

These developments come at a certain cost, however. In contrast to controlled experiments, these more naturalistic experiments are subject to the whims of surrounding drivers, which cannot be predicted. One only obtains data about situations one was lucky enough to be part of, and no exertion on the part of the experimenter can (or should) yield situations that were particularly desirable but previously unobserved. For example, it is not ethical to set up situations where one measures the following vehicle's reaction to an extreme braking event by creating such a braking event oneself, as in so doing this places the safety of the following (anonymous) driver (and the experimenter, for that matter) at risk. The data collected, therefore, include perhaps only very few useable trajectories of following vehicles, along with hours and hours of useless data. This is particularly true when focusing on events that can be characterized as tailgating, since this more aggressive behavior is observed less often.

The data that were required for the analysis are as follows:

- Spacing between lead and following vehicles
- Speed of the lead and the following vehicles
- Duration of tailgating

The spacing between the lead and following vehicles was measured by the IR Sensor. The speed of the lead vehicle was obtained both by the in-vehicle CAN as well as by the DMI. The speed of the following vehicle was calculated using the speed of the lead vehicle and the relative speed between the vehicles, as obtained from the IR Sensor.

4.1 Data Collection Method

The instrumented vehicle was used to collect data from field experiments. The driver of the instrumented vehicle drove in a naturalistic manner at the prevailing speed of surrounding traffic in order to represent realistic driving behavior. The driver was particularly instructed *not* to make any driving decisions based on the behavior of any following vehicles, and not to perform any maneuvers that would affect the likelihood of a following vehicle to tailgate, change lanes, brake, or make any other evasive action. Essentially, the instrumented vehicle was intended to seem as a normal part of the traffic flow on the highway. Any vehicle which followed the instrumented vehicle was monitored automatically by the hardware and software systems described above, with no necessary intervention on the part of the driver of the instrumented vehicle. The video camera, which was put in the back of the instrumented vehicle close to the rear windshield, was disguised in order not to distract the following driver and also not to give a clue to the following drivers that he or she was being monitored. The experiments were conducted on the urban freeways in the Washington metropolitan area. They were conducted at different times of day and under varying weather conditions.

4.2 Calibrations of Sensors

The sensors in the instrumented vehicle needed to be calibrated before using them in the field experiments to ensure their accuracy and system integrity. Any problems with the sensor needed to be identified and corrected during calibration. The calibrations of the various sensors are explained below.

4.2.1 Infrared Radar Sensor

The Infrared Radar (IR) Sensor that came with the instrumented vehicle was developed to be used looking in the forward direction, as per the requirements of an Adaptive Cruise Control (ACC). In such an application, it expects to receive strong reflections from the rear of the vehicle in front of it, which it is tracking. For these experiments, however, it is installed looking backward, in order to monitor the anonymous following vehicle. In most cases, each vehicle type has a different frontal shape, compared to a more standard back in general. It was important, therefore, to examine whether the sensor beams would function accurately with the front of a following vehicle or not. Kim (2005) conducted tests to examine the proper mounting height and working offset (angle) of the infrared radar sensor using a mobile station. He used six different types of vehicles to compare the reading from the sensor with the actual distance between the vehicle and the sensor. He experimented with different heights e.g. 30, 40, and 50 cm and orthogonal distances e.g. 5, 10, 15m, etc. between the sensor and target vehicle. The sensor gave accurate readings for the short distances; however, it failed to read the target vehicle at distance of 45m and higher. He found that the best mounting height for the infrared sensor was 30cm above the ground.

The Infrared Radar Sensor emits 5 beams and it detects an object which comes into the path of any of its beams. The five beams are called center, left cut-in, left support, right cut-in, and right support as shown in Figure 14.

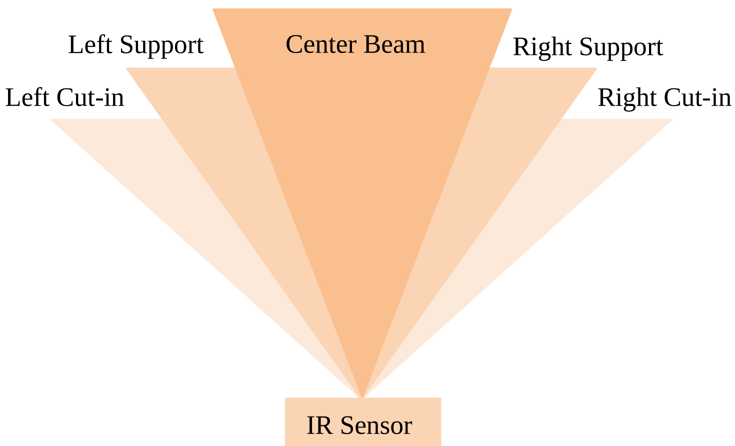


Figure 14: Schematic Diagram of Beams of IR Sensor

We calibrated the Infrared Radar Sensor, which is mounted at the center of the back bumper of the instrumented vehicle. We parked the instrumented vehicle in a huge parking lot in University of Maryland at College Park in such a way that the white straight marking of the parking lot runs parallel to the vehicle through the middle of the IR Sensor. This white line is assumed as the longitudinal center line of the vehicle. We used a reflector which is 70 cm wide and 40 cm high to reflect the rays emitted from IR Sensor in order to calibrate longitudinal and angular object detection range. A wheel distance measuring instrument was used to measure distance of the reflector from the IR Sensor. A person holding the reflector stood 5 m apart at the longitudinal center line with center of the reflector at 30 inches height from the ground. We checked whether the reflector was detected by the IR Sensor or not. Then the reflector was moved to the right and left orthogonal to the vehicle to determine the offset distance range the IR Sensor can detect. When we moved the reflector to the right perpendicular to the center line, we noted at what offset distance the center beam failed to detect the object, at what distance the Left Support and Left Cut-in beams start to detect and at what distance they failed to detect the object. In the same manner we moved the reflector to the left of center line and repeat the measurement as mentioned above. We repeated the process by increasing the distance by 5 m interval along the center line until IR Sensor was able to detect the object. The IR Sensor was able to detect the object as far as 45 m. Table 3 shows the offsets for various longitudinal and transverse distances.

Table 3: Calibration of IR Radar Sensor

Distance (m)	Height of Reflector (m)	Offset (m)									
		Left Cut-in		Left Support		Center		Right Support		Right Cut-in	
5	0.76	0.46	0.23	0.43	0.15	0.33	0.38	0.15	0.41	0.25	0.64
10		0.74	0.43	0.69	0.25	0.43	0.53	0.20	0.89	0.38	1.45
15		1.02	0.45	0.99	0.39	0.57	0.66	0.30	1.02	0.69	1.96
20		1.55	0.38	1.09	0.76	0.89	1.12	0.66	1.52	1.17	2.51
25				1.24	0.89	1.02	1.27	1.09	2.08		
30				1.30	1.04	1.14	1.30	1.24	2.13		
35						1.22	1.42				
40						1.32	1.57				
45						1.47	1.73				
50											

4.2.2 Distance Measuring Instrument

The Distance Measuring Instrument (DMI) has as one of its inputs a time-dependent square wave signal from the vehicle's transmission, which contains a fixed integer number of pulses for every full revolution of the vehicle wheels. The exact number of pulses per revolution can vary by automobile, so the sensor has a primary self-calibration phase where one drives at a specified speed (about 20 miles per hour) and presses a button on the sensor. Only one signal frequency would make sense corresponding to that speed, so the sensor is then able to determine how many pulses per revolution that particular vehicle manufacturer uses.

The sensor then has a very accurate indication of the velocity of revolution of the wheels themselves. This can only be converted into the vehicle's ground speed by knowing the precise radius of the wheels. Since many different radii are possible, the sensor then relies on a second, more detailed stage of calibration.

Initially, we performed this calibration by comparing the DMI distance reading with a known distance travelled. We used a wheel distance measuring device to measure the actual distance traveled by the car. We drove 1000 ft. and checked the distance reading from the DMI, which showed 678 ft. Thus, we were able to input the value 0.678 into the DMI as a speed correction factor. This measurement is subject to some error, however, primarily due to the manual distance measurement from the measuring wheel. Thus, it was decided to use a different technique that would enforce better agreement between orthogonal measurements of vehicle speed.

Figure 15 shows the speeds obtained from the IR Sensor, the Q45 vehicle CAN and the DMI, for a particular trip with the instrumented vehicle. From the pattern of the graphs in this figure, we observed that the reported DMI speed was slightly greater than the Q45 and IRS speeds, whereas the Q45 and IRS speeds match nearly exactly. While no precise ground truth measurement was possible, we decided that the in-vehicle and IRS speed measurements should be the best set of data available, particularly because they had been factory calibrated. To fix the slight difference in speed observed in Figure 15, we fine tuned the DMI by doing re-calibration.

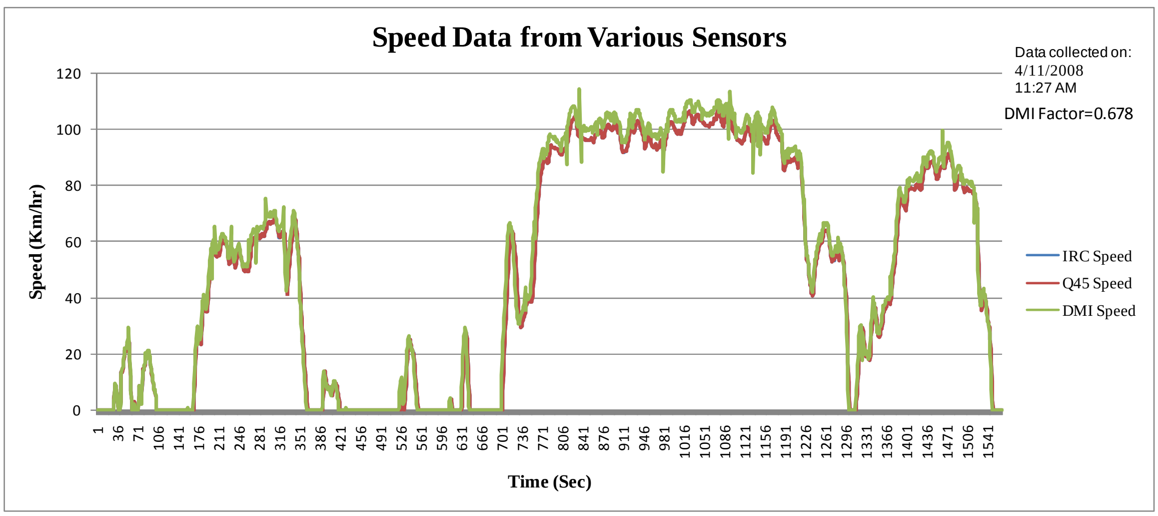


Figure 15: Speed Data from Sensors and Vehicle CAN

We changed the DMI speed factor slightly and collected speed data for about 5 minutes and compared the DMI speed data with the Q45 CAN and IR Sensor speed data. Figures 16 to 19 show a number of successive experiments with various values of the speed correction factor. We measured the RMS error between the DMI and the Q45 CAN speeds over each entire trajectory as a measure of calibration accuracy, and changed the speed factor until this error was minimized.

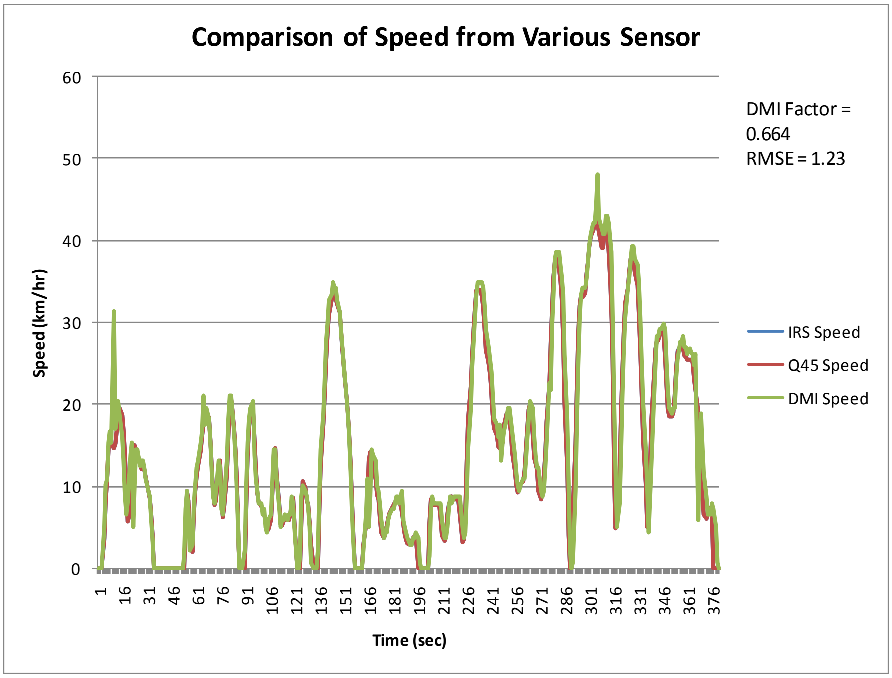


Figure 16: Speed Data when DMI Factor is 0.664

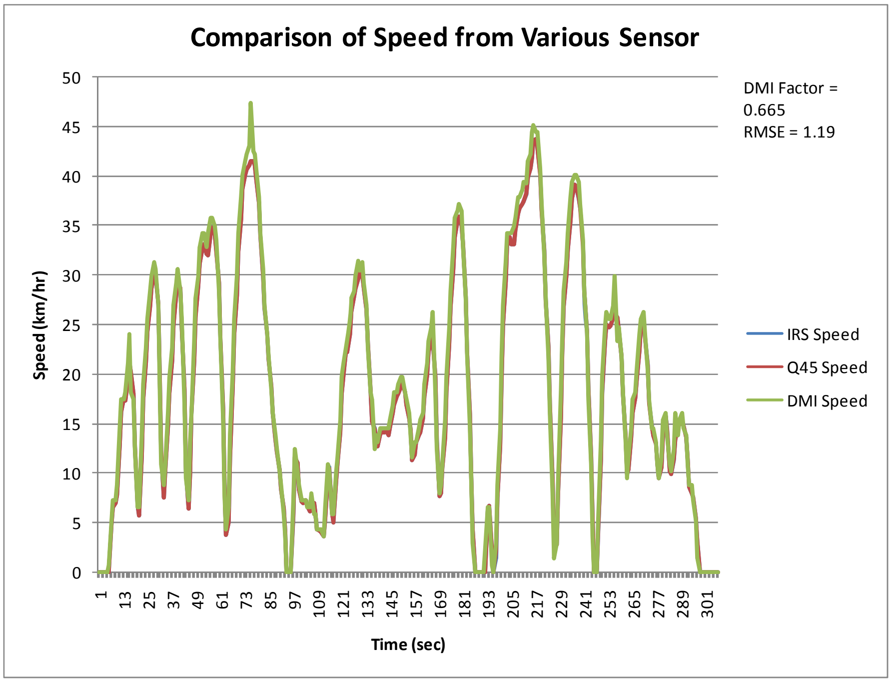


Figure 17: Speed Data when DMI Factor is 0.665

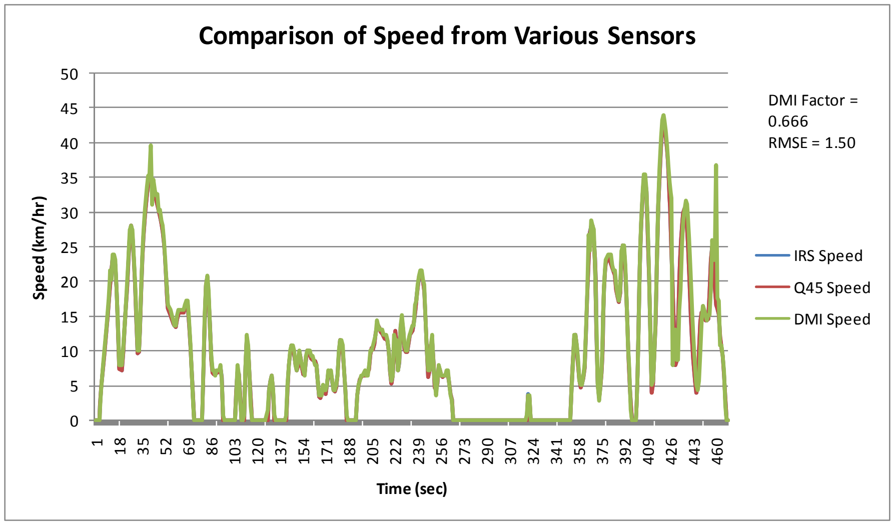


Figure 18: Speed Data when DMI Factor is 0.666

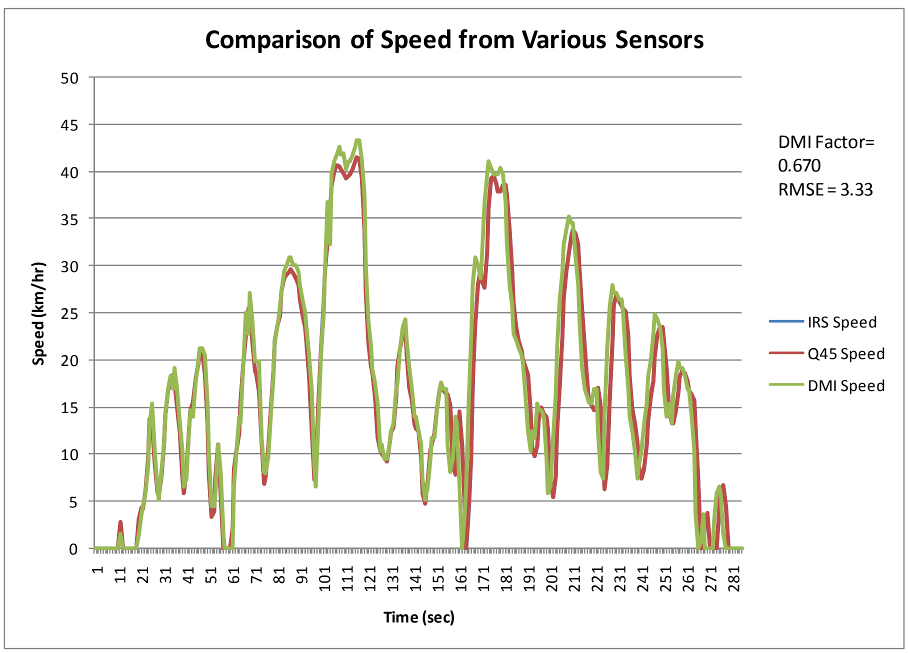


Figure 19: Speed Data when DMI Factor is 0.670

Figure 20 shows the RMS error for various DMI factors. The least RMS error was found for a DMI speed factor of 0.665, so we used 0.665 as the factor to convert DMI readings for all of the remaining experiments in this study. This factor can be input directly into the DMI device itself, and it then reports calibrated distance and speed measurements, so this is not an adjustment that has to be made *ex post facto*.

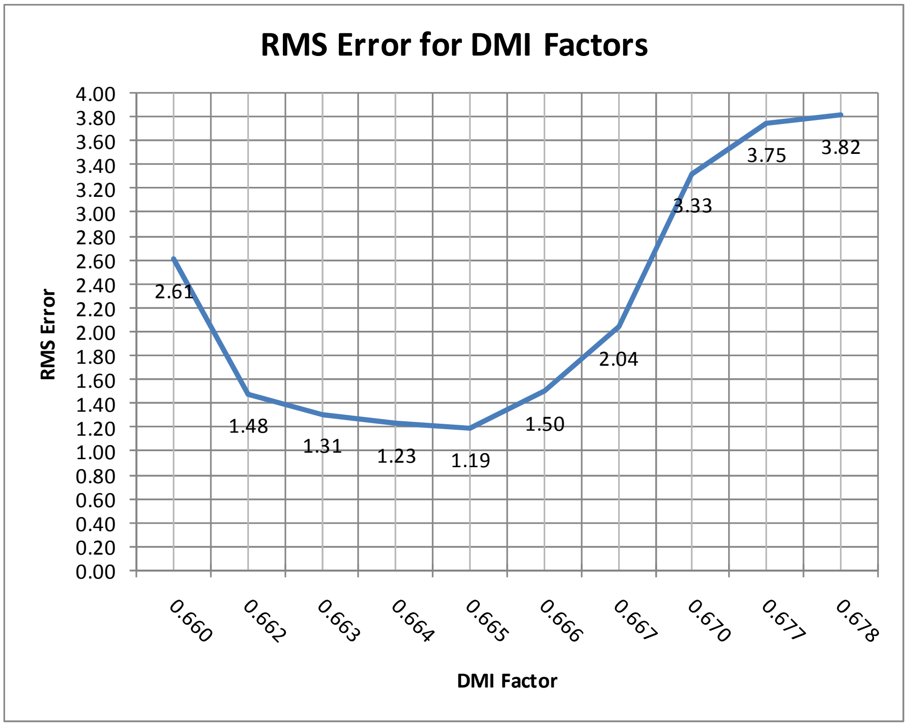


Figure 20: Root Mean Square Error for various DMI Factors

4.3 Preliminary Survey

A preliminary survey was done by driving the instrumented vehicle on I-495, the capital beltway, and I-295, the Baltimore-Washington Parkway, in the College Park, MD area, which is a suburb of Washington, D.C. This was done as a test drive to see if there would be any foreseen issues or problem while collecting data. The survey was done by driving at different hours of a day. We found that generally the above highways get congested in the morning and evening rush hours, which are 7am to 9am and 4:30pm to 6pm, respectively. So, we avoided collecting data during these hours as the data at congested traffic is not appropriate to study tailgating behavior. In congested traffic, the drivers would be forced to drive closely to the lead vehicle and that does not necessarily represent an act of tailgating. This survey helped to determine the appropriate stretch of the highway for data collection. This survey also helped us to collect auxiliary information such as the number of lanes, traffic density, speed limits and to observe general driving behavior such as aggressive drivers. Figure 21 shows the map of the area roads with I-495 and I-295 where we conducted our experiments to collect data.

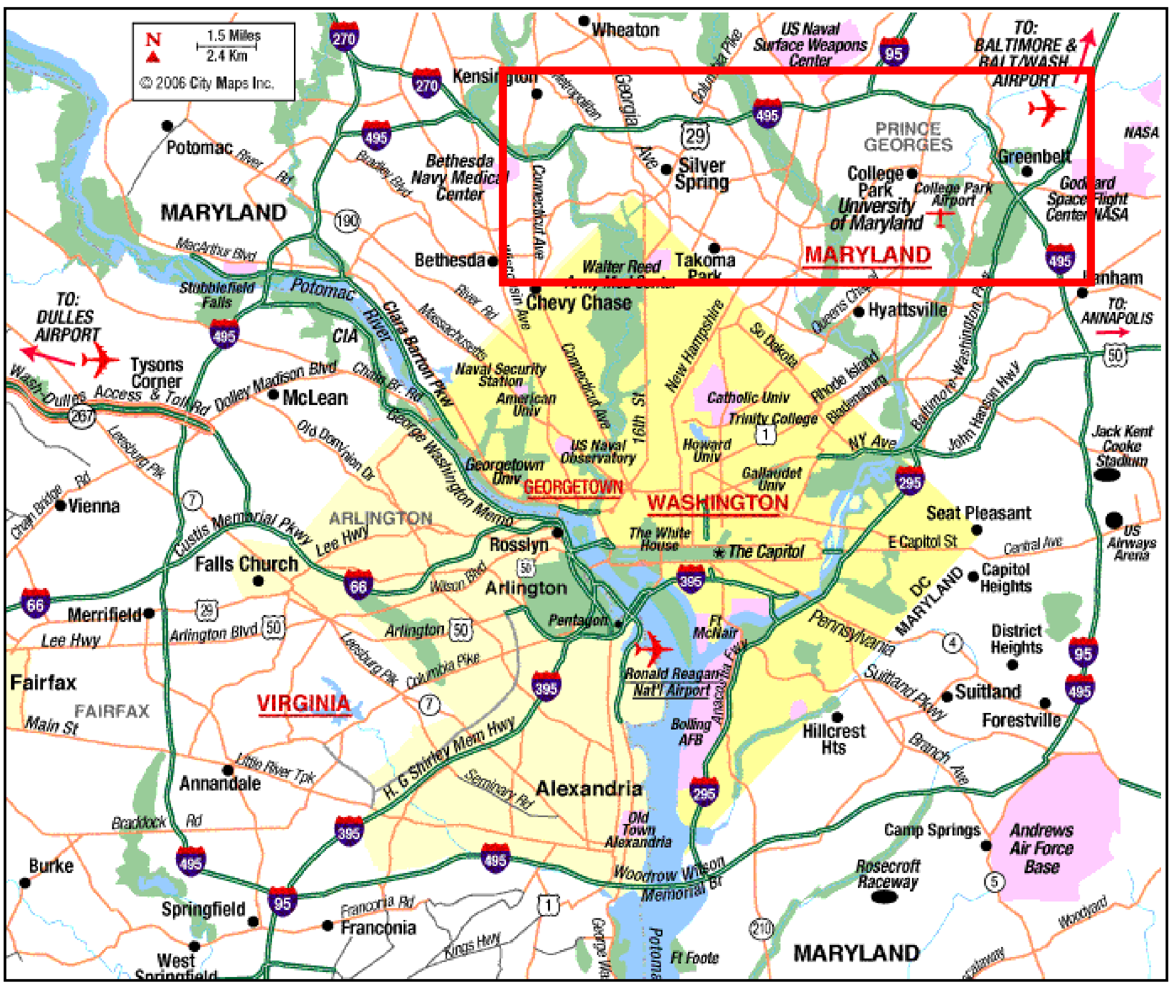


Figure 21: Map of the Experiment Area in the Inset

4.4 Data Format

We collected data by driving the instrumented vehicle on highways. We drove several trips over many different days to collect data. The driver in the instrumented vehicle drove the vehicle in a naturalistic way and did not slow down or perform any maneuvers deliberately to force the follower to tailgate him. We did not give any clue to the anonymous following driver that we were collecting his or her driving data, to ensure that naturalistic driving behavior was captured.

Each trip results in four data files: three separate text files containing data from the DMI, IR sensor, and the in-vehicle CAN, and an AVI file with video data from the camcorder. The data from the vehicle CAN was obtained at an interval of every 10 ms, IR sensor data are obtained every 100 ms and DMI data are obtained every second. We designed the format for the data output file for each sensor in our data acquisition system software VDAS. The data files are space delimited files. So, each data string contains values separated by a space. Each data string contains the precise date and time those data were obtained (calibrated to the GPS time from the DMI) and values of the data for a variable parameter. The data files are explained below.

<u>The IR sensor data file</u>

The primary data of interest from the IR sensor are the following distance, relative speed, and following duration, which are obtained every 100 ms along with the date and time stamp through the IR Sensor. Each data string starts with a date stamp in the format month (mm), date (dd) and year (yyyy), all in numeric form and each separated by a space. After that, time is captured in the format as hour (hh), minute (mm) and second (ss), each separated by a space. The next 3 characters represent the CAN message ID, which corresponds to a specific set of parameters as shown in Table 2 in section 3.6. Next to message ID are the octets of 2 characters each separated by a space, giving the values of the parameters in hexadecimal form.

Q45 CAN data file

We get vehicle data such as speed, brake pressure and torque at every 10 ms through the in-vehicle CAN bus. The data format for in-vehicle CAN is similar to the IR Sensor described above.

The DMI data file

Distance traveled, position (latitude and longitude), altitude and GPS clock time are obtained through the DMI every sec. Each data string starts with the date and time stamp in the format month (mm), date (dd), year (yyyy), hour (hh), minute (mm) and second (ss) all in numeric and each separated by a space. Next is the DMI sentence, which contains GPS clock time, date, latitude and longitude data in hexadecimal. A DMI message is 59 characters long.

The AVI video file

Our software directly records the video data in our laptop instead of recording in a digital tape as a camcorder typically does. The video file is in AVI format which contains the sequence of video images. We overlay the video images with a visual time stamp to synchronize the video with the other numerical data being collected at the same time.

4.5 Data Summary

Each of the data files contains thousands of records (rows) of data, sometimes more than a hundred thousand records in a single file. Processing such a huge quantity of data was a challenging task. We developed a code to convert the hexadecimal data into decimal data and to generate a data file of desired parameters from original data files. After processing and extracting the necessary data, we calculated values of some parameters which we did not get directly from any of the sensors, such as the speed of the following vehicle. We used the speed of the lead vehicle and the relative speed measured by the IR sensor to get the speed of the following vehicle.

We calculated the speed of the lead vehicle using distance covered and travel time from the DMI and compared with the speed obtained from the IR sensor and vehicle CAN. The speed data from the three sensors were found to be very close and comparable. Using our model, we determined the trajectories of tailgating drivers from data in each file. This yielded 125 trajectories of different tailgating drivers. Then we verified these trajectories with their associated video images to find if there were any erroneous data. We found 31 trajectories not suitable for our analysis due to sensor drop or loss in a curve. So, we considered 94 trajectories for our data analysis to study the tailgating behavior of drivers. These are the 94 drivers who tailgated and not the ones who just followed without tailgating.

The detailed information of all 125 trajectories with reason for termination of tailgating as well as reason for discarding the data are given in Appendix A. Figure 22 shows the distribution of tailgating by duration, both in histogram and cumulative form for the 94 trajectories considered for data analyses. Half of the tailgating events were not longer than 10 sec. This means most of the drivers tend not to tailgate for long. Tailgate typically terminated either by a lane change by the following vehicle or by the lead vehicle whenever they got a chance to do so. Table 4 shows the summary of data collected, sensor used and frequency of data for both the lead and following vehicle.

Table 4: Summary of Data for the Lead and Following Vehicle

For	Data	Sensor	Frequency
Lead Vehicle	Speed	CAN Bus	10 ms
	Distance traveled	DMI	1 sec
	Position	DMI	1 sec
	Time	DMI	1 sec
Following Vehicle	Distance between 2 vehicles	IR Sensor	100 ms
	Relative speed	IR Sensor	100 ms
	Following duration	IR Sensor	100 ms

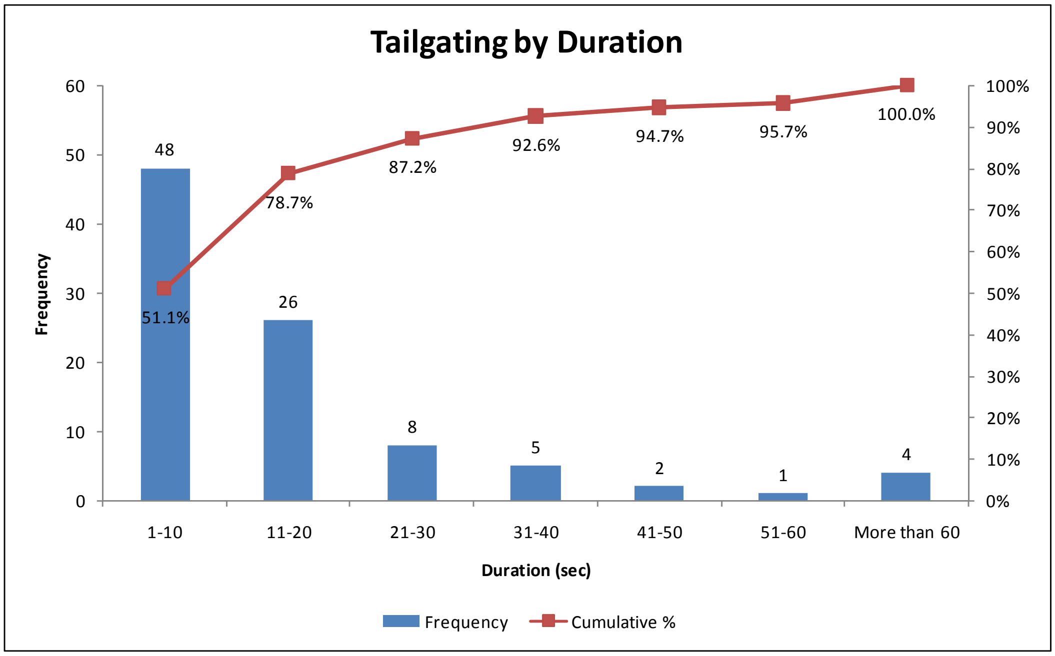


Figure 22: Distribution of Tailgating by Duration

Figure 23 shows the distribution of tailgating by vehicle type. Out of all the tailgating drivers, 46% were driving SUVs. It indicates that drivers of SUVs are more aggressive than others.

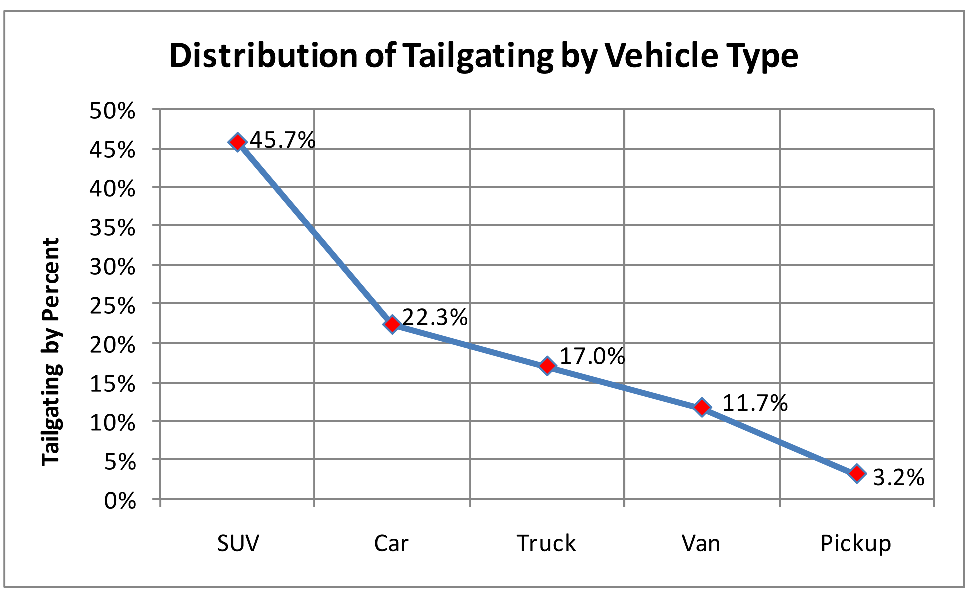


Figure 23: Distribution of Tailgating by Vehicle Type

We compared the tailgating data and the traffic volume by vehicle types. We obtained traffic count data by vehicle class on I-495 west of MD-650 in Montgomery County from the Maryland State Highway Administration (MDSHA). This is one of the locations where we collected most of our data. This traffic count data was from November 2008. MDSHA classified the vehicles into 13 classes. Class 1 is motorcycles, which we did not consider in our study. Class 2 is passenger cars, Class 3 is light trucks, which includes SUVs, vans and pickups and Class 4 is buses. Classes 5 to 9 are single-unit trucks and trailers with axles from 2 to 5 and 6 tires. Classes 10 to 13 are multi-trailer trucks. So, we considered passenger cars (class 2), light trucks (class 3), buses (class 4) and trucks (classes 5 to 13) for our comparison. Table 5 shows the daily traffic volume by class on I-495 as per MDSHA (2008) data. The mean share in percentage of each class is shown in the table.

Table 5: Daily Traffic Volume by Vehicle Class on I-495

Location: IS495-1.0 W OF MD 650 (ATR0041)
Source: MD SHA

Vehicle Class	Eastbound				Westbound				Mean
	11/11/2008	Share %	11/12/2008	Share %	11/11/2008	Share %	11/12/2008	Share %	
Motorcycles	141	0.13%	156	0.14%	111	0.11%	214	0.21%	0.15%
Passenger Cars	81692	75.67%	87682	76.16%	80880	76.90%	78087	76.46%	76.30%
Light Trucks	16125	14.94%	16942	14.72%	14451	13.74%	13241	12.96%	14.09%
Buses	944	0.87%	970	0.84%	1054	1.00%	944	0.92%	0.91%
Trucks (>=2 axles, 6 tires)	9058	8.39%	9382	8.15%	8680	8.25%	9645	9.44%	8.56%
Total	107960	100.00%	115132	100.00%	105176	100.00%	102131	100.00%	100.00%
Volume w/o motorcycle	107819		114976		105065		101917		107,444

Table 6 shows the comparison of tailgating and volume by vehicle class as well as standard deviation of them. We have shown data for both 94 and 125 trajectories to ensure that our removal of 31 erroneous trajectories was not biased removing one particular type of vehicle.

Table 6: Comparison of Tailgating & Volume by Vehicle Class on I-495

Vehicle Class	Tailgating - 125 Trajectories	Tailgating - 94 Trajectories	Volume	SD of Tailgating - 94 Traj.	SD of Volume
Car	21.6%	22.3%	76.3%	3.7%	0.1%
Light Truck	61.6%	60.6%	14.1%	4.4%	0.1%
Bus	0.0%	0.0%	0.9%	0.0%	0.0%
Truck (2 axle or more)	16.8%	17.0%	8.6%	3.3%	0.1%

Figure 24 shows a comparison of the distribution of tailgaters by vehicle class with the distribution of general traffic vehicle class. The volume of passenger car was 76% of the total daily traffic volume whereas only 22% of the total tailgating vehicles were passenger cars. Light trucks constituted 14% of the total daily traffic volume but 60% of the total tailgating vehicles were light trucks. The interesting thing we observed here is that the drivers of light trucks which constitute SUVs seem to be the most aggressive drivers, by this standard.

Using the standard error values we plotted error bars in the chart in Figure 24. They are shown by yellow and green bars. The standard error for tailgating passenger cars was 4% whereas the same for volume of passenger car was 0.1%. This is due primarily to the big difference in sample size of tailgating vehicles and volume. The sample size of tailgating vehicles was 94 but the same for volume was 107,444. Tailgating data of anonymous vehicles in naturalistic driving conditions is extremely hard to obtain and these 94 tailgating trajectories were obtained after collecting a huge amount of field data. A sample size of 94 trajectories is certainly far less than the sample size of traffic volume, nevertheless it would be a good sample size for this study considering the difficulties of collecting such data.

To estimate the standard errors of the above data, we considered the estimator of probability p which is the percentage value for each class of vehicle. Then we estimated the sample variance and standard error of this estimator using method of moments estimators. The process for determining standard error in this case is shown by equations as below.

Estimator of probability p: $\hat{p} = \frac{x}{n}$

Where, x is number of a vehicle class e.g. passenger cars in the sample

n is the sample size.

Variance of estimator: $\operatorname{var}(\hat{p}) = \frac{p(1-p)}{n} \simeq \frac{\hat{p}(1-\hat{p})}{n}$

Standard deviation of estimator: $SD(\hat{p}) \simeq \sqrt{\frac{\hat{p}(1-\hat{p})}{n}}$

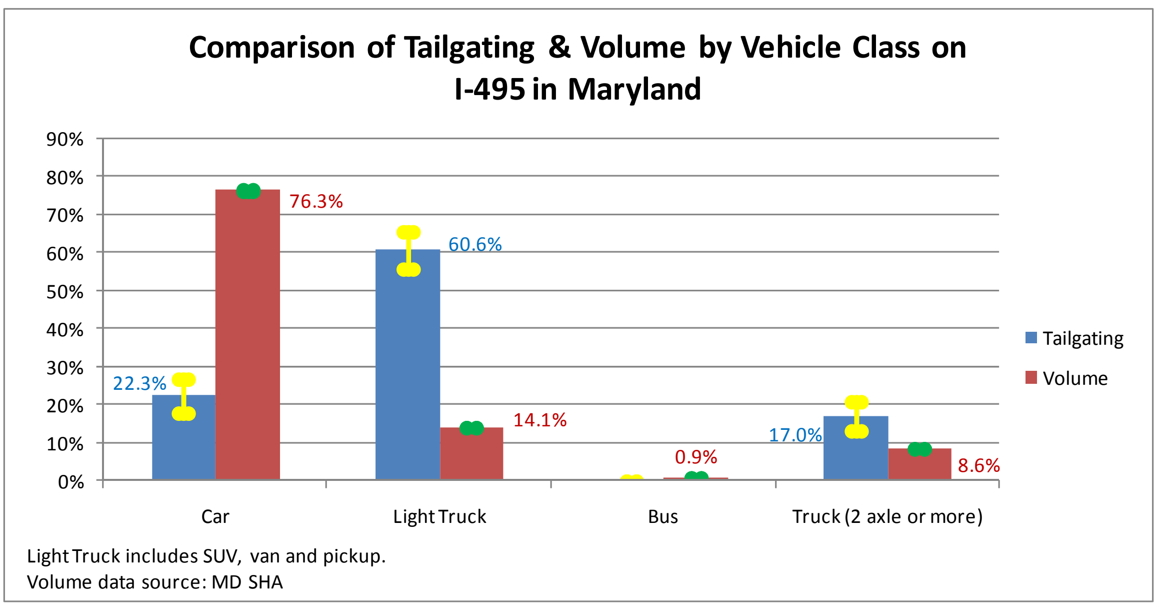


Figure 24: Distribution of Tailgating by Vehicle Class

We used sedan as lead vehicle to collect data. If a taller vehicle like SUV was following us, the driver of such taller vehicle would be able to see several vehicles ahead which might impact on tailgating behavior. This might be one of the reasons for having more SUVs tailgating us than sedans. So, it is recommended to also use taller vehicles to collect data in future research.

Figure 25 shows the distribution of average mean speed of following vehicle, average following distance and number of tailgating vehicles based on lane number. The average of the mean speeds of all recorded tailgating vehicles on lane number 1 (starting from left) was found to be 70 kmph with average mean following distance of 15.2 m whereas the same was found to be 44 kmph and 10 m respectively for lane number 4. It was also observed in our data that the highest number of tailgating vehicles was on lane number 2 and the least on lane number 4.

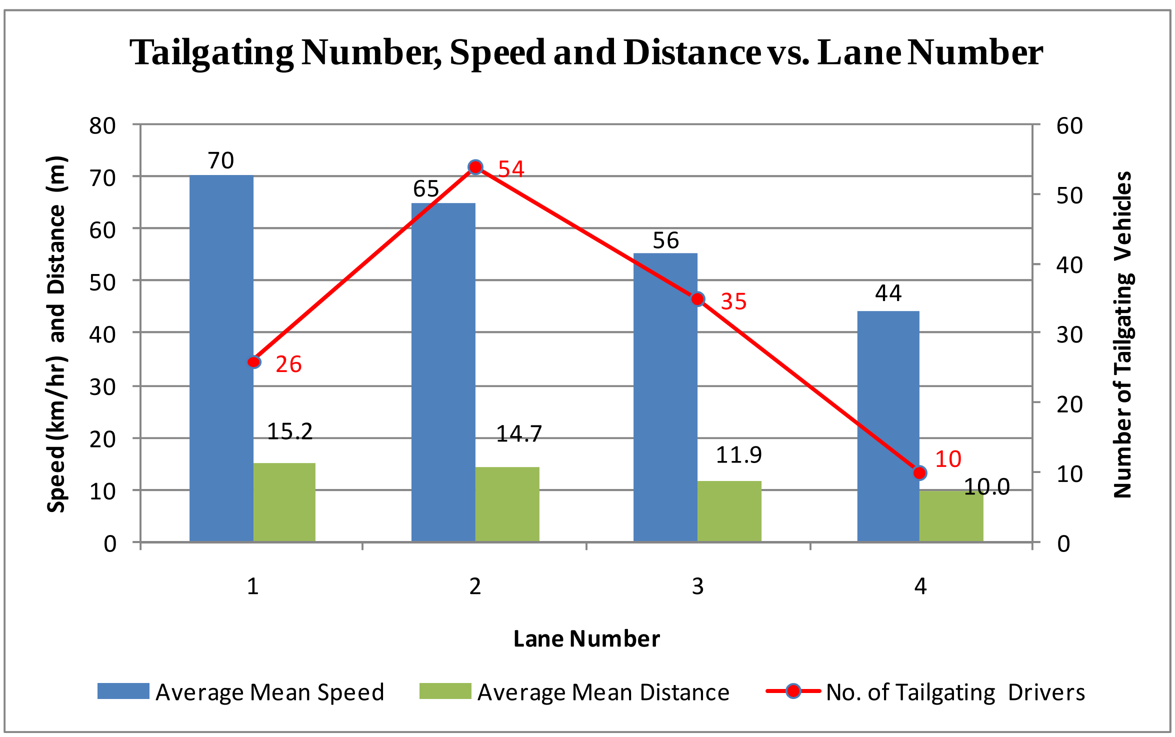


Figure 25: Tailgating Numbers, Speed and Distance vs. Lane Number

We got actual distance between the lead and following vehicles, speed of the lead vehicle and relative speed directly from the field data with some data processing. Then we could find out the speed of following vehicle using the relative speed and speed of the lead vehicle. Similarly, we calculated safe following distance using speed data in equation 12 of our model. The characteristics of these data can be examined with the help of some charts. Figure 26 shows speeds of lead and following vehicles and these data were collected on April 29, 2008 starting at 4:08:55 PM. These charts are for all following vehicles including tailgating vehicles. The two curves almost fit on one-another and the correlation coefficient was found very high at 0.95. Figure 27 shows the actual and safe following distances whereas in Figure 28 the three variables actual and safe distances and following speed are compared. The distances were smaller in the beginning but increases at later stage with the increase of speed. The fluctuation of distances grows when the speed gets bigger. At certain portions of the chart where actual distance is smaller than the safe distance, tailgating occurs.

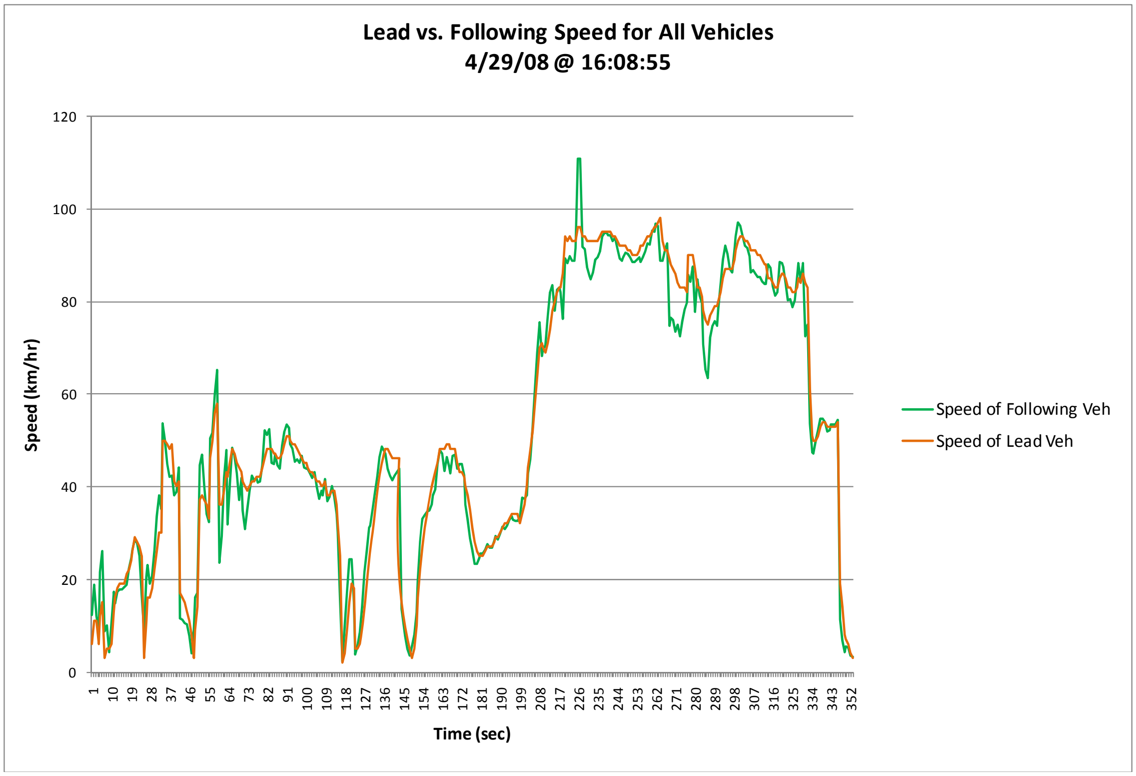


Figure 26: Speed of Lead and Following Vehicles

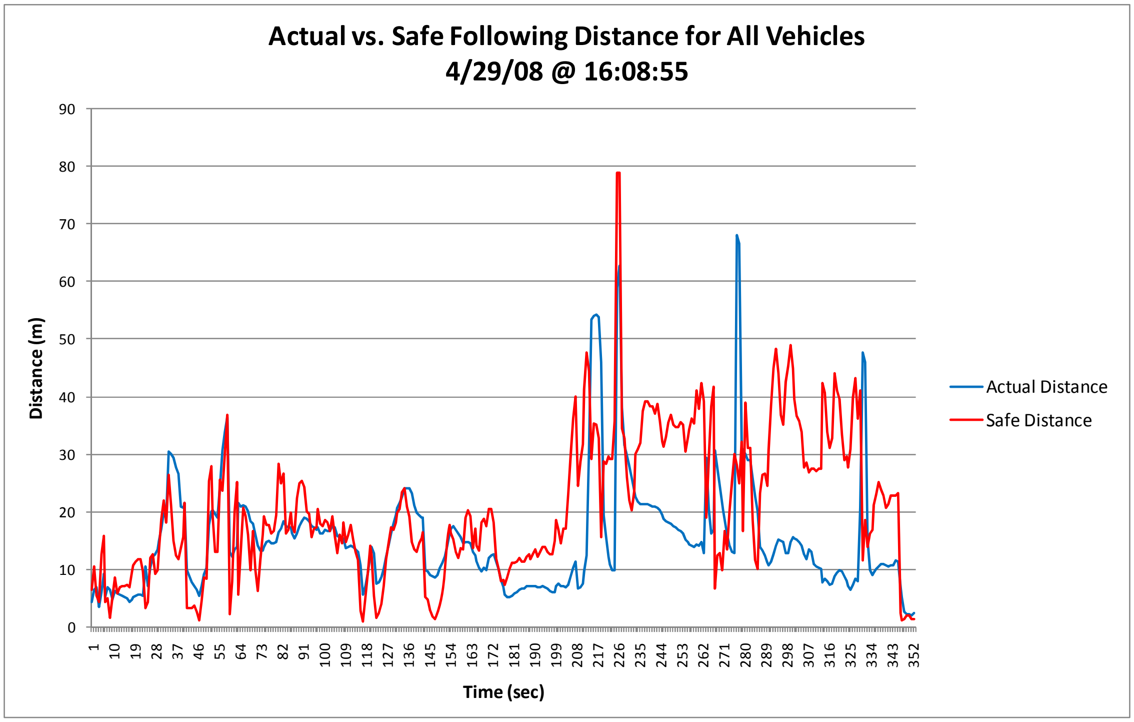


Figure 27: Actual Distance and Safe Following Distance

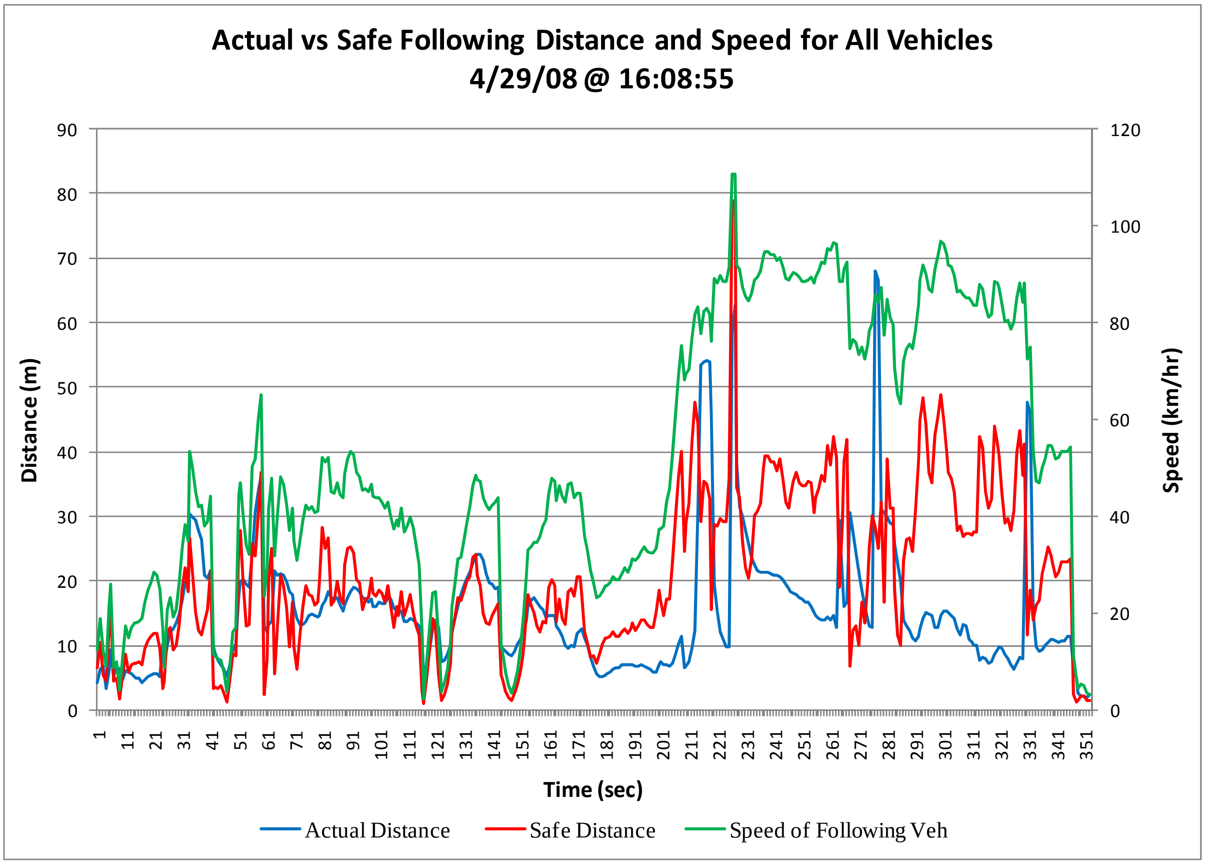


Figure 28: Comparison of Distances and Following Speed

Chapter 5: Data Analyses

In this study, each trajectory corresponds to an independent vehicle and a driver. These vehicles were following the lead instrumented vehicle in a naturalistic driving manner on highways when their data were captured by the sensors and video installed in the back of the lead vehicle. These were anonymous following drivers who had no knowledge that they were being observed. So, the experiment did not distract the following drivers or cause them to change their natural driving behavior.

There might be some circumstances that cause data collected in this manner, with these technologies, to be corrupted. In particular, the IR sensor occasionally loses track of its target, for a variety of reasons. In some cases, excessive curvature in the road, despite the ability of the sensor to measure and respond to yaw rate, can cause a sensor drop. Other factors can be sunlight or reflections overwhelming the sensor, vertical curvature, occlusion from other vehicles, etc. As a result, there are occasional erroneous trajectory data that need to be removed before further processing the data. To eliminate such erroneous data, we verified the trajectory data obtained from sensors by observing the video data. As explained in the previous chapter, after verifying with the video data, we discarded 31 erroneous trajectories and considered a final set of 94 trajectories for our analyses. We calibrated our sensors before collecting data to ensure accuracy and minimize error and hence measurement errors are not included in statistical analyses. Based on initial observations and analysis of these 94 trajectories data, some hypotheses could be formed about drivers' following and tailgating behaviors, which are explained below.

5.1 Hypothesis 1

In some interval of time, mean following distance for short term tailgating drivers is less than that for long term tailgating drivers.

To test this hypothesis, we began by splitting the vehicle trajectories into two groups, one that represents vehicles that tailgated the lead vehicle for a short duration, and the other group for a longer duration. If this is done objectively, and there is an underlying difference between the two resulting groups, differences between the groups can then be tested statistically. Two different schemes for splitting the group were studied. Both of those can be characterized as a form of cluster analysis, whereby the goal is to choose the membership in the different groups in such a way that a metric related to the resulting differences between members within the same group is minimized.

Suppose trajectory *i* is defined as a discrete set $\{D_{i,t}\}_{t=0}^{T_i}$ where $D_{i,t}$ is the following distance between vehicle *i* and the lead vehicle at time *t*, and *t* follows a discrete lattice from $t = 0$, when the vehicle first started following the lead vehicle until time $t = T_i$, which is the last time period observed for that particular vehicle. The set of vehicle numbers *i* is the set $I = \{1, 2, \ldots, 94\}$. A candidate for the cluster algorithm is then a pair of sets *A* and *B* that partition *I*; i.e., such that $A \cup B = I$ and $A \cap B = \varnothing$. In this case, because we want to segregate the groups by the duration of time that the vehicles were tailgating (i.e., "short" and "long"), the single decision variable is that value of *t** that splits the groups into $A = \{i \mid T_i \leq t^*\}$ and $B = I \setminus A$ in such a way that the objective function is minimized.

In particular, our goal was to minimize the variance amongst all members of a group. To determine the dividing line between the two groups, we did cluster analysis. Cluster analysis divides data into two or more groups such that the data in a group share some common characteristics. Data were divided into two groups such that the variance of data is kept minimum within a group and maximum between the groups.

Cluster analysis was done with these data by which the trajectories were divided into two groups based on tailgating duration to give significant difference between their means. In the first analysis, all 94 trajectories were considered, and the optimal threshold time was 30 seconds. Thus, the first group (group *S*) is with tailgating durations up to 30 seconds and the second group (group *L*) is with tailgating durations longer than 30 seconds. There were 81 trajectories in the first group and 13 trajectories in the second group. Table 7 shows an example of the data matrix in two groups. The trajectories are shown renumbered after the optimal clustering. This table also shows how we derived the mean at each time interval for each group. For purposes of comparison, the trajectories were all truncated at 30 seconds (those that were that long to begin with), and the groups were compared based on the performance within the first 30 seconds. For the remaining analysis, any time an average was taken across a group for a particular time epoch, of course only those trajectories that lasted at least as long as that time could be included. As a result, averages taken at different time epochs might be constructed from different sample sizes, and the resulting effects on variance estimates were incorporated into the results.

The means of groups S and L are denoted by μ_S and μ_L, respectively, with an additional sub-index for time epoch where appropriate. The means for the two groups can be expressed as following.

$$\mu_{S,t} = \frac{1}{n(t)} \sum_{81-n(t)+1}^{81} D_{n,t}^{S} \qquad \textit{for the short duration} \qquad (13)$$

$$\mu_{L,t} = \frac{1}{13} \sum_{n=1}^{13} D_{n,t}^{L} \qquad \textit{for the long duration} \qquad (14)$$

Table 7: Example of Data Matrix for two Groups

	Group S 81 Trajectories with Duration <=30 sec						Group L 13 Trajectories with Duration >30 sec					
Vehicle / **Time**	V_1	V_2	..	V_{80}	V_{81}	$\mu_{S,t}$	V_{82}	V_{83}	..	..	V_{94}	$\mu_{L,t}$
1	$D_{1,1}$	$D_{2,1}$	..	$D_{80,1}$	$D_{81,1}$	$\mu_{S,1}$	$D_{82,1}$	$D_{83,1}$	..	..	$D_{94,1}$	$\mu_{L,1}$
2	$D_{1,2}$	$D_{2,2}$	..	$D_{80,2}$	$D_{81,2}$	$\mu_{S,2}$	$D_{82,2}$	$D_{83,2}$	..	..	$D_{94,2}$	$\mu_{L,2}$
3		$D_{2,3}$	..	$D_{80,3}$	$D_{81,3}$	$\mu_{S,3}$	$D_{82,3}$	$D_{83,3}$	..	..	$D_{94,3}$	$\mu_{L,3}$
..			..	..	..	..	..	..	..	..	..	..
..					..	..	..	..	..	..	..	..
29					..	$\mu_{S,29}$	..	..	..	..	..	$\mu_{L,29}$
30					$D_{81,30}$	$\mu_{S,30}$	$D_{82,30}$	$D_{83,30}$	..	..	$D_{94,30}$	$\mu_{L,30}$

Thus, the mean following distance for each group was calculated at every second from 1 to 30 seconds. The two means were plotted over time as shown in Figure 29. The error bars for each mean graph were also plotted, as plus or minus one standard error, as estimated from the data, taking varying sample sizes into account. It is observed that the mean following distance for tailgating durations equal to or less than 30 sec gradually increased for the first 11 sec to reach a peak around 15 m and then fluctuated very gently. On the other hand, the mean following distance for tailgating durations more than 30 sec was almost steady with little fluctuation around 16 m. The mean of the following distances for tailgating durations more than 30 sec was found to be always larger than that for tailgating durations equal to or less than 30 sec. Visually, this seems to support the above hypothesis that “Drivers are willing to take higher risk by driving close to lead vehicle when they tailgate for a short duration.” To examine this statistically, we conducted hypothesis tests which are explained in the next pages.

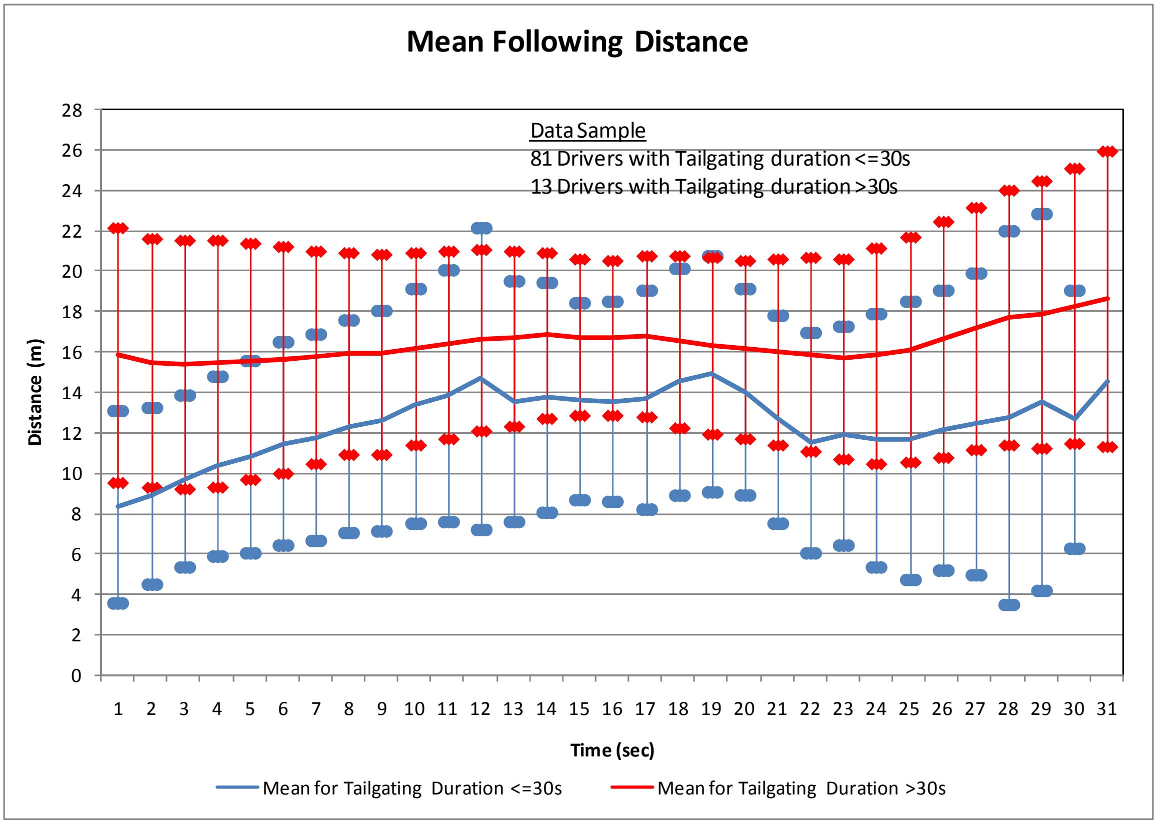


Figure 29: Mean Following Distance of Two Clusters

Each of the two means of group 1 and 2 is really a trajectory of mean values taken at 30 consecutive time epochs. Using a Central Limit Theorem argument, these sample means should be approximately normally distributed random variables with variance σ_t^2 / n_t, where σ_t is the standard error from time epoch t and n_t is the sample size from epoch t. Within group S, n_t is a non-increasing function of t, beginning at 81. For group L, n_t is equal to 13 always, since all trajectories in group L last at least 30 seconds. Because the data have unequal sample sizes and unequal variances between the two groups, we proposed to use

Welch's *t* test (Welch, 1974), which is suitable for testing the difference between mean trajectories with unequal sample sizes and unequal variances along the trajectories.

It is also worth examining two clusters with some time gap in between, for example one group with duration equal to or less than 20 sec and the other with duration equal to or greater than 40 sec. The 20 sec gap between the two groups should make it easy to study the behavior of the subjects that fall into these groups. This approach removes the dependence on the details of the clustering algorithm result, because it produces two groups that are more obviously distinct. Figure 30 shows the means for two groups, one with tailgating duration up to 20 sec and the other for duration more than 40 sec. As in Figure 29, here also the mean for the duration of 20 sec is observed constantly increases up to 11 sec and after that the two means merge at some point. Between 17 and 20 sec, the mean for 20 sec duration seems to be larger than that for the duration more than 40 sec. One would hope that if there were behavioral differences between the classes, they would be more obvious when the classes themselves were more distinct. However, to make that better distinction, a loss in sample size is required, with a commensurate increase in the confidence interval surrounding the means. As a result, this form of partition, for the data sample at our disposal, is no more powerful than the initial method with a single threshold value, so we revert to that system for the remaining analysis.

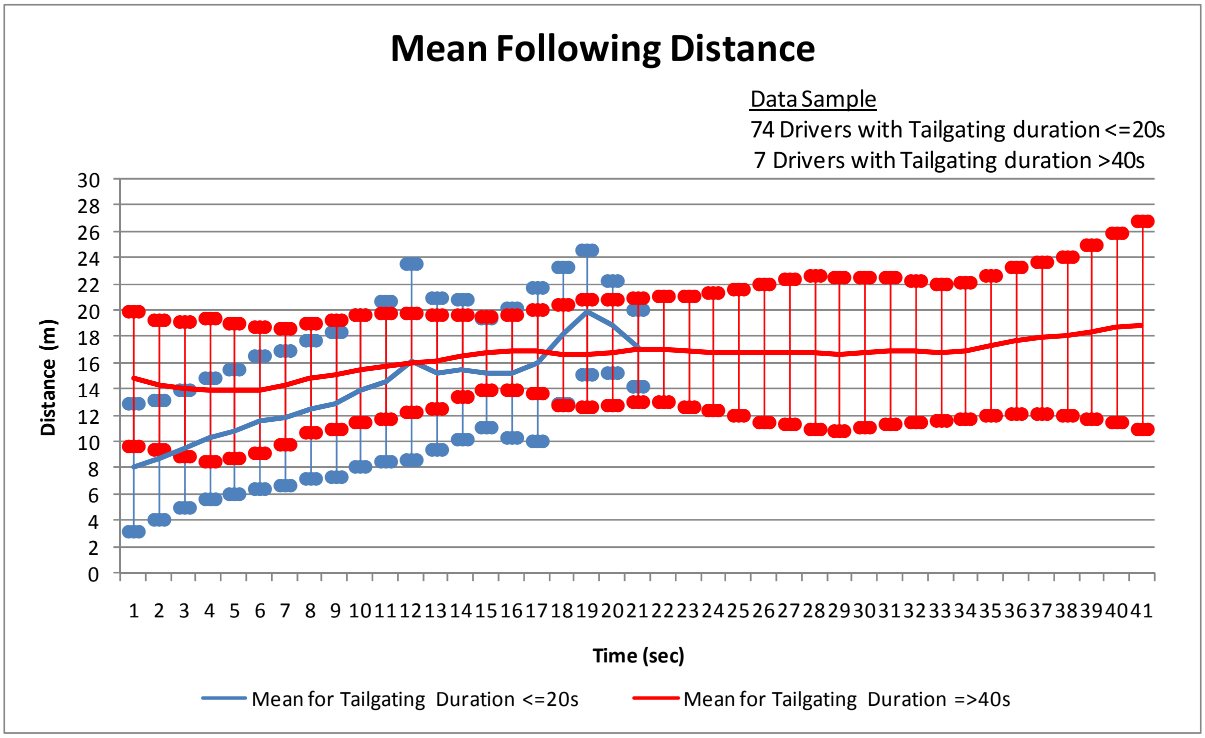


Figure 30: Means of Clusters with 20 sec and 40 sec Duration Partition

The hypotheses of our interest are:

$$\textit{Null Hypothesis},\ H_{0,t} : \mu_{s,t} = \mu_{L,t} \qquad \textit{for}\ t = 1, 2, \ldots\ldots, 30 \qquad (15)$$

$$\textit{Alternate Hypothesis},\ H_{A,t} : \mu_{s,t} \neq \mu_{L,t} \qquad \textit{for}\ t = 1, 2, \ldots\ldots, 30 \qquad (16)$$

Where,

$\mu_{s,t}$ *is mean following distance during the first 30 sec for vehicles whose tailgating duration was equal to or less than 30 sec (Group S)*

$\mu_{L,t}$ *is mean following distance during the first 30 sec for vehicles whose tailgating duration was more than 30 sec (Group L)*

$\mu_{s,t}$ *and* $\mu_{L,t}$ *are independently distributed normals by the Central Limit Theorem.*

The null hypothesis will be rejected in favor of alternate hypothesis if the t-statistic is greater than or equal to the critical value which can be written as $t_{stat} \geq t_{\alpha,DoF}$ where α is confidence level and DoF is degree of freedom.

According to Welch's *t* test, the test statistic and degree of freedom are calculated as follows:

$$\textit{Test statistic value} = t_{stat} = \frac{\Delta\mu}{\sigma_{\Delta\mu}} \qquad (17)$$

Where,

$\Delta\mu = \mu_{L,t} - \mu_{S,t}$

$$\sigma_{\mu_D} = \sqrt{\frac{\sigma^2{}_1}{n_1} + \frac{\sigma^2{}_2}{n_2}}$$

σ_1 *and* σ_2 *are the standard deviations whereas* n_1 *and* n_2 *are the sample sizes of the two groups.*

The idea behind the Welch *t*-test is that, because the different points of the trajectory have different sample sizes associated with them, and because they have different sample variances, the test must be conducted with a linear combination of the individual sample variances. The test statistic cannot be derived perfectly analytically, but it can be approximated with another χ^2 distribution whose "effective degrees of freedom" is determined by:

$$DoF = \frac{\left(\frac{\sigma_1^2}{n_1} + \frac{\sigma_2^2}{n_2}\right)^2}{\left(\frac{\sigma_1^2}{n_1}\right)^2 \Big/ (n_1 - 1) + \left(\frac{\sigma_2^2}{n_2}\right)^2 \Big/ (n_2 - 1)} \qquad (18)$$

The above equation is called the Welch-Satterthwaite equation.

Using the above equations, we calculated the values of t_{stat} and *DoF* at each time epoch for the two means. This equation for "effective" degrees of freedom can produce non-integer values. Accordingly, we rounded non-integer results down to the next lower integer, which is a conservative approach. We also determined the values of $t_{\alpha,DoF}$ and then compared the values of t_{stat} and $t_{\alpha,DoF}$ for each time epoch. If $t_{stat} \geq t_{\alpha,DoF}$ then the null hypothesis is rejected for the alternate hypothesis which means the two means are not equal. Table 8 shows the results of *t* test. We used a confidence level of 95% for the tests. Out of the 30 tests, 10 showed successful results whereas 20 results were unsuccessful. For the first 9 seconds, the test showed that the null hypothesis is rejected and the alternate hypothesis is accepted which indicates that the mean following distance for the first 9 seconds of tailgating for tailgaters whose total tailgating duration is 30 seconds or less is smaller than that for those who ultimately tailgated 30 seconds or longer.

This suggests a possible behavioral mechanism at play, although this cannot be confirmed simply with observational data. The results suggest that (some) tailgaters who remain in that condition for a short period of time know ahead of time that they will not remain behind the lead vehicle for a long period of time, and hence are willing to accept shorter tailgating distances during that time because the higher risk of the shorter distance is mitigated by the known intent to keep the interval of risk short. Tailgaters who perceive otherwise, that they may be behind the lead vehicle for a longer period of time, while still technically tailgating (driving closer than the physics of the problem suggest is safe), are less willing to accept the risk of an extremely close following distance.

Both groups can be seen to extend their tailgating distance on average for some period starting from the outset of tailgating, with the closest tailgaters (the short duration tailgaters) doing so at a higher rate than the longer tailgaters.

Table 8: Results of the Welch's *t* test

Time (t)	μ_S	μ_L	$\Delta\mu = \mu_L - \mu_S$	$\sigma_{\Delta\mu}$	*t_stat*	*d.o.f.*	*D.o.F*	$t_{\alpha/2,dof}$	*Result*
1	8.33	15.83	7.50	1.83	4.094	14.31349	14	2.144787	Reject
2	8.84	15.45	6.61	1.78	3.711	14.04531	14	2.144787	Reject
3	9.61	15.36	5.75	1.78	3.237	13.95893	13	2.160369	Reject
4	10.36	15.41	5.05	1.77	2.856	14.1599	14	2.144787	Reject
5	10.79	15.52	4.73	1.71	2.772	14.77567	14	2.144787	Reject
6	11.44	15.61	4.16	1.67	2.494	15.77368	15	2.13145	Reject
7	11.77	15.72	3.95	1.60	2.464	17.07044	17	2.109816	Reject
8	12.30	15.90	3.60	1.55	2.315	18.8241	18	2.100922	Reject
9	12.58	15.90	3.33	1.58	2.099	20.72468	20	2.085963	Reject
10	13.33	16.16	2.83	1.59	1.781	23.56825	23	2.068658	Do not reject
11	13.83	16.35	2.52	1.62	1.559	26.74714	26	2.055529	Do not reject
12	14.69	16.58	1.90	1.80	1.053	36.33051	36	2.028094	Do not reject
13	13.55	16.65	3.11	1.71	1.818	31.98558	31	2.039513	Do not reject
14	13.73	16.83	3.10	1.66	1.865	31.5681	31	2.039513	Do not reject
15	13.58	16.72	3.15	1.54	2.050	29.55242	29	2.04523	Reject
16	13.54	16.68	3.13	1.64	1.913	26.95631	26	2.055529	Do not reject
17	13.64	16.78	3.15	1.87	1.684	22.01885	22	2.073873	Do not reject
18	14.53	16.49	1.96	2.00	0.979	20.38224	20	2.085963	Do not reject
19	14.91	16.30	1.39	2.14	0.650	18.41079	18	2.100922	Do not reject
20	14.00	16.14	2.14	2.03	1.055	17.8894	17	2.109816	Do not reject
21	12.66	15.98	3.33	2.14	1.557	15.99228	15	2.13145	Do not reject
22	11.49	15.85	4.37	2.45	1.780	11.12187	11	2.200985	Do not reject
23	11.87	15.65	3.78	2.47	1.534	11.51443	11	2.200985	Do not reject
24	11.63	15.80	4.17	2.80	1.491	10.72518	10	2.228139	Do not reject
25	11.63	16.10	4.47	3.03	1.477	10.32855	10	2.228139	Do not reject
26	12.11	16.63	4.51	3.08	1.463	10.7054	10	2.228139	Do not reject
27	12.41	17.17	4.75	3.28	1.449	10.28634	10	2.228139	Do not reject
28	12.74	17.67	4.93	4.50	1.095	5.484705	5	2.570582	Do not reject
29	13.50	17.85	4.35	4.55	0.957	5.625845	5	2.570582	Do not reject
30	9.00	18.27	9.27	4.88	1.899	1.381097	1	12.7062	Do not reject

In Table 8, the μ_S data in the 1^{st} row is the mean following distance of 81 short term tailgating drivers at time 1 sec. Similarly, the data in the 2^{nd}, 3^{rd},..., 30^{th} rows are data for the short term tailgating drivers in 2^{nd}, 3^{rd},..,30^{th} sec, respectively, minus those drivers whose tailgating times did not last long enough to be present at that epoch. Similarly, the μ_L represents the mean following distance of 13 long term tailgating drivers at time epochs from 1st to 30th seconds. All of these drivers are assumed to be operating independently. One possible criticism of this approach is that while the drivers are assumed to be independent of each other, their behavior along their individual trajectories is certainly not independent across time epochs. As a result, some serial correlation might be expected in the mean behavior as a function of time as well. With this critique in mind, we used an alternative method as follows to test the same hypothesis to take into account possible serial correlation in the time series data.

In this method, we used regression of the mean following distances at different times. First, we computed the difference in mean following distances of the two groups at each time epoch and then centered this by subtracting the average of all mean differences over the span of 30 seconds to make eye observation of data easy.

$$Centered\ mean\ difference = \Delta\mu'_t = \Delta\mu_t - \frac{\sum_{t=1}^{30}(\mu_{Lt} - \mu_{St})}{30} \qquad (19)$$

Then, we did regression of the centered mean by introducing time lags to take into account of the serial correlation of time series data. The regression was done between the centered mean at time *t* and at time *t-1* for a time lag of 1 sec and at time *t-2* for a time lag of 2 sec.

$$Regressed\left(\Delta\mu'_t\right)_{t=3}^{30}\ against\left(\Delta\mu'_t\right)_{t=2}^{29}\ and\ \left(\Delta\mu'_t\right)_{t=1}^{28}$$

The p-values for the time lag of 1 sec was found to be 0.003 and that for lag 2 sec was 0.925 at confidence level of 95%. Thus lag of 1 sec was found to be significant whereas lag of 2 was found insignificant. So, we did significance testing for the hypothesis for time lag of 1 sec. Based on the result of regression, we calculated the confidence intervals using the following formula:

$$CI_t = \frac{1}{30}\sum_{t=1}^{30}\Delta\mu_t + \Delta\widehat{\mu}_t \pm t_{\alpha/2,dof}\sqrt{\frac{MSE}{1-\beta^2}} \qquad (20)$$

Where,

$\Delta\mu_t = \mu_{L,t} - \mu_{S,t}$

$\widehat{\mu}$ is Predicted Centered difference of Mean from Regression

MSE is Mean Square Error

β is Regression Coefficient

Table 9 shows the values of upper and lower confidence intervals. For the first 7 seconds of following, both lower and upper confidence intervals are found to be positive, which indicates that the difference of the means is not equal to zero. From 8th to 21st seconds, the lower confidence intervals were found to be negative, suggesting that the notion that the means are the same cannot be rejected with the same high confidence level. Again, for 22 to 29 seconds, both the lower and upper confidence intervals are found to be positive, suggesting the means are not equal.

Table 9: Confidence Intervals based on Regression

Observation	*Predicted* $\Delta\mu(t)$	*Lower CI*	*Upper CI*	*Result*
1	6.8096	3.0312	10.5880	Reject
2	6.1746	2.3962	9.9531	Reject
3	5.4647	1.6863	9.2432	Reject
4	4.8840	1.1055	8.6624	Reject
5	4.6162	0.8378	8.3946	Reject
6	4.1539	0.3754	7.9323	Reject
7	3.9662	0.1878	7.7446	Reject
8	3.6814	-0.0970	7.4598	Do not reject
9	3.4564	-0.3220	7.2348	Do not reject
10	3.0513	-0.7271	6.8297	Do not reject
11	2.7964	-0.9820	6.5748	Do not reject
12	2.2885	-1.4899	6.0670	Do not reject
13	3.2430	-0.5354	7.0214	Do not reject
14	3.2677	-0.5107	7.0461	Do not reject
15	3.3033	-0.4752	7.0817	Do not reject
16	3.2924	-0.4860	7.0708	Do not reject
17	3.3024	-0.4760	7.0808	Do not reject
18	2.3529	-1.4255	6.1313	Do not reject
19	1.8707	-1.9077	5.6491	Do not reject
20	2.4555	-1.3229	6.2339	Do not reject
21	3.4255	-0.3529	7.2039	Do not reject
22	4.2846	0.5062	8.0630	Reject
23	3.8403	0.0619	7.6187	Reject
24	4.1379	0.3594	7.9163	Reject
25	4.3870	0.6086	8.1654	Reject
26	4.4270	0.6485	8.2054	Reject
27	4.6218	0.8434	8.4002	Reject
28	4.7669	0.9885	8.5453	Reject
29	4.3106	0.5322	8.0890	Reject

So, for the first 7 seconds the two means are consistently not equal. Interestingly, the results from the first method and this alternative method are similar for the first 10 seconds of following duration. Based on this analysis, we feel it safe to conclude that drivers who are willing to tailgate are willing to do so even more closely when they are following for a short duration. If one could surmise that the plan was to tailgate for a short duration, then one could conclude that drivers are willing to make smaller inter-vehicle separation if they know they will be tailgating for a short duration.

5.2 Hypothesis 2

The tailgating driver's speed is influenced by the lead driver's speed.

On the surface, this proposition seems obvious. Certainly, if the lead vehicle decelerated, then at some point the following vehicle would have to do so as well. The opposite maneuver might not be guaranteed, however; if the lead vehicle increases its speed, the follower is certainly not compelled to do so, but one definition of tailgating might include such aggressive behavior as a necessary component.

The speeds of lead and tailgating vehicles for each trajectory were compared to examine the relationship between the two speeds. The tailgating vehicle or driver is also mentioned as following vehicle or driver in this dissertation. Figure 31 shows the speed of lead and tailgating vehicles for the first 11 trajectories. VL represents the speed of the lead vehicle whereas VF represents the speed of the following vehicle and D1, D2,.. represent the drivers or vehicle number 1, 2,…, etc. So, in this notation, D1-VL is the speed of the lead vehicle number 1 and D1-VF is the speed of the following vehicle number 1. Thus D1-VL and D1-VF make a pair of the 1st lead and following drivers (vehicles). Similarly D2-VL and D2-VF make a 2nd pair, D3-VL and D3-VF make a 3rd pair of drivers and so on. Recall that in all cases, the lead vehicle was in fact the instrumented vehicle used in this research, driven by a member of the research team. The followers were anonymous subjects captured by happenstance. The speed graphs of lead and following drivers are very close for most of the pairs, as observed from the Figure 31. Similar results hold true for all of the trajectory pairs, but only a few visually distinguishable trajectory pairs are shown in the figure for illustration purposes.

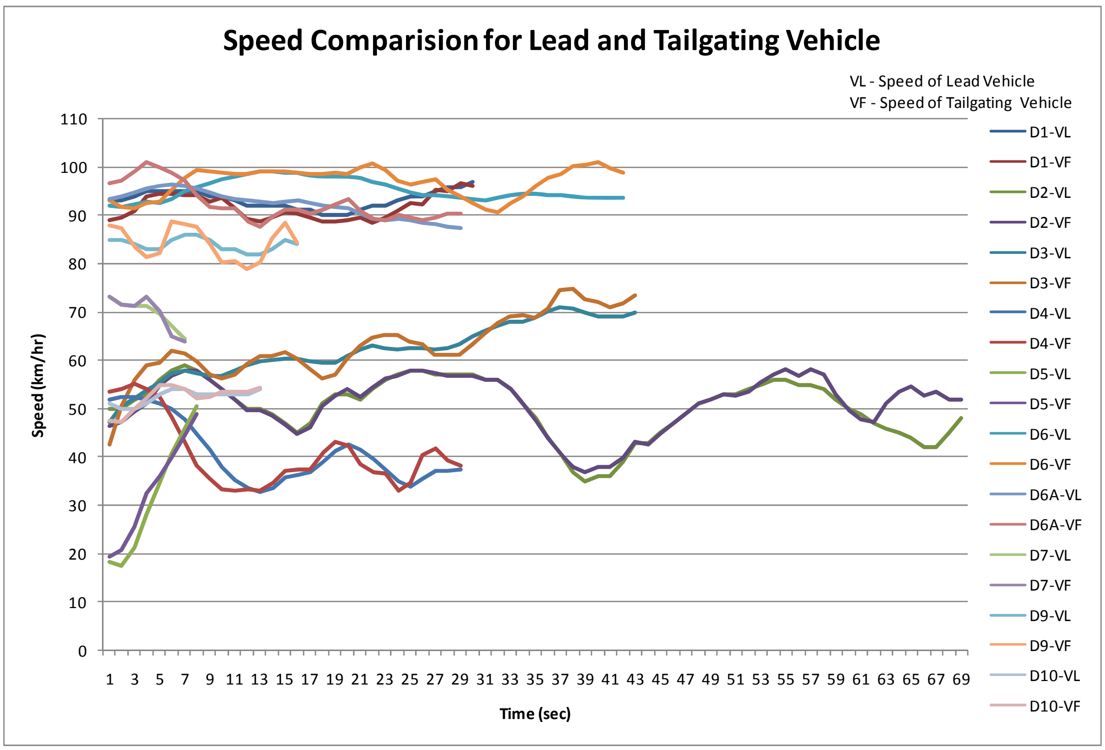


Figure 31: Speed Trajectories of Tailgating Vehicle and Lead Vehicle

The correlation coefficients for the speeds of the lead and following vehicles for all the trajectories are listed in Table 10. The correlation coefficients were found to be very high for most of the trajectories and the mean of all the correlation coefficients was found to be 0.85. This high value of correlation coefficient suggests that there is a strong relationship between the lead and following speeds for tailgating situations. Ordinarily, of course, one has to be very careful making causal inferences about correlated data, but in this case it certainly makes more sense that the lead vehicle influences the follower than the other way around. It is observed from the Table 10 that for a few pairs, the correlation coefficients are low or even negative. The speeds for five such pairs are also plotted to compare the pattern of relationship as shown in Figure 32. All these trajectories are of short duration ranging from 4 sec to 11 sec. Most of the pairs started wide apart but tend to converge at some points and again diverged towards the end in some of them.

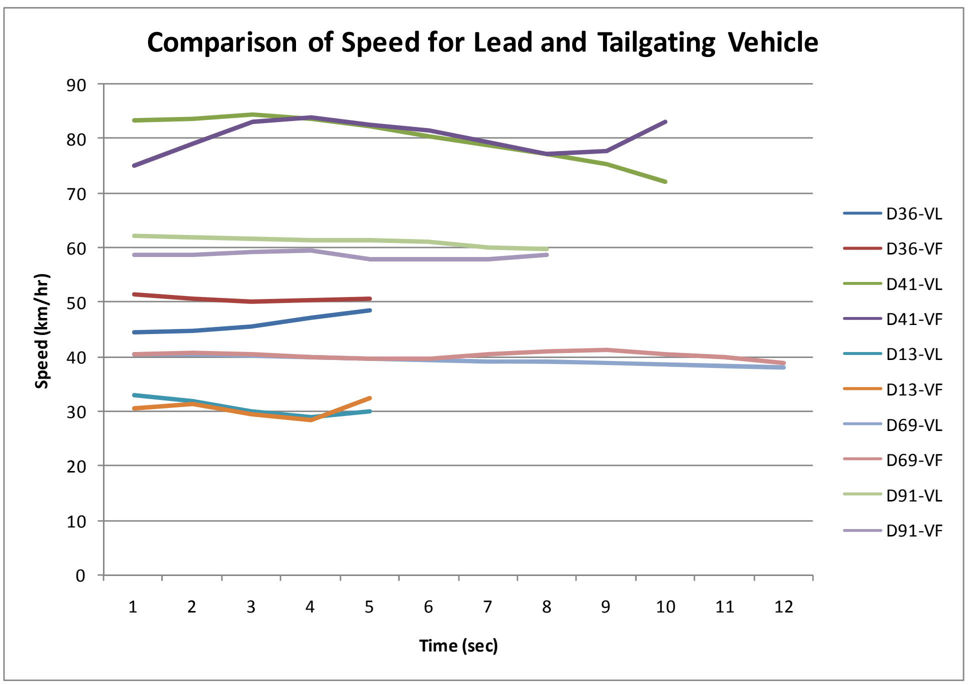


Figure 32: Comparison of Speeds for Pairs with Weak Correlation

The two curves for D36, shows opposite pattern of one another, when one is inclining the other is declining suggesting a negative correlation between them. In fact, they have negative correlation as shown in the Table 10.

Table 10: Correlation of Following and Lead Vehicle Speed

Driver #	Correlation Coefficient of Following and Lead Speed		Driver #	Correlation Coefficient of Following and Lead Speed		Driver #	Correlation Coefficient of Following and Lead Speed
D1	0.912		**D43**	0.960		**D83**	0.887
D2	0.883		**D44**	0.853		**D84**	0.805
D3	0.945		**D47**	0.756		**D85**	0.952
D4	0.902		**D48**	0.968		**D86**	0.969
D5	0.992		**D50**	0.977		**D87**	0.978
D6	0.634		**D53**	0.887		**D91**	0.359
D6A	0.713		**D54**	0.973		**D92**	0.855
D7	0.958		**D56**	0.874		**D95**	0.803
D9	0.889		**D57**	0.644		**D97**	0.610
D10	0.858		**D58**	0.962		**D99**	0.995
D11	0.869		**D59**	0.994		**D100**	0.998
D12	0.791		**D60**	0.976		**D102**	0.916
D13	0.389		**D61**	0.902		**D106**	0.962
D14	0.572		**D62**	-0.540		**D107**	0.957
D15	0.520		**D63**	0.723		**D108**	0.968
D18	0.991		**D64**	0.938		**D109**	0.968
D20	0.797		**D65**	0.927		**D112**	0.967
D21	0.995		**D66**	0.820		**D113**	0.992
D22	0.982		**D67**	0.926		**D114**	0.996
D26	0.965		**D68**	0.786		**D115**	0.924
D27	0.951		**D69**	0.247		**D116**	0.967
D28	0.972		**D70**	0.968		**D117**	0.986
D30	0.868		**D71**	0.946		**D118**	0.935
D31	0.896		**D72**	0.970		**D120**	0.965
D33	0.680		**D73**	0.976		**D121**	0.941
D35	0.964		**D75**	0.866		**D122**	0.973
D36	-0.439		**D76**	0.988		**D123**	0.977
D37	0.975		**D77**	0.901		**D124**	0.982
D38	0.883		**D78**	0.932		**D125**	0.970
D39	0.964		**D79**	0.970			
D40	0.509		**D80**	0.912			
D41	0.094		**D81**	0.962			
D42	0.944		**D82**	0.961			
Mean for all the data							**0.846**

The following distances of these five trajectories are also plotted as shown in Figure 33. The distance curve for D36 has a steep inclination from start to end for 4 seconds of tailgating duration. The trajectory of D91appears to be constantly declining whereas the remaining other trajectory did not show any abrupt changes in their pattern.

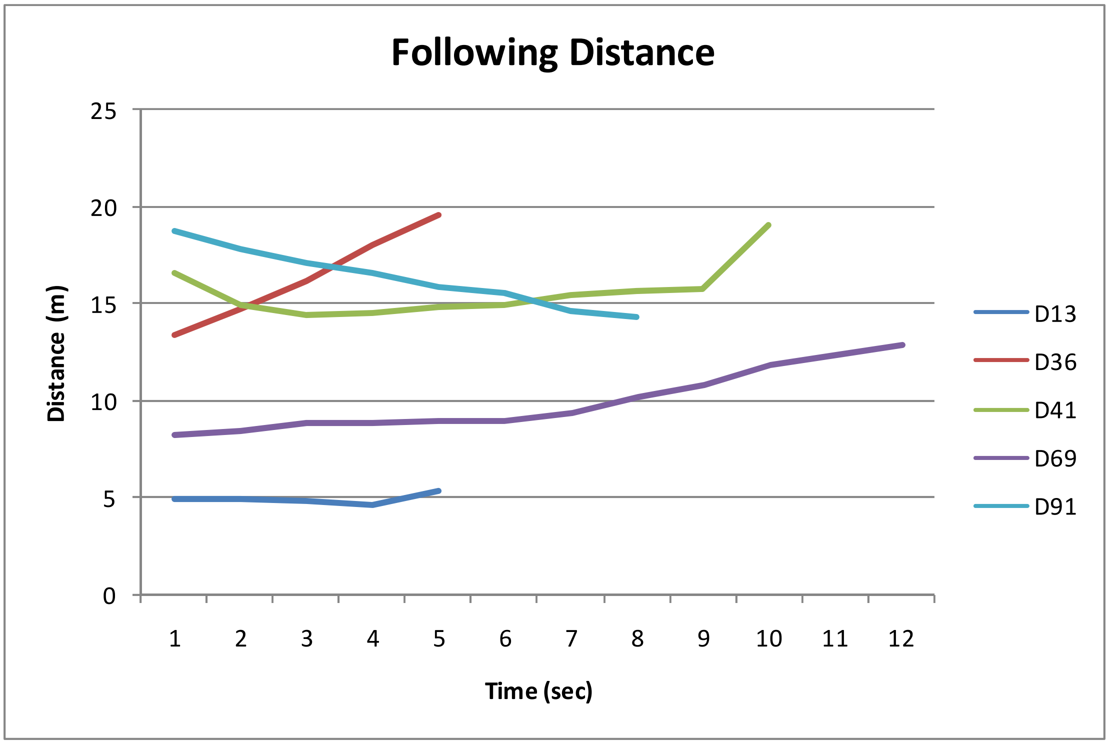


Figure 33: Following Distances for Drivers with Weak Correlation

We plotted the correlation coefficients of lead and following speeds for the two groups short and long term tailgaters as shown in Figure 34. Most of the correlation coefficients lie in a high range between 0.7 and 1 except a few outliers. The correlation coefficients for short term tailgaters are closely distributed in higher range than that for the long term tailgaters which seem to be scattered in a wider range than the former ones.

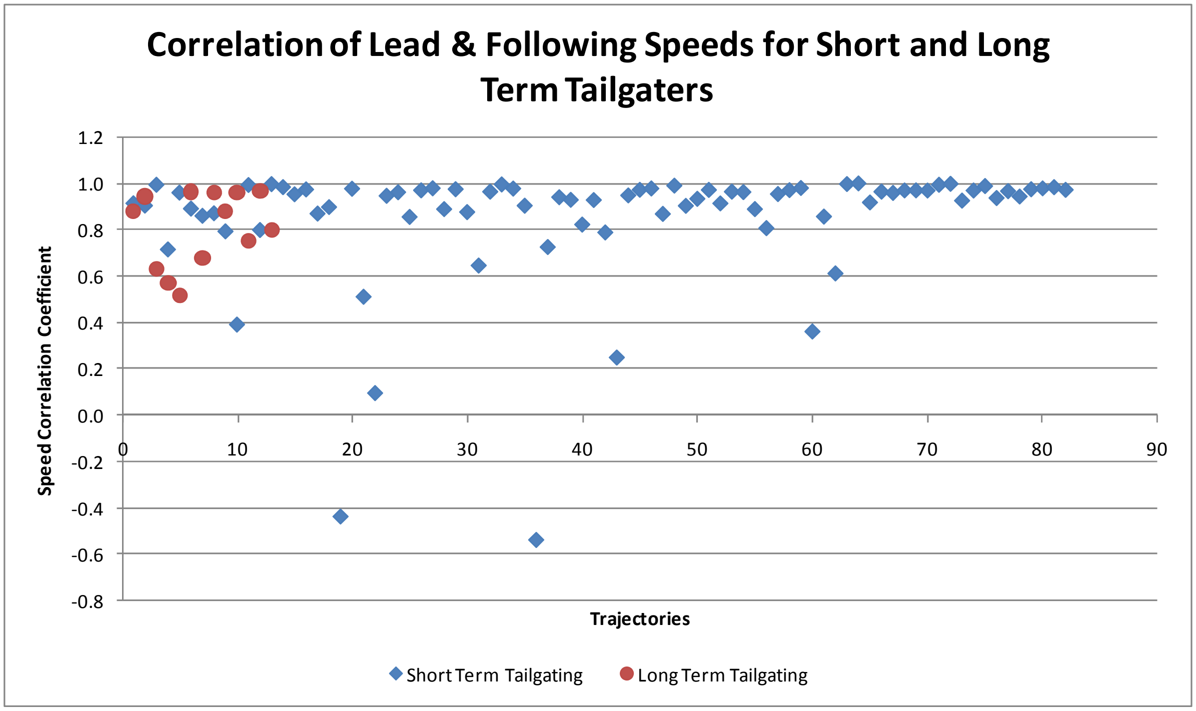


Figure 34: Correlation Coefficients of Speeds for the two Groups

In addition to high correlation coefficient, it is desirable to have some statistical test to support the hypothesis 2. So, t-Test for unequal variances was selected for testing since the datasets in each trajectory have unequal variances. The t-Test was performed for each trajectory. The hypotheses can be stated as follows:

$$Null\ Hypothesis: \mu_L - \mu_F = 0$$

$$Alternate\ Hypothesis: \mu_L \neq \mu_F$$

If $t_{stat} \geq t_{\alpha,DoF}$, then reject the null hypothesis in favor of alternate hypothesis. The test was performed for all the 94 trajectories and it was found that the null hypothesis was rejected for 3 trajectories while accepted for 91 trajectories. The results of the t-test for the first 40 trajectories are shown in Table 11. The results for the remaining trajectories are given in the Appendix B. The last column of the table summarizes whether the hypothesis is accepted or rejected based on the test criteria. Acceptance of the null hypothesis means the two means of lead and following speeds are equal. In tailgating situation, the following driver normally tends to follow the lead vehicle so closely that many of the times the following vehicle will be adjusting its speed to the lead vehicle's speed. This makes possible that mean speed of the lead and following vehicles be equal. In other words, when the means of two becomes equal, the following speed is highly dependent on the lead speed and the following driver is adjusting its speed to the lead vehicle's speed. Ordinarily, only a correlation, not a causal relationship, can be inferred from such an analysis. In this case, however, we feel comfortable adopting the more aggressive conclusion because experience suggests that a following driver reacts to the actions of the driver in front, rather than the other way around.

Table 11: Summary of the Results of t-test for Hypothesis 2

Driver No.	Lead Speed μ_L	Following Speed μ_F	*t-Stat*	$t_{\alpha, dof}$	Is *t-Stat*>=$t_{\alpha ,dof}$?	Result
D1	93.2	91.6	2.62	1.674	Yes	Reject
D2	50.3	51.2	-0.866	1.656	No	Do not reject
D3	61.9	62.9	-0.687	1.663	No	Do not reject
D4	40.8	40.6	0.131	1.673	No	Do not reject
D5	32.2	33.4	-0.199	1.761	No	Do not reject
D6	95.3	96.9	-2.711	1.665	No	Do not reject
D6A	92.3	92.4	-0.158	1.675	No	Do not reject
D7	69.7	69.7	0	1.782	No	Do not reject
D9	84.0	84.2	-0.196	1.729	No	Do not reject
D10	52.5	52.2	0.305	1.729	No	Do not reject
D11	87.6	86.2	0.774	1.677	No	Do not reject
D12	44.9	45.1	-0.135	1.813	No	Do not reject
D13	30.8	30.4	0.414	1.859	No	Do not reject
D14	43.3	43.8	-0.578	1.673	No	Do not reject
D15	82.8	83.8	-1.366	1.661	No	Do not reject
D18	23.6	27.4	-1.031	1.734	No	Do not reject
D20	95.9	95.5	0.425	1.724	No	Do not reject
D21	49.2	50.6	-0.177	1.833	No	Do not reject
D22	27.0	34.6	-1.256	1.761	No	Do not reject
D26	77.4	78.6	-0.36	1.669	No	Do not reject
D27	69.1	70.3	-1.186	1.729	No	Do not reject
D28	20.0	22.9	-0.916	1.812	No	Do not reject
D30	90.5	88.7	2.134	1.725	Yes	Reject
D31	95.7	95.4	0.226	1.692	No	Do not reject
D33	75.4	75.3	0.103	1.674	No	Do not reject
D35	83.1	83.2	-0.042	1.668	No	Do not reject
D36	46.1	50.7	-5.554	2.015	No	Do not reject
D37	51.8	54.3	-0.696	1.701	No	Do not reject
D38	97.9	97.4	1.532	1.649	No	Do not reject
D39	98.9	99.4	-0.891	1.653	No	Do not reject
D40	90.9	91.4	-0.322	1.729	No	Do not reject
D41	80.1	80.3	-0.114	1.746	No	Do not reject
D42	35.4	35.5	-0.019	1.745	No	Do not reject
D43	64.8	66.7	-1.546	1.701	No	Do not reject
D44	79.6	81.2	-1.302	1.696	No	Do not reject
D47	93.51	93.16	1.27	1.67	No	Do not reject
D48	37.66	41.08	-1.10	1.77	No	Do not reject
D50	31.13	34.54	-1.00	1.75	No	Do not reject
D54	77.63	79.84	-1.41	1.83	No	Do not reject
D56	92.04	92.71	-0.45	2.02	No	Do not reject

5.3 Time Lag between Lead and Following Drivers

Most models of car-following behavior treat the system in question as a time-lagged stimulus-response situation, where the behavior of the following vehicle is predicated to some extent on that of the leader, that knowledge of the leader's behavior can only be gained by observation, and that there is a finite amount of time necessary to perceive, understand, and respond to that information. In total, this lag can include attention, sensory and cognitive delays on the part of the following driver, plus mechanical delays in the driver and vehicle while an action is implemented.

We determined an "optimal" time lag (δ) by minimizing the Root Mean Square Error (RMSE) between the lead and following vehicle speeds at various candidates for δ. We considered the speeds at 100 millisecond intervals for this purpose in order to have a substantial amount of resolution in the determination of the appropriate value of δ. We introduced time lags of 100 milliseconds (msec) to the lead vehicle speed, starting from 100 up to 1500 msec. Then we determined the RMSE by using the following equation for various δ and identified the value of δ which gave minimum RMSE.

$$RMSE = \sqrt{\frac{\sum_{t=\delta+1}^{n}\left(\dot{x}_f(t) - \dot{x}_l(t-\delta)\right)^2}{n-\delta}} \qquad (20)$$

Figure 35 compares δ with RMSE for the tailgating driver #D1. The minimum RMSE was found when lag was 1,100 msec. We can see from the figure that the RMSE seems to follow a nice convex shape, making the selection of the "optimal" lag time of 1100 milliseconds fairly straightforward. Interestingly, this time lag is about half of what is normally predicted for routine driving (AASHTO, 2001). Presumably, this shorter reaction time is either necessary or typical of drivers engaged in tailgating behavior, whereas the larger values assumed for design purposes are intended to incorporate the full spectrum of driving circumstances one might find.

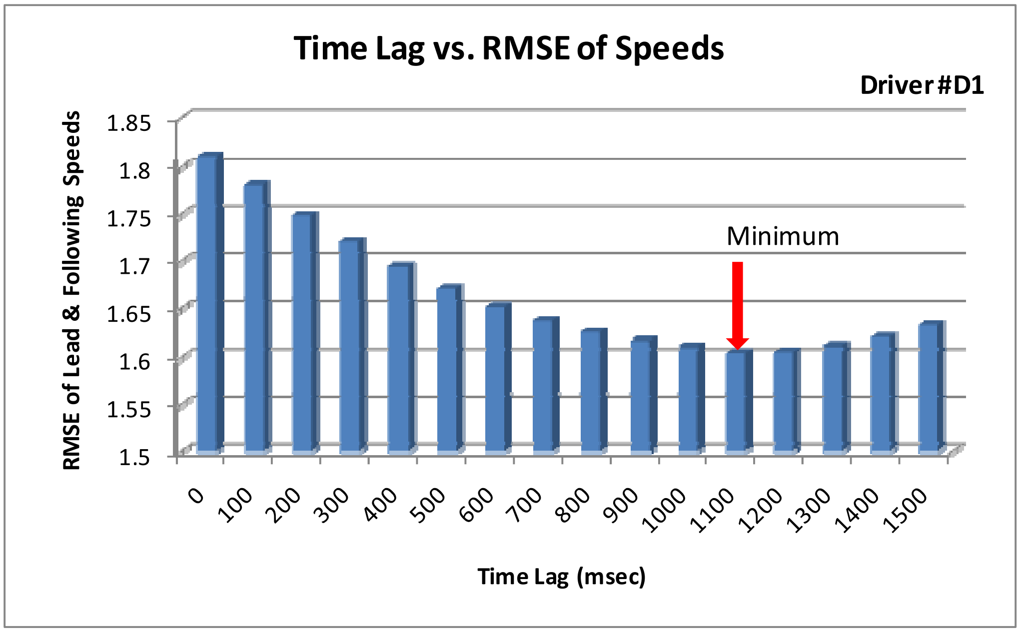


Figure 35: Time Lag and RMSE of Lead & Following Speeds for Driver D1

Similarly, Figure 36 shows the lag vs. RMSE for driver # D2. For this driver, the RMSE was the minimum at the lag of 300 msec. The charts for other drivers are given in Appendix C. Table 12 shows the lags for other drivers. The table shows only those drivers for whom we got lags higher than 0 for the minimum RMSE.

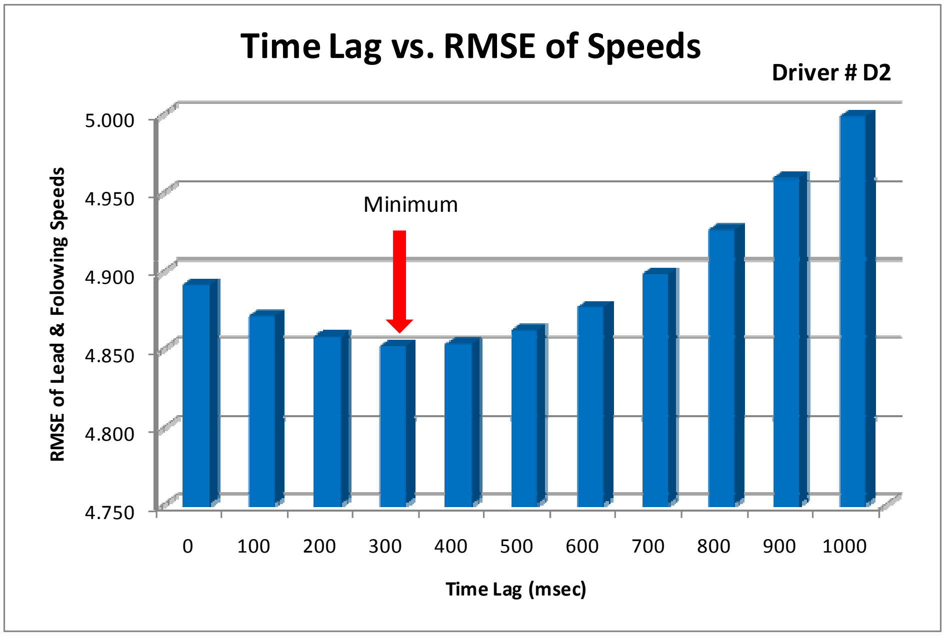


Figure 36: Time Lag and RMSE of Lead & Following Speeds for Driver D2

Table 12: Time Lag for the Minimum RMSE for all Drivers

Driver #	**Time Lag for Minimum RMSE (msec)**	**Driver #**	**Time Lag for Minimum RMSE (msec)**
D1	1100	D44	800
D2	300	D61	100
D6	400	D64	100
D9	300	D66	300
D10	200	D69	1500
D20	400	D76	500
D21	200	D81	100
D27	300	D84	1500
D30	1500	D97	100
D31	100	D102	200
D33	600	D106	300
D41	1100		
Mean Time Lag of all (msec)			522
Number of drivers			23

Based on the data of 23 drivers as shown in the above table, the mean lag for the minimum RMSE was found to be 522 msec. So, in an average, the following driver mimicked the speed of the lead driver in about half a second. Since our data was for tailgating drivers who would remain alert during the tailgating event would be able to respond more quickly to the stimuli from the lead vehicle than the whole population of drivers.

5.4 Following Distance, Headway and Speed

In this section, the safe following distances, estimated by equation 12 in section 3.1, is compared with the actual following distances observed from the vehicle trajectory data. The safe following distance is the distance required between the two vehicles such that the following vehicle will be able to stop or slow down without having a collision in case the lead vehicle suddenly stops or slows down. Figure 37 shows comparison of actual distance maintained by the following vehicle and safe following distance for one of the trajectories. It is observed that the actual distance was less than the safe following distance for almost entire duration of trajectory, which is not surprising, given that this was a tailgating event. The correlation coefficient between actual and safe following distance was found to be 0.63 showing a fair positive relationship between them. Such a correlation would be possible for two trajectories whose peaks and valleys were roughly consistent, but which exhibited a marked translation between them. In this case, there is certainly a consistent fixed difference between the two curves, although the variations in the actual speed profile are not as pronounced as those in the safe speed profile.

The actual distance fluctuates strongly and with positive correlation with the speed of the following vehicle. The correlation coefficient for actual distance and following speed was found to be 0.85 and that for safe distance and following speed was found to be 0.91. Thus, the correlation coefficient between the speed of following vehicle and the actual distance as well as safe distance were found to be high indicating high dependency on each other. In this case, it is not clear which one might have the causal influence over the other, if indeed it is such a simple one-sided relationship. The strong fluctuations in the safe following distance follow immediately from those in the following vehicle speed curve. Because this is derived from a simple mathematical model at equilibrium that does not take into account inertial effects, this might explain the readiness with which the safe distance curve fluctuates in response to the speed curve, where the actual distance curve is much more attenuated.

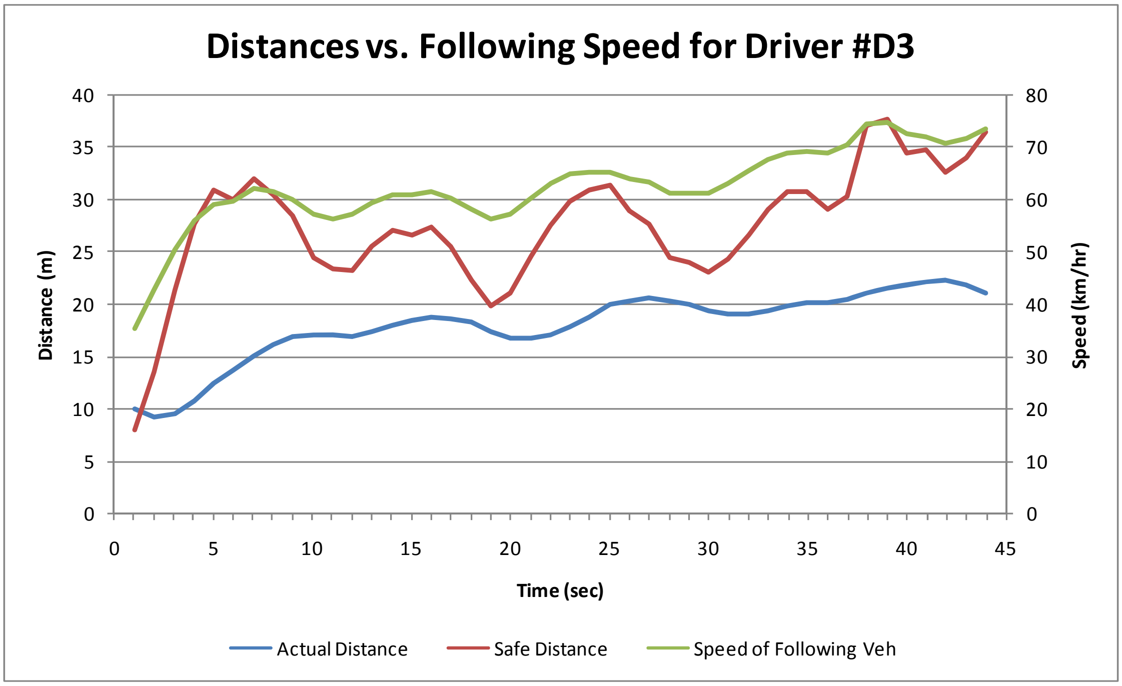


Figure 37: Actual vs. Safe Following Distance and Speed for a Trajectory

It is found that the following speed and distance are highly correlated. It is also observed from the figure that with the increasing following speed the following distance also increased or vice versa. It would be interesting to examine the relation between the actual distance, following distance and following speed not just for the tailgating conditions but also for the normal following condition. So, for next figure we considered all the following vehicles including tailgating ones for the whole day of data collection and determined the variables: actual and safe following distance as well as following speed for all the following vehicles. The charts for these variables are shown in Figure 38. The tailgating sections are those situations where the actual distance curve is lower than the safe distance curve. The safe distance seems to increase with the increase of following speed. However, the actual distance does not increase that much with the jump in the following speed. This is where mostly tailgating occurred. So, tailgating drivers seem to be not increasing the following distance but continue the smaller distance even when the speed is increased.

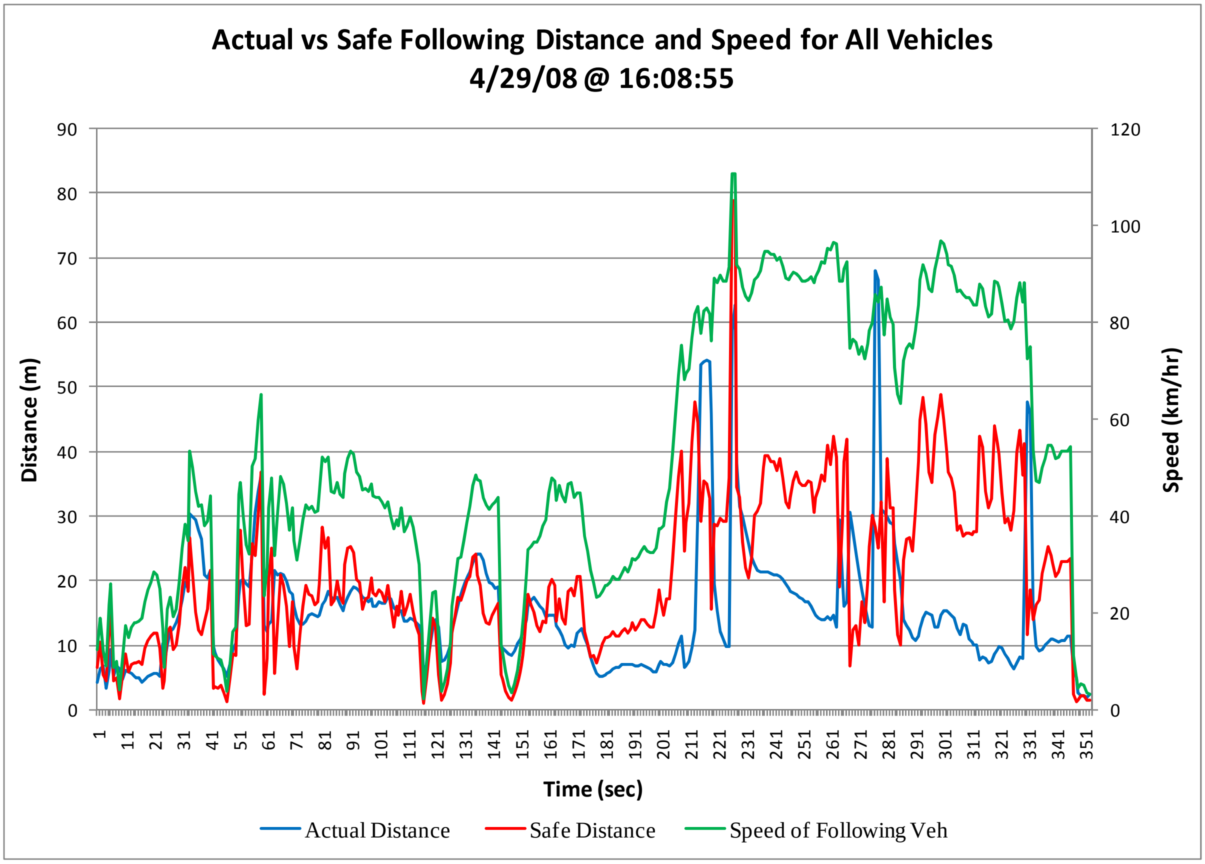


Figure 38: Actual vs. Safe Following Distance and Following Speed

In traffic engineering the distance between the two vehicles is often expressed as headway and measured in terms of time. Headway can be defined as the time between two vehicles passing the same point traveling in the same direction. Headway for our trajectory data can be found using the distance and following speed. Since distance in our study is a clear gap between two vehicles, it is necessary to add the length of a lead vehicle to the actual distance in order to find headway. Headway can be obtained by dividing this total distance by following speed. Using the above procedure, we determined actual and safe headway for all the trajectories. Since distance is in meter, the unit of speed was used as meter per second and length of lead car was assumed as 5 meter in average. Thus, actual headway was found by using the actual distance and following speed whereas safe headway was found by using safe following distance and following speed. The mean actual headway was found to be 1.26 seconds and mean safe headway was found to be 1.99 seconds. Similarly, the means of actual following distance and safe following distance for all the trajectories were found to be 12.04 and 24.08 m, respectively. Table 13 shows the actual and safe headways and distances for the first 40 trajectories. Since all the trajectories were of tailgating drivers, the actual headway would obviously be less than the safe headway. The results for all the trajectories are given in Appendix D.

Figure 39 shows the distribution of actual headways. The mean of actual headways of all the trajectories was found to be 1.26 seconds whereas the mean safe headway was found to be 1.99 seconds. We also found that the mean of actual following distances and safe following distance as 12.04 and 24.08 m, respectively.

Table 13: Actual and Calculated Safe Following Distance & Headway

Driver #	Mean Actual Distance (m)	Mean Safe Distance (m)	Mean Following Speed (km/Hr)	Actual Headway (sec)	Safe Headway (sec)
D1	17.89	35.70	91.64	0.90	1.60
D2	15.05	22.48	51.16	1.41	1.93
D3	18.12	27.87	62.90	1.32	1.88
D4	5.84	17.00	40.58	0.96	1.95
D5	5.93	13.85	33.67	1.17	2.02
D6	19.14	44.13	96.85	0.90	1.83
D6A	13.74	39.37	92.43	0.73	1.73
D7	6.21	29.45	69.66	0.58	1.78
D9	8.05	35.96	84.18	0.56	1.75
D10	10.41	21.81	52.21	1.06	1.85
D11	12.96	34.34	86.34	0.75	1.64
D12	9.81	19.19	45.11	1.18	1.93
D13	4.94	12.55	32.52	1.10	1.94
D14	10.96	18.91	43.82	1.31	1.96
D15	19.96	37.37	83.82	1.07	1.82
D18	8.65	14.36	34.06	1.44	2.05
D20	11.67	39.49	95.52	0.63	1.68
D21	13.06	26.30	55.16	1.18	2.04
D22	13.13	19.64	38.37	1.70	2.31
D26	16.42	35.19	78.59	0.98	1.84
D27	21.34	31.57	70.35	1.35	1.87
D28	7.08	10.97	26.63	1.63	2.16
D30	14.36	34.24	88.73	0.79	1.59
D31	24.95	39.87	95.42	1.13	1.69
D33	16.49	31.76	75.32	1.03	1.76
D35	17.76	35.42	83.21	0.98	1.75
D36	16.38	25.98	50.66	1.52	2.20
D37	11.53	25.81	54.33	1.10	2.04
D38	20.00	40.19	97.37	0.92	1.67
D39	19.55	43.17	99.43	0.89	1.74
D40	13.55	39.37	91.37	0.73	1.75
D41	15.61	34.13	80.27	0.92	1.75
D42	7.48	14.92	35.47	1.27	2.02
D43	11.34	30.86	66.67	0.88	1.94
D44	16.05	37.14	81.21	0.93	1.87
D47	12.42	38.66	93.16	0.67	1.69
D48	11.89	20.00	41.08	1.48	2.19
D50	9.65	17.79	34.54	1.53	2.38
D54	13.99	37.53	79.84	0.86	1.92
D56	7.18	40.49	92.71	0.47	1.77

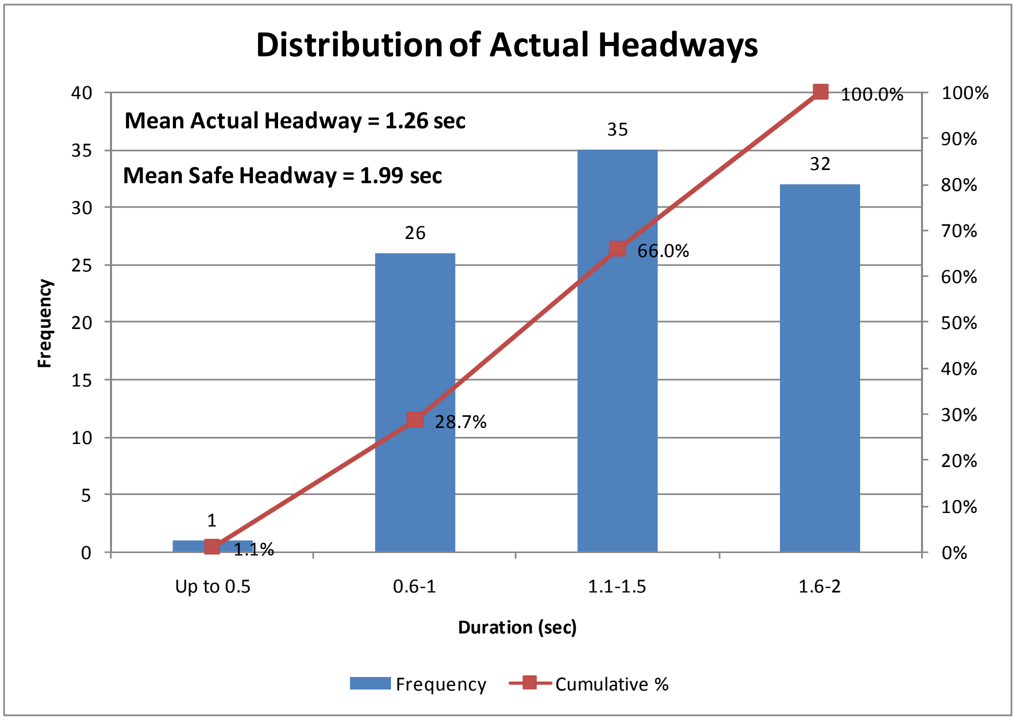


Figure 39: Distribution of Actual Headways

5.5 Traffic Hysteresis observing Distance and Speed Curves

As adopted in traffic engineering, traffic hysteresis is a phenomenon in which the acceleration and deceleration phases have different speed-density curves which are asymmetric. Newell (1965) had first recognized this phenomenon and proposed two speed-distance curves for transient flow. His theory gave a behavioral explanation for the formation of hysteresis loops and hypothesized that drivers react differently to acceleration and deceleration phases. His theory remained unnoticed for decades, probably due to the difficulty in obtaining mathematical formulae for acceleration and deceleration curves. Treiterer and Myers (1974) did experimental observation to study speed-occupancy curves distinguishing acceleration and deceleration and their observations were found to be in accord with Newell's theory. Zhang (1999) gave a mathematical theory for modeling the hysteresis phenomenon in traffic flow by distinguishing acceleration, deceleration and equilibrium flow to obtain the speed and density relationship. The speed-density curves obtained by this approach were hysteresis loops. Zhang and Kim (2005) proposed a new car-following theory that can reproduce traffic hysteresis. They believed that the traffic hysteresis is related to driver's behavioral shifts during phase transitions.

We plotted distance vs. following speed for a following driver D15, who tailgated for 53 seconds before changing lane to terminate tailgating, as shown in Figure 40. The distance here is the gap between the two consecutive vehicles measured from the back of the lead vehicle to front of the following vehicle. The points in the scatter plot are linked with lines according to the chronology of the events. Thus, one can discern from the figure not just which combinations of speed and distance prevailed, but in what order these combinations occurred.

In the first graph of Figure 40, we observed two clockwise loops. This means that the distances that prevailed when the vehicle was accelerating are in general less than the corresponding measurements when the vehicle was decelerating. This asymmetric behavior between speed and distance can be called *hysteresis*, borrowing a term from physics or electrical engineering, and the loops *hysteresis loops*.

A common explanation for hysteresis loops in temporally connected bi-variate plots is that a consistent relationship exists between the two variables, but that one is observed with a lag relative to the other. If the lag is accounted for (i.e., rather than plotting the data in a coincident fashion, one variable is plotted with respect to a lagged version of the other variable), the loops can be removed, and the resulting functional relationship between the variables will be clarified. If an injective function is the result, then the relationship is simple and most of the influences are accounted for. Additional ambiguities in the plot, on the other hand, would suggest exogenous influences beyond the two variables being plotted.

We studied the relation between the distance and following speed by introducing various time lags to the data to observe the resulting effects on the hysteresis loops. We introduced time lags of 1, 2, 3,……,7 seconds to the following speed. In the first figure with no time lag, we observed two hysteresis loops. The subsequent graphs are with times lags 1, 2, 3, 4, 5, 6 and 7 seconds. These loops kept shrinking with increasing time lags up to lags of 4 seconds. The first loop almost disappeared and the second became its narrowest at a lag of 4 seconds. The loops started widening again at the lag of 5 seconds and kept increasing with increasing time lags. For this vehicle, the hysteresis loops were narrowest for the time lag of 4 seconds. So, from the curves in Figure 38, we observed that the transition from one phase of traffic flow to another (e.g. acceleration to deceleration and vice versa) for the following driver D15 happened at 4 sec time lag. In the hysteresis loop, the acceleration and deceleration phases will be represented by separate opposite curves.

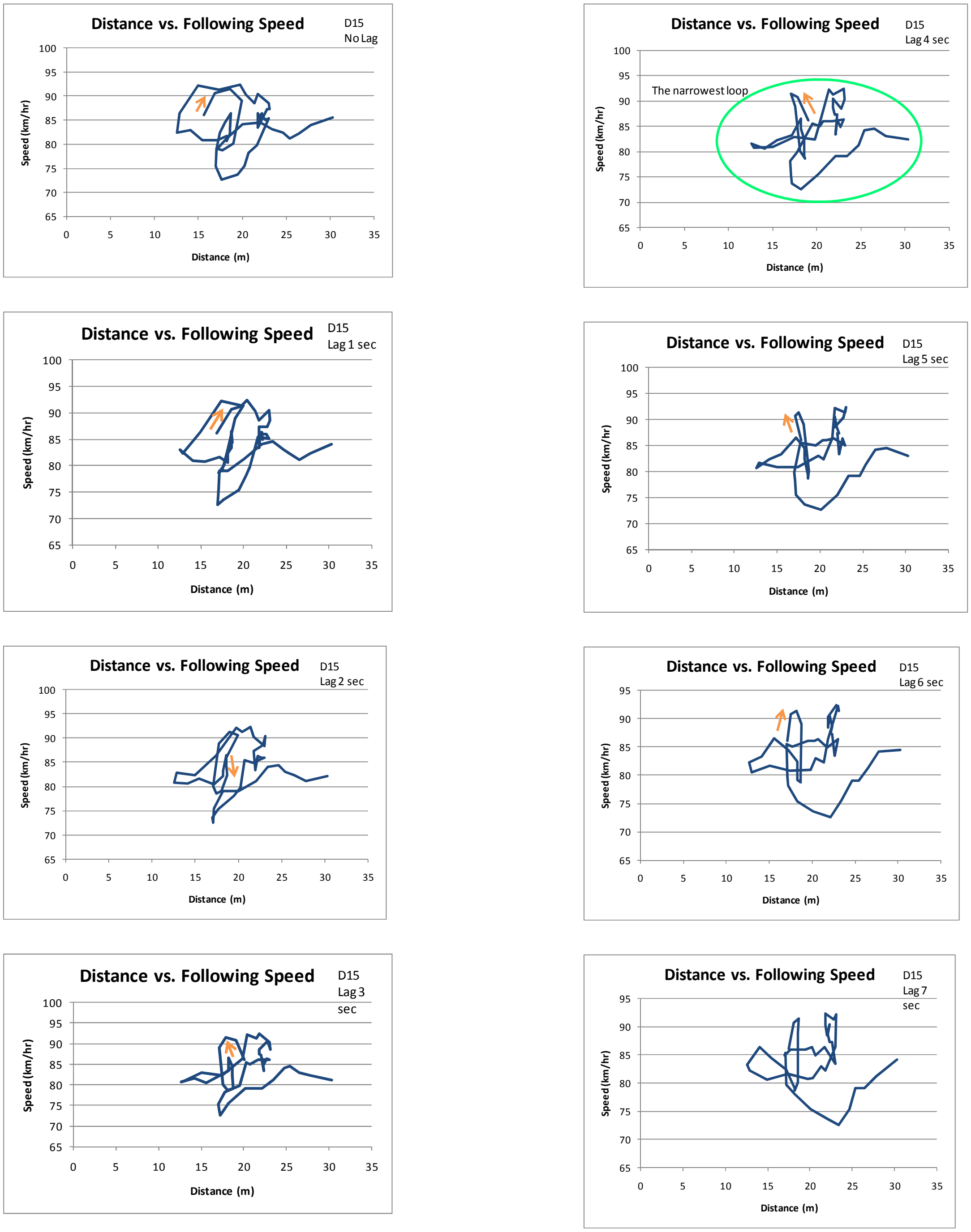


Figure 40: Hysteresis Loops at Various Time Lags for Driver D15

Another interesting observation from the figure, particularly from the first graph, is that changes in distance, whether increasing or decreasing, tend to be occurring fairly regularly and consistently. Changes in speed, however, seem to occur in rapid bursts. The distance measurements are, of course, a function of the behavior of two drivers, so it is easy to imagine how the following driver could keep the same speed even while distance was changing, if the change in distance was effected solely by the lead vehicle. One could even argue that the follower would be happy not to change speeds even if the lead driver was changing speed in such a way that the distance changed, as long as certain thresholds related to the follower's intent were not violated. If he/she were tailgating, then an excessive amount of distance would eventually prompt an acceleration maneuver. Any driver would eventually reduce speed in response to shortening distance for safety reasons. A content driver not intending to tailgate, however, might do nothing in response to an increasing distance.

One could also argue that driver attentiveness is a bursty process, rather than the continuous process reflected in prevailing car-following models such as those described above (and calibrated in the following section). Others have hypothesized the same thing, and it is the intent here to just make an observation. Most recently perhaps, Kim (2005) addressed this issue in his dissertation.

We plotted similar charts as above for all drivers and the results from observation of these charts are summarized in Table 14. The additional charts are given in Appendix E. We did not get loops in case of some trajectories as mentioned in the table. The mean of lags based on the results of the 53 trajectories was found to be 2.58 seconds.

Table 14: Results of Observations of Hysteresis for all the Trajectories

Driver #	Time Lag for Narrowest Loop (sec)	Driver #	Time Lag for Narrowest Loop (sec)	Driver #	Time Lag for Narrowest Loop (sec)
D1	No loop	**D43**	2	**D83**	4
D2	1	**D44**	3	**D84**	No loop
D3	3	**D47**	2	**D85**	4
D4	6	**D48**	No loop	**D86**	No loop
D5	No loop	**D50**	1	**D87**	No loop
D6	3	**D53**	No loop	**D91**	No loop
D6A	6	**D54**	No loop	**D92**	No loop
D7	No loop	**D56**	No loop	**D95**	No loop
D9	4	**D57**	6	**D97**	2
D10	1	**D58**	2	**D99**	No loop
D11	2	**D59**	No loop	**D100**	No loop
D12	1	**D60**	1	**D102**	1
D13	1	**D61**	2	**D106**	No loop
D14	5	**D62**	No loop	**D107**	1
D15	4	**D63**	2	**D108**	1
D18	No loop	**D64**	3	**D109**	3
D20	1	**D65**	No loop	**D112**	No loop
D21	No loop	**D66**	3	**D113**	No loop
D22	No loop	**D67**	No loop	**D114**	No loop
D26	2	**D68**	1	**D115**	No loop
D27	1	**D69**	No loop	**D116**	No loop
D28	No loop	**D70**	2	**D117**	1
D30	2	**D71**	No loop	**D118**	No loop
D31	1	**D72**	No loop	**D120**	No loop
D33	5	**D73**	No loop	**D121**	1
D35	1	**D75**	1	**D122**	No loop
D36	No loop	**D76**	No loop	**D123**	No loop
D37	No loop	**D77**	4	**D124**	1
D38	7	**D78**	No loop	**D125**	3
D39	5	**D79**	3		
D40	3	**D80**	4		
D41	1	**D81**	6		
D42	1	**D82**	No loop		
Mean for all the data (sec)					**2.58**
Number of trajectories with visible loop					**53**

5.6 Calibration of Car-Following Model

While the subject of this dissertation is tailgating, and not car following per se, it happens that the microscopic data collected could be used to calibrate any of the car-following models that prevail in the literature. As a sidebar, then, we conducted this calibration with the same data used for other analyses in this dissertation, and compared the results to some classic and more recent calibration attempts using the same models.

We calibrated a car-following model by comparing the speed data from field experiments with the speeds obtained from car-following theory. We used a generalized form of the car-following model that was proposed by Gazis et al. (1961) which is also known as the GM model, as the development of this model was supported by General Motors. The model can be expressed as follows:

$$\ddot{x}_f(t) = \frac{\alpha_{l,m}\left[\dot{x}_f(t)\right]^m}{\left[x_l(t-T) - x_f(t-T)\right]^l}\left[\dot{x}_l(t-T) - \dot{x}_f(t-T)\right] \qquad (20)$$

The subscripts *f* and *l* are used for following and lead vehicles, respectively. The second derivative of distance x on the left hand side is acceleration of the following vehicle whereas the first derivatives of distance on the right hand side are the speeds of the lead and following vehicles. *T* is the perception and reaction time of the following driver and *t* is the time epoch of observation. α is a sensitivity parameter and *l* and *m* are other calibration parameters.

Because the following vehicle is the actor in this scenario, all observations of the lead vehicle (and some self-observations) are rendered at time $t-T$ to take into account the perception and reaction time of the following driver. Written this way, the model can be perceived as a present action predicated on past observations. In some literature, the same model can be seen written with the time epoch translated in such a way that the model reflects a future action predicated on present observations. Both models are equivalent by means of a simple time shift.

We conducted the calibration by varying the values of the above parameters and calculating the Root Mean Square Error (RMSE) for the speeds from field data and from the car-following model for the following driver. This is a combinatorial exercise, and the goal is to find that combination of parameters that minimizes the error. We conducted this process separately for each individual vehicle, and then repeated the process with all vehicle trajectories pooled. Table 15 shows the best values of the parameters and corresponding minimum RMSE for the individual drivers as well as mean values for all the drivers combined. We filtered some trajectories having erroneous values of parameters and the results for 60 drivers are shown in the table. The mean values of α, l and m are computed as 1.30, 0.31 and 0.53, respectively.

Table 15: Values of Parameters for Minimum RMSE

Driver #	α	l	m	RMSE	Driver #	α	l	m	RMSE
D1	0.096	0.01	0.892	2.250	D65	19.293	1.297	0.002	3.531
D2	0.097	0.01	0.892	3.716	D69	0.407	0.475	0	0.646
D4	0.096	0.01	0.892	0.000	D71	0	0	5.895	5.149
D6	0.9	0.4	0.5	12.740	D75	0	0	6.418	6.105
D6A	0.884	0	0.261	2.794	D77	1.387	0	0	6.450
D7	1.193	0	0	2.652	D79	1.041	0	0	7.668
D11	0.731	0	0	6.448	D80	0.907	0	0	5.180
D15	0.987	0.029	0	4.388	D82	1.957	0	0	16.199
D21	1.211	0	0	11.071	D83	0.828	0	0	3.291
D26	1.505	0	0.09	4.987	D85	0.742	0	0	2.076
D27	1.48	0	0.049	3.132	D87	7.61	1.225	0	3.159
D30	1.469	0	0	4.053	D91	0	0.129	0.072	0.638
D31	1.307	0.952	0.412	2.721	D97	0.525	0.46	0	1.885
D33	0.762	4.444	4.095	4.501	D100	2.237	0	0	6.093
D36	0.121	0.333	0.128	0.546	D107	0.193	1.778	2.618	3.005
D37	0.481	0	0	7.625	D108	0	0.115	0.076	14.605
D38	0	1.3999	0	3.963	D109	0	0.134	0.07	11.680
D39	0.094	0	0.891	1.991	D112	3.534	0	0	17.204
D40	0.656	0.366	0	5.224	D113	1.537	0	0	10.613
D42	1.341	1.034	1.235	2.832	D114	3.983	0	0	3.133
D43	0	0.279	0.086	3.900	D115	1.285	0	0	6.566
D47	1.018	0.937	0	1.916	D116	0	0.125	0.08	4.200
D48	0.733	0	0	6.601	D117	1.61	0	0	5.270
D50	0.004	2.012	4.618	2.397	D118	1.097	0	0.209	4.220
D54	0	0.123	0.069	4.642	D120	1.097	0	0.209	5.543
D56	0.596	0	0.565	1.637	D121	0	0.12	0.082	6.316
D58	0	0.124	0.068	8.170	D122	3.396	0	0	8.700
D59	1.187	0	0	9.032	D123	2.603	0	0	6.293
D61	0	0.117	0.076	4.127	D124	0.658	0	0	4.993
D64	0.476	0	0	2.387	D125	0.658	0	0	8.675
Mean α					1.30				
Mean l					0.31				
Mean m					0.53				
Number of Observations					60				

Table 16 shows the values of the calibration parameters of the car-following model as estimated by various other researchers. Figure 41 shows the plotting of these values. The mean was taken for plotting when there was more than one value for a parameter for the same researcher. The values of parameters from our study were found to be close to Aron (1988) and Ozaki (1993) which are fairly contemporary studies. This may be due to the availability of modern equipments and their level of accuracy in obtaining data. They used video data in their experiment whereas we used IR sensor data verified by video images.

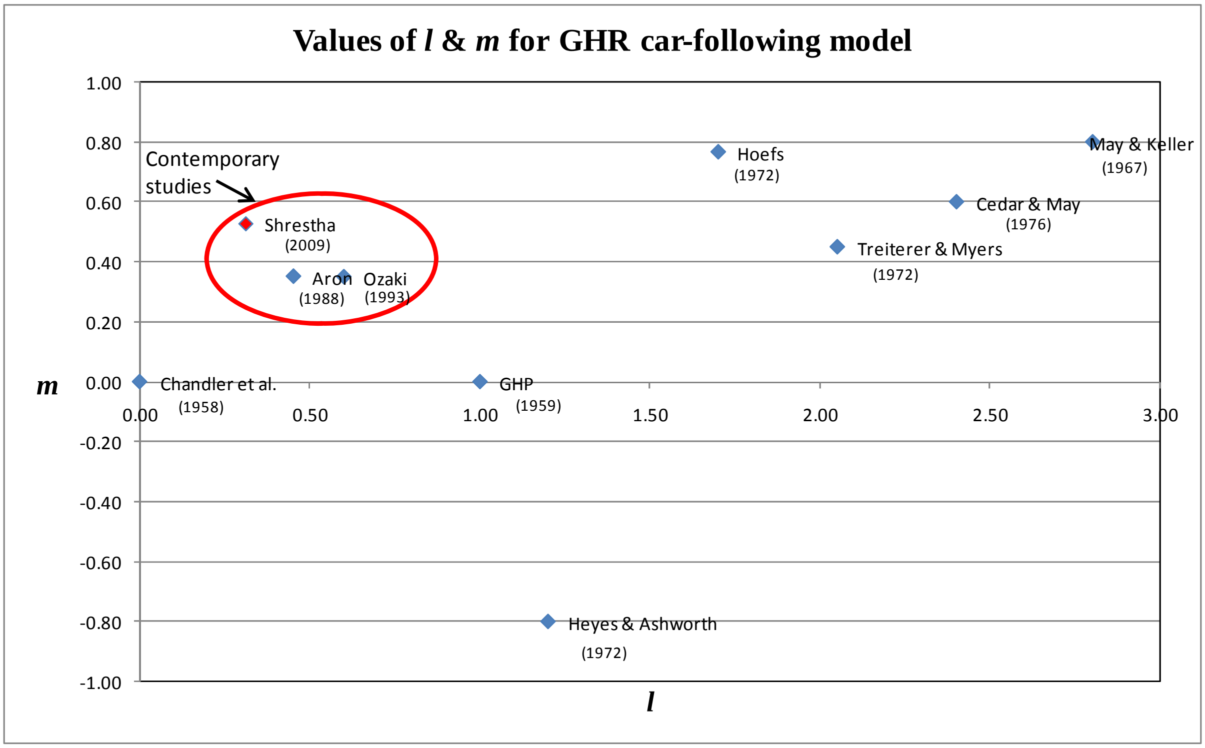


Figure 41: Comparison of Car-following Model Parameters from various Studies

Table 16: Values of Parameters of Car-following Model

Source	*l*	*m*	Remark
Chandler et al. (1958)	0	0	
Gazis, Herman and Potts (1959)	1	0	
May and Keller (1967)	2.8	0.8	
Hoefs (1972)	0.9 0.9 3.3	1.5 0.2 0.6	Acceleration Deceleration w/o brake Deceleration w/brake
Heyes and Ashworth (1972)	1.2	-0.8	
Treiterer and Myers (1974)	2.5 1.6	0.7 0.2	Deceleration Acceleration
Cedar and May (1976)	2.4	0.6	
Aron (1988)	0.67 0.5 0.18	0.65 0.26 0.14	Deceleration Steady state Acceleration
Ozaki (1993)	1 0.2	0.9 -0.2	Deceleration Acceleration
Shrestha (2009)	0.31	0.53	

We plotted the speeds from the field data and the ones calculated from car-following model using our data. Figure 42 shows a comparison of the actual speed of the lead vehicle and following vehicle and the predicted speed of the following vehicle calculated from the car-following model for Driver #2. In this case, the speed of the lead and following vehicles ranged between 60 and 35 km/hr. Speed fluctuated up to 40% whereas following distance only by 30%. This suggests that the following driver #2 was trying to maintain following distance within some narrow interval over a wide range of speeds. The trajectory from the car-following model using the above parameter values was found to be very close to the actual trajectory. Given that there are only three calibration parameters and that a perfect polynomial fit to the empirical data curve would certainly be of much higher order than quadratic, there is strong evidence that the model is at least reasonable, and that the calibration was legitimate. Similarly, Figure 43 and 44 show the trajectories of speed data for Driver #4 and Driver #26, respectively. The graphs for some additional trajectories are given in Appendix F.

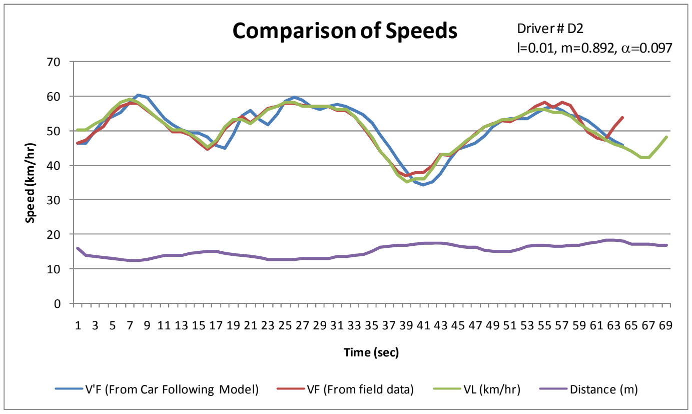


Figure 42: Comparison of Speed Data for Driver D2

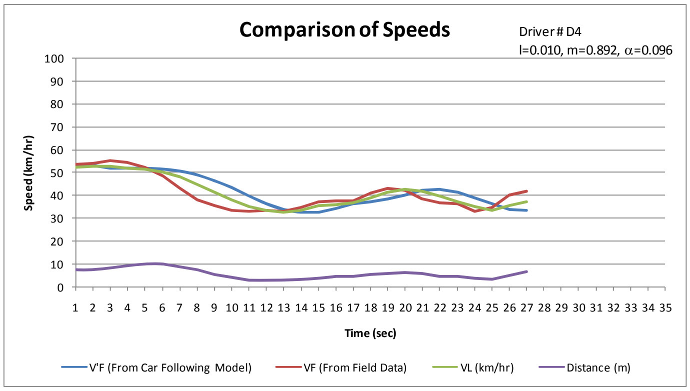


Figure 43: Comparison of Speed Data for Driver D4

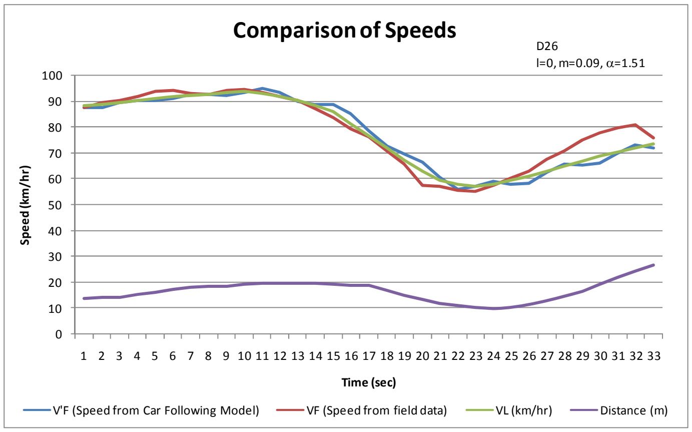


Figure 44: Comparison of Speed Data for Driver D26

Table 17 shows the range and fluctuation of speed and following distance for the above trajectories. The fluctuations for speed are somewhat steady but the fluctuations for following distance vary. This may be due to the drivers controlling their speed to the posted speed limit and adjusting to the speed of the lead vehicle.

Table 17: Range and Fluctuation of Data for Trajectories

Driver #	Lead Speed (km/hr)			Following Speed (km/hr)			Following Speed from CFM (km/hr)			Actual Following Distance (m)		
	Min	Max	Fluctuation	Min	Max	Fluctuation	Min	Max	Fluctuation	Min	Max	Fluctuation
D2	35	59	41%	37	58	37%	34	60	43%	12.3	18.2	32%
D4	33	53	38%	33	55	40%	33	53	39%	2.9	9.9	71%
D26	57	94	39%	55	95	42%	56	94	40%	9.7	26.7	64%

It is observed from the above table that speed fluctuated about 40% while the distance fluctuated by 56%. The less fluctuation in speed and higher fluctuation in following distance indicate that the tailgating drivers are more concerned to maintain the speed than maintaining the following distance.

Chapter 6: Conclusions

The goal of this research was to conduct a microscopic study of tailgating behavior of drivers. The losses in lives and property caused by rear-end crashes due to tailgating are too large to be neglected. But there were very few researches that focused on tailgating. So, this research shed some light on microscopic study of tailgating behavior of drivers. We developed a simple model to identify tailgating vehicles using vehicle dynamics and human behavior. With the help of this model and field data we collected, we studied tailgating in depth and breadth.

It has been a big challenge for researchers to acquire naturalistic driving data for driver's behavior study. In past studies, driver and vehicle data had been collected by using different methods such as driving on test track, driving simulator, using roadside video camera, installing sensors and video camera in driver's cockpit, etc. But test track and driving simulator are short of real road conditions and represent very artificial driving environments. Roadside video cameras can capture the video of vehicles for a limited stretch only which is covered by its line of sight but cannot produce full trajectory. Sensors and video cameras in the driver's cockpit can impart some awareness to the driver that an experiment is being conducted, which may influence his or her driving behavior. Our method of data collection, which is same as that used by Kim (2005), captures data of anonymous following vehicles. Since the following driver would not have any clue that we were collecting his vehicle data, it will not have an effect on his driving behavior at all. So, this method allows us to capture naturalistic driving data of following drivers. Also this method gives us some flexibility in that we can collect data at any location and for any length of the road. The tradeoff, of course, is complexity. This is an extraordinarily tedious and time-consuming method of collecting detailed data, and it must place a heavy reliance on serendipity, since our method requires the lead vehicle driver to fit in with the traffic and not engage in any maneuvers designed to induce following vehicles into tailgating.

6.1 Summary and Findings of this Research

After identifying all necessary data for this study and devices to collect them, a decision was made to use the instrumented vehicle which Dr. Lovell and his students used for cellular geo-location, car-following, and lane departure warning system studies. The vehicle was an Infiniti Q45 provided by Nissan Technical Center North America. The devices used in the vehicle were CAN bus, an Infrared Radar (IR) sensor, a Distance Measuring Instrument (DMI) with differential GPS and a digital camcorder. A software package (Vehicle Data Acquisition System, VDAS) with graphical user interface was developed to connect with all these devices, synchronize them, acquire necessary data through them and finally to save these data in the laptop computer.

The instrumented vehicle was driven on freeways in Maryland to collect data over a span of several days to cover as many diverse drivers as possible. The congested peak hours were avoided to collect data since the vehicles would be forced to follow closely during such hours. From the pool of collected data, we obtained trajectory data for 125 tailgating drivers.

But after reviewing sensor data with video images, we narrowed this down to 94 trajectories for the data analysis, rejecting 31 erroneous trajectory data.

Based on observation of the initial results of data analysis, we made the following hypotheses to describe the tailgating behavior of drivers. The first hypothesis states that "**In some interval of time, mean following distance for short term tailgating drivers is less than that for long term tailgating drivers**." Statistical test and analysis was done to support this hypothesis. A cluster analysis technique, which keeps the variance of data minimum within the group and maximum between the groups was used to divide the trajectory data into two groups based on the following durations. For each group, the means of the following distances were determined at a time intervals of every second for all the trajectories in both groups for up to 30 seconds of duration and the two means were compared. Welch t-test was performed for hypothesis testing because of the different points of the trajectory have different sample sizes associated with them, and they have different sample variances. Using a confidence level of 95%, it was found that out of the 30 tests, 10 showed successful results whereas 20 results were unsuccessful. For the first 9 seconds, the test consistently supported the hypothesis.

This suggests a possible behavioral mechanism at play, although this cannot be confirmed simply with observational data. The results suggest that (some) tailgaters who remain in that condition for a short period of time know ahead of time that they will not remain behind the lead vehicle for a long period of time, and hence are willing to accept shorter tailgating distances during that time because the higher risk of the shorter distance is mitigated by the known intent to keep the interval of risk short. Tailgaters who perceive otherwise, that they may be behind the lead vehicle for a longer period of time, while still technically tailgating (driving closer than the physics of the problem suggest is safe), are less willing to accept the risk of an extremely close following distance.

One possible criticism of this approach is that while the drivers are assumed to be independent of each other, their behavior along their individual trajectories is certainly not independent across time epochs. As a result, some serial correlation might be expected in the mean behavior as a function of time as well. With this critique in mind, we used an alternative method as explained in chapter 5 to test the same hypothesis to take into account possible serial correlation in the time series data. Interestingly, the results from the first method and this alternative method were close for the first several seconds of following duration. Based on this analysis, we feel it safe to conclude that drivers who are willing to tailgate are willing to do so even more closely when they are following for a short duration. If one could surmise that the plan was to tailgate for a short duration, then one could conclude that drivers are willing to take a higher risk with regard to inter-vehicle separation if they know they will be tailgating for a short duration.

By our own driving experience, most of us agree that our speed is influenced by the speed of the vehicle ahead of us except in a situation where the lead vehicle is too far from the follower having negligible interaction between them. Our second hypothesis states that "**Tailgating driver's speed is influenced by the lead driver's speed**." The mean correlation coefficient for the lead and following speeds of all the trajectories was found to be 0.85. This high value of correlation coefficient suggests that the following speed is dependent on lead speed for tailgating vehicles. Ordinarily, of course, one has to be very careful making causal inferences about correlated data, but in this case it certainly makes more sense that the lead vehicle influences the follower than the other way around. A statistical test was also done to support this hypothesis and the result of test overwhelmingly supported the hypothesis.

Several other interesting facts were determined by analyzing the trajectory data as listed here. Half of the tailgating events were terminated within 10 seconds mostly by lane change maneuver by the following drivers. The passenger cars were two third of the total daily traffic volume whereas only one in four tailgating vehicles was a passenger car in the location of our study in Maryland. Light trucks constituted 14% of the total daily traffic volume but 60% of the total tailgating vehicles were light trucks. It was observed that nearly half of the tailgating drivers were SUV drivers indicating the aggressiveness among these drivers. The actual headway maintained by tailgating drivers was found to be 1.26 sec and safe headway was found to be 1.99 sec based on data from 94 drivers. It is to be noted that all these drivers were tailgating and therefore the headways they maintained would obviously be less than the safe headway.

It is found that in general the following speed and distance are highly correlated. However, in some tailgating cases the actual distance does not increase that much with the jump in the following speed. So, tailgating drivers seem to be not increasing the following distance but continue the smaller distance even when the speed is increased.

We observed asymmetric behavior between following speed and distance by plotting these variables. Such an asymmetric behavior between speed and distance can be called *hysteresis* and the loops from this plot can be called as *hysteresis loops.* The plots were repeated by introducing various time lags to following speed to determine the time lag for minimizing the hysteresis loops.

Most models of car-following behavior treat the system in question as a time-lagged stimulus-response situation, where the behavior of the following vehicle is predicated to some extent on that of the leader, that knowledge of the leader's behavior can only be gained by observation, and that there is a finite amount of time necessary to perceive, understand, and respond to that information. In total, this lag can include attention, sensory and cognitive delays on the part of the following driver, plus mechanical delays in the driver and vehicle while an action is implemented. An "optimal" time lag was determined by minimizing the Root Mean Square Error between the lead and following vehicle speeds at various candidates of time lags.

Since tailgating is a form of car-following events, yet one that we suspect is not well represented in typical models, we calibrated the GHR car-following model, which is one of the generalized forms of a car-following model with our field data and compared the results with other studies.

6.2 Contribution of this Research

The main contributions of this dissertation can be considered as follows:

- A wealth of microscopic trajectory data of anonymous following drivers. These data can be used for a variety of important purposes, including understanding more details about driver behavior, developing in-vehicle safety countermeasures for aggressive driving, and improving the fidelity of microscopic traffic simulators by adding behaviors or drive cycle components not currently considered.
- A methodology for collecting naturalistic driver behavior data in microscopic form, that allows for the full range of variance between and within drivers to be manifest in the data. Other efforts to study naturalistic driving are still reliant on non-anonymous techniques that introduce experimental error and artificially attenuate the natural variance in these measurements.
- Quantifying some detailed behavioral patterns amongst tailgating drivers and relating that to potential risk-taking willingness on the part of those drivers. These are important aspects of driving behavior that are not currently captured in traffic flow models, and that could be added to better represent the variance in driver activities that should be expected on the road.
- Quantifying a detailed relationships between speeds of lead and following vehicles, following distances, and headways in tailgating situations. This is directly relevant to simulation studies.

- Developed a simple model for identifying whether a given following trajectory is tailgating or not, based on a presumptive model of safe following distance. This could be useful for developing countermeasures, or as a simple data filter for other researchers also interested in segregating tailgating data from normal following vehicle data.
- Measurements of vehicle/driver reaction times in tailgating situations. These measurements suggest a higher level of attentiveness for tailgating drivers than would be expected for the normal population. These values could be used in simulations.
- Investigations of causal influence between detailed aspects of lead and following vehicle interaction. This information could be adopted into an algorithm for following behavior in aggressive driving situations.
- An additional calibration of the most popular car-following model. In this case, the calibration was done with contemporary vehicles in a naturalistic driving environment, so we would expect these values to be more representative of real drivers than the calibration values currently in popular use, which were derived under more artificial conditions.

The findings of this study would be useful information for developers of microscopic traffic simulation, auto and insurance industries, policy makers, traffic safety experts, traffic safety enforcement agencies and highway designers.

6.3 Future Research

This research was successful in studying some of the most salient aspects of tailgating, which is a complex driving behavior not well represented in current simulation models. Based on empirical data collected in a naturalistic and anonymous fashion, new findings on tailgating behavior were hypothesized and tested statistically. Further work could be done to bolster these conclusions; some of the future possible research topics in this field can be listed as following:

- Examine if a driver's ability to see more than one vehicle ahead of him affects his tailgating behavior by using different sizes of lead vehicle to collect the data.
- Study impact of presence of vehicle in adjacent lanes in tailgating behavior.
- Study impact of drivers' profiles e.g. gender and age in tailgating behavior.
- Study impacts of external factors such as road geometry, number of lanes, location, weather and visibility in tailgating behavior.
- Sensitivity analysis of various values of perception reaction time, coefficient of friction and coefficient of deceleration.

APPENDICES

APPENDIX A: Detail Information of Trajectories

Driver #	M	D	Y	Hr	Min	Sec	Duration (sec)	Veh Type	Location	Reason for Termination	Lane #	Mean Speed	Mean Distance	Reason for Discarding
D1	4	29	2008	15	22	11	29	SUV	I-495	Lane Change	2 of 4	91.60	17.80	
D2	4	29	2008	15	36	51	69	SUV	I-495	Lead exit	1 of 4	51.20	15.00	
D3	5	29	2008	16	14	54	47	Pickup	I-495	Cut in by another vehicle	2 of 4	62.90	18.12	
D4	6	25	2008	10	44	16	29	SUV	I-495	Lane Change	4 of 4	40.58	5.84	
D5	6	25	2008	12	33	48	8	SUV	I-495	Slowed down in curve	3 of 4	33.37	6.29	
D6	6	25	2008	12	43	35	42	Truck	I-495	Another Truck cut-in	3 of 4	96.85	19.14	
D6A	6	25	2008	12	44	18	29	Truck	I-495	Lane Change	3 of 4	92.43	13.74	
D7	6	7	2008	17	39	25	6	Van	I-495	Lead changed lane	4 of 4	69.66	6.21	
D8	4	29	2008	15	12	59	11	Car	I-495	Sensor drop	3 of 4	84.18	8.05	Sensor drop
D9	4	29	2008	15	28	12	16	SUV	I-495	Lane Change	4 of 4	84.18	8.05	
D10	4	29	2008	15	29	21	13	Car	I-495	Lead exit	3 of 4	52.21	10.41	
D11	4	29	2008	15	27	7	27	SUV	I-495	Lane Change	3 of 4	86.34	12.96	
D12	4	29	2008	15	36	42	7	SUV	I-495	Lane Change	1 of 4	45.11	9.81	
D13	4	29	2008	15	36	30	5	Car	I-495	Lane Change	1 of 4	30.37	4.94	
D14	4	29	2008	15	38	22	31	Pickup	I-495	Increased gap	1 of 4	43.82	10.96	
D15	4	29	2008	15	49	38	53	Car	I-495	Lane change	3 of 4	83.82	19.96	
D16	7	22	2008	15	37	50	9	Car	I-495	Lost in curve	3 of 4	29.92	7.24	Lost in curve
D17	7	22	2008	15	38	39	9	Car	I-495	Sensor drop	3 of 4	29.80	8.39	Sensor drop, D17 and D18 are same
D18	7	22	2008	15	38	58	11	Car	I-495	Lead veh change lane	1 of 2	27.40	8.65	
D19	7	22	2008	15	42	19	10	Car	I-495	Sensor drop	3 of 4	28.86	5.28	Sensor drop
D20	7	22	2008	15	45	56	10	SUV	I-495	Lane change	4 of 4	95.52	11.67	

APPENDIX A: Detail Information of Trajectories

Driver #	M	D	Y	Hr	Min	Sec	Duration (sec)	Veh Type	Location	Reason for Termination	Lane #	Mean Speed	Mean Distance	Reason for Discarding
D21	7	22	2008	16	4	2	5	Van	I-495	Increased gap	3 of 4	50.57	12.90	
D22	7	22	2008	16	4	24	7	SUV	I-495	Increased gap	3 of 4	34.62	13.13	
D23	7	22	2008	16	5	8	8	SUV	I-495	Sensor drop	3 of 4	48.36	15.86	Sensor drop
D24	7	22	2008	16	6	8	7	SUV	I-495	Lost in curve	3 of 4	36.39	14.90	Lost in curve
D25	7	22	2008	16	10	42	10	SUV	I-495	Sensor drop	3 of 4	80.98	22.45	Sensor drop
D26	7	22	2008	16	10	58	32	SUV	I-495	Lane change	3 of 4	78.59	16.42	
D27	7	22	2008	16	11	55	13	SUV	I-495	Increased gap	3 of 4	70.35	21.34	
D28	7	24	2008	14	43	16	5	Car	I-495	Increased gap	3 of 4	32.90	7.08	
D29	7	24	2008	14	44	38	5	SUV	I-495	Sensor drop	3 of 4	53.15	19.15	Sensor drop
D30	7	24	2008	14	48	21	17	Truck	I-495	Lane change	2 of 4	88.73	14.36	
D31	7	24	2008	14	48	45	18	Van	I-495	Increased gap	2 of 4	95.42	24.95	
D32	7	24	2008	14	49	5	11	Van	I-495	Lost in curve	2 of 4	87.15	26.23	Lost in curve
D33	7	24	2008	14	49	23	32	Van	I-495	Lane change	2 of 4	75.32	16.49	
D34	7	24	2008	14	50	1	7	Van	I-495	Sensor drop	2 of 4	56.12	21.46	Sensor drop
D35	7	24	2008	14	50	33	34	SUV	I-495	Lane change	2 of 4	83.21	17.76	
D36	7	24	2008	14	30	47	4	Car	I-495	Increased gap	1 of 4	50.66	16.38	
D37	7	24	2008	14	32	3	14	Car	I-495	Lane change	1 of 4	54.33	11.53	
D38	7	24	2008	14	35	6	206	Truck	I-495	Lane change	2 of 4	97.37	20.00	
D39	7	24	2008	14	38	34	102	Truck	I-495	Increased gap	2 of 4	99.43	19.55	
D40	7	24	2008	14	40	39	10	Truck	I-495	Lane change and exit	2 of 4	91.37	13.55	
D41	7	24	2008	14	40	56	9	Truck	I-495	Lead veh exit	3 of 4	80.27	15.61	

APPENDIX A: Detail Information of Trajectories

Driver #	M	D	Y	Hr	Min	Sec	Duration (sec)	Veh Type	Location	Reason for Termination	Lane #	Mean Speed	Mean Distance	Reason for Discarding
D42	7	24	2008	15	0	34	8	Car	I-295	Exit to ramp	1 of 2	35.47	7.48	
D43	7	24	2008	15	5	29	15	Car	I-295	Lane Change	1 of 2	66.67	11.34	
D44	7	24	2008	15	7	26	19	SUV	I-495	Lane Change	4 of 4	81.21	16.05	
D45	7	29	2008	15	7	45	6	SUV	I-495	Lost in curve	2 of 4	26.96	8.80	Lost in curve
D47	7	29	2008	15	17	35	33	SUV	I-495	Lane Change	3 of 4	93.16	12.42	
D48	7	29	2008	15	28	56	7	Van	I-495	Exit to ramp	3 of 4	41.08	11.89	
D49	7	29	2008	15	31	10	3	Truck	I-495	Sensor drop	3 of 4	29.32	10.90	Sensor drop
D50	7	29	2008	15	33	4	11	SUV	I-495	Increased gap	3 of 4	34.54	9.65	
D51	7	29	2008	15	35	45	6	SUV	I-495	Lost in curve	3 of 4	81.72	9.26	Lost in curve
D52	7	29	2008	15	37	38	9	SUV	I-495	Lost in curve	3 of 4	94.44	16.09	Lost in curve
D53	7	29	2008	15	38	24	5	SUV	I-495	Sensor drop	3 of 4	87.32	12.03	Sensor drop
D54	7	29	2008	15	39	3	8	SUV	I-495	Increased gap	3 of 4	79.84	13.99	
D55	7	29	2008	15	39	52	4	SUV	I-495	Sensor drop at vertical grade	3 of 4	89.70	6.38	Sensor drop
D56	7	29	2008	15	40	9	3	Truck	I-495	Lane change	3 of 4	92.71	7.18	
D57	7	29	2008	15	40	19	16	SUV	I-495	Lane change	3 of 4	99.56	10.79	
D58	7	29	2008	15	41	39	30	SUV	I-495	Lane change	3 of 4	78.08	10.92	
D59	7	29	2008	15	43	39	6	Car	I-495	Lane change	3 of 4	28.88	8.96	
D60	7	29	2008	15	57	54	10	SUV	I-495	Lane change	4 of 4	29.92	8.11	
D61	7	29	2008	16	8	32	20	SUV	I-295	Lane change	2 of 2	41.97	11.15	
D62	7	29	2008	16	9	12	3	SUV	I-295	Lead lane change	2 of 2	18.82	7.60	

APPENDIX A: Detail Information of Trajectories

Driver #	M	D	Y	Hr	Min	Sec	Duration (sec)	Veh Type	Location	Reason for Termination	Lane #	Mean Speed	Mean Distance	Reason for Discarding
D63	7	29	2008	16	9	23	6	SUV	I-295	Increased gap	2 of 2	40.97	14.09	
D64	7	29	2008	16	9	31	11	SUV	I-295	Lane change	2 of 2	44.58	12.60	
D65	7	29	2008	16	9	44	11	SUV	I-295	Lane change	2 of 2	56.27	20.17	
D66	7	29	2008	16	10	39	10	SUV	I-295	Lane change	2 of 2	35.23	8.67	
D67	7	29	2008	16	10	56	10	SUV	I-295	Increased gap	2 of 2	32.10	9.48	
D68	7	29	2008	16	11	14	13	SUV	I-295	Increased gap	2 of 2	31.23	8.49	
D69	7	29	2008	16	13	4	11	SUV	I-295	Increased gap	2 of 2	40.30	9.96	
D70	7	29	2008	16	13	50	62	SUV	I-295	Lane change	2 of 2	41.64	9.48	
D71	7	29	2008	16	14	54	7	SUV	I-295	Lead veh exit	2 of 2	28.22	8.40	
D72	7	29	2008	16	20	38	12	Pickup	I-295	Increased gap	2 of 2	57.64	13.18	
D73	7	29	2008	16	22	35	5	SUV	I-295	Exit to ramp	2 of 2	35.05	7.17	
D74	8	1	2008	15	22	40	5	SUV	I-495	Sensor drop	4 of 4	30.19	10.75	Sensor drop
D75	8	1	2008	15	23	21	10	SUV	I-495	Exit to ramp	3 of 4	26.45	8.60	
D76	8	1	2008	15	23	35	3	Truck	I-495	Lane change	3 of 4	34.89	8.30	
D77	8	1	2008	15	24	36	11	SUV	I-495	Lane Change	3 of 4	34.03	8.96	
D78	8	1	2008	15	27	44	4	SUV	I-495	Increased gap	2 of 2	24.01	6.66	
D79	8	1	2008	15	27	56	11	SUV	I-495	Increased gap	2 of 2	29.81	9.35	
D80	8	1	2008	15	29	42	10	SUV	I-495	Lane change	2 of 2	30.64	8.24	
D81	8	1	2008	15	33	36	14	SUV	I-495	Lane change	2 of 4	62.82	8.23	
D82	8	1	2008	15	41	23	4	Truck	I-495	Lane change	1 of 4	27.64	11.16	
D83	8	1	2008	15	42	7	15	SUV	I-495	Exit	4 of 4	86.40	14.47	

APPENDIX A: Detail Information of Trajectories

Driver #	M	D	Y	Hr	Min	Sec	Duration (sec)	Veh Type	Location	Reason for Termination	Lane #	Mean Speed	Mean Distance	Reason for Discarding
D84	8	1	2008	15	43	1	7	Car	I-495	Lane change	4 of 4	84.50	7.69	
D85	8	1	2008	15	45	27	11	Van	I-495	Lane change	3 of 4	97.61	8.83	
D86	8	1	2008	15	49	15	7	Van	I-495	Lane change	2 of 4	31.45	8.88	
D87	8	1	2008	15	50	1	14	Van	I-495	Lane change	1 of 4	44.47	12.35	
D88	8	1	2008	15	50	26	9	Van	I-495	Sensor drop	4 of 4	67.58	22.32	Sensor drop, 88-90 same vehicle
D89	8	1	2008	15	50	44	8	Van	I-495	Sensor drop	4 of 4	68.99	26.87	Removed
D90	8	1	2008	15	51	1	6	Van	I-495	Sensor drop	4 of 4	65.77	28.03	Removed
D91	8	1	2008	15	51	37	7	Van	I-495	Lead changed lane	4 of 4	58.55	16.30	
D92	8	14	2008	13	51	49	5	SUV	I-495	Lane change	4 of 4	35.75	10.62	
D93	8	14	2008	13	58	8	6	Van	I-495	Lost in curve	2 of 4	105.68	25.70	Lost in curve, 93-94 are same
D94	8	14	2008	13	58	30	5	Van	I-495	Lost in curve	2 of 4	100.53	26.95	Lost in curve, 93-94 are same
D95	8	14	2008	13	58	48	31	Van	I-495	Increased gap	2 of 4	97.97	28.27	
D96	8	14	2008	13	59	37	11	Van	I-495	Sensor drop	2 of 4	98.58	34.86	Sensor drop
D97	8	14	2008	14	3	53	14	SUV	I-495	Lane change	3 of 4	96.56	13.53	
D98	8	14	2008	14	12	3	8	Van	I-495	Sensor drop (lost in curve)	3 of 4	42.31	17.90	Sensor drop
D99	8	21	2008	15	5	15	4	Car	I-495	Lane change	3 of 4	35.17	3.38	
D100	8	21	2008	15	6	45	4	Car	I-495	Lane change	3 of 4	36.87	13.58	
D101	8	21	2008	15	11	50	5	Car	I-495	Sensor drop	3 of 4	30.63	10.55	Sensor drop
D102	8	21	2008	15	12	1	6	Van	I-495	Another vehicle cut in	3 of 4	33.89	8.74	

APPENDIX A: Detail Information of Trajectories

Driver #	M	D	Y	Hr	Min	Sec	Duration (sec)	Veh Type	Location	Reason for Termination	Lane #	Mean Speed	Mean Distance	Reason for Discarding
D103	8	21	2008	15	17	38	8	SUV	I-495	Sensor drop	2 of 4	91.16	39.20	Sensor drop
D104	8	21	2008	15	18	44	15	Truck	I-495	Sensor drop	2 of 4	104.64	33.76	Sensor drop
D105	8	21	2008	15	19	9	8	Truck	I-495	Sensor drop	2 of 4	104.73	23.98	Sensor drop, 104-105 are same
D106	8	21	2008	15	24	27	9	SUV	I-495	Increased gap	4 of 4	34.10	10.32	
D107	8	21	2008	15	24	41	8	SUV	I-495	Lane change	4 of 4	42.61	12.79	
D108	8	21	2008	15	25	23	28	Truck	I-495	Lane change	3 of 4	56.95	13.13	
D109	8	21	2008	15	25	54	11	Truck	I-495	Lane change	3 of 4	79.26	33.22	
D110	8	21	2008	15	27	11	26	Truck	I-495	Sensor drop	3 of 4	96.07	28.51	Sensor drop
D111	8	21	2008	15	28	7	4	Truck	I-495	Sensor drop	3 of 4	102.93	48.24	Sensor drop
D112	8	21	2008	15	37	22	3	Car	I-495	Lane change	2 of 2	27.52	8.85	
D113	8	21	2008	15	41	0	5	Car	I-495	Lane change	2 of 2	31.13	12.15	
D114	8	29	2008	14	28	59	6	Car	I-495	Lane change	1 of 4	38.52	7.69	
D115	8	29	2008	14	30	22	4	SUV	I-495	Lane change	1 of 4	41.83	5.48	
D116	8	29	2008	14	45	39	3	SUV	I-495	Lane change	1 of 4	30.22	13.18	
D117	8	29	2008	14	47	7	7	Car	I-495	Lane change	2 of 4	31.48	11.50	
D119	8	29	2008	14	51	47	3	Car	I-495	Sensor drop	2 of 4	28.34	9.63	Sensor drop
D120	8	29	2008	14	52	41	6	Car	I-495	Increased gap	2 of 4	33.02	10.39	
D121	8	29	2008	14	53	3	5	Car	I-495	Lane change	2 of 4	37.44	9.10	
D122	8	29	2008	14	54	37	4	Car	I-495	Lane change	2 of 4	51.53	8.72	
D123	8	29	2008	14	55	14	3	Car	I-495	Lane change	2 of 4	57.18	7.25	
D124	8	29	2008	15	9	44	20	Truck	I-495	Lane change to exit	2 of 4	43.48	8.12	
D125	8	29	2008	15	10	7	26	Truck	I-495	Lane change	2 of 4	51.65	15.63	

APPENDIX B: Results of t-test for Hypothesis 2

Driver No.	Lead Speed μ_L	Following Speed μ_F	*t-Stat*	$t_{\alpha, dof}$	Is *t-Stat*>=$t_{\alpha, dof}$?	Result
D1	93.2	91.6	2.62	1.674	Yes	Reject
D2	50.3	51.2	-0.866	1.656	No	Do not reject
D3	61.9	62.9	-0.687	1.663	No	Do not reject
D4	40.8	40.6	0.131	1.673	No	Do not reject
D5	32.2	33.4	-0.199	1.761	No	Do not reject
D6	95.3	96.9	-2.711	1.665	No	Do not reject
D6A	92.3	92.4	-0.158	1.675	No	Do not reject
D7	69.7	69.7	0	1.782	No	Do not reject
D9	84.0	84.2	-0.196	1.729	No	Do not reject
D10	52.5	52.2	0.305	1.729	No	Do not reject
D11	87.6	86.2	0.774	1.677	No	Do not reject
D12	44.9	45.1	-0.135	1.813	No	Do not reject
D13	30.8	30.4	0.414	1.859	No	Do not reject
D14	43.3	43.8	-0.578	1.673	No	Do not reject
D15	82.8	83.8	-1.366	1.661	No	Do not reject
D18	23.6	27.4	-1.031	1.734	No	Do not reject
D20	95.9	95.5	0.425	1.724	No	Do not reject
D21	49.2	50.6	-0.177	1.833	No	Do not reject
D22	27.0	34.6	-1.256	1.761	No	Do not reject
D26	77.4	78.6	-0.36	1.669	No	Do not reject
D27	69.1	70.3	-1.186	1.729	No	Do not reject
D28	20.0	22.9	-0.916	1.812	No	Do not reject
D30	90.5	88.7	2.134	1.725	Yes	Reject
D31	95.7	95.4	0.226	1.692	No	Do not reject
D33	75.4	75.3	0.103	1.674	No	Do not reject
D35	83.1	83.2	-0.042	1.668	No	Do not reject
D36	46.1	50.7	-5.554	2.015	No	Do not reject
D37	51.8	54.3	-0.696	1.701	No	Do not reject
D38	97.9	97.4	1.532	1.649	No	Do not reject
D39	98.9	99.4	-0.891	1.653	No	Do not reject
D40	90.9	91.4	-0.322	1.729	No	Do not reject
D41	80.1	80.3	-0.114	1.746	No	Do not reject
D42	35.4	35.5	-0.019	1.745	No	Do not reject
D43	64.8	66.7	-1.546	1.701	No	Do not reject
D44	79.6	81.2	-1.302	1.696	No	Do not reject
D47	93.51	93.16	1.27	1.67	No	Do not reject
D48	37.66	41.08	-1.10	1.77	No	Do not reject
D50	31.13	34.54	-1.00	1.75	No	Do not reject
D54	77.63	79.84	-1.41	1.83	No	Do not reject
D56	92.04	92.71	-0.45	2.02	No	Do not reject

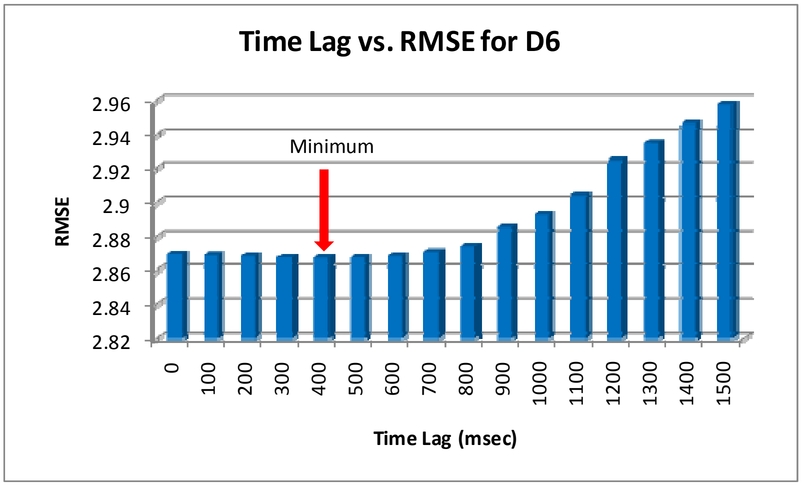
APPENDIX B: Results of t-test for Hypothesis 2

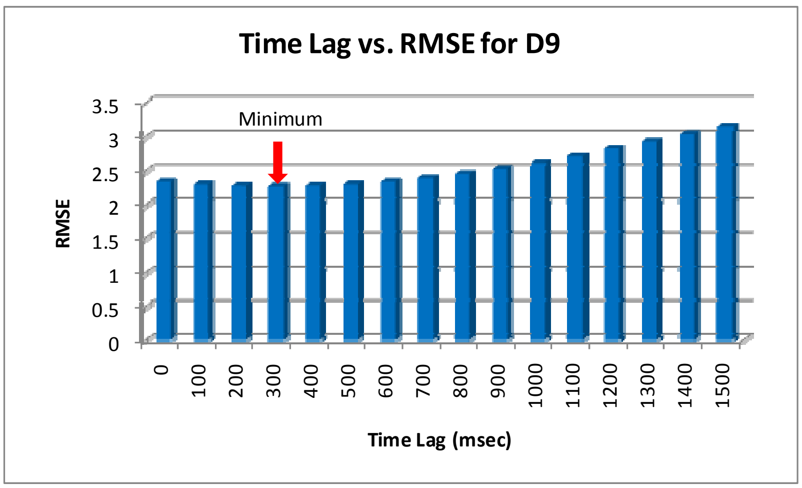
Driver No.	Lead Speed μ_L	Following Speed μ_F	*t-Stat*	$t_{\alpha, dof}$	Is $t\text{-}Stat >= t_{\alpha, dof}$?	Result
D57	99.58	99.56	0.04	1.73	No	Do not reject
D58	77.97	78.08	-0.07	1.67	No	Do not reject
D59	25.31	28.88	-0.64	1.78	No	Do not reject
D60	27.28	29.92	-0.65	1.72	No	Do not reject
D61	40.07	41.97	-1.98	1.69	No	Do not reject
D62	17.41	18.82	-1.92	2.35	No	Do not reject
D63	40.33	40.97	-0.40	1.78	No	Do not reject
D64	43.87	44.58	-0.51	1.76	No	Do not reject
D65	53.86	56.27	-1.70	1.72	No	Do not reject
D66	24.76	26.23	-1.09	1.76	No	Do not reject
D67	28.68	32.10	-1.62	1.72	No	Do not reject
D68	21.09	23.23	-1.25	1.72	No	Do not reject
D69	39.28	40.30	-3.36	1.72	No	Do not reject
D70	42.03	41.64	0.28	1.66	No	Do not reject
D71	24.41	28.22	-1.13	1.78	No	Do not reject
D72	53.86	57.64	-1.36	1.72	No	Do not reject
D73	20.94	24.05	-0.74	1.81	No	Do not reject
D75	25.16	26.45	-0.55	1.73	No	Do not reject
D76	34.80	34.89	-0.03	2.13	No	Do not reject
D77	28.74	34.03	-1.26	1.72	No	Do not reject
D78	17.57	22.01	-1.12	1.86	No	Do not reject
D79	26.77	29.81	-0.78	1.72	No	Do not reject
D80	27.94	30.64	-0.98	1.73	No	Do not reject
D81	62.12	62.82	-0.51	1.72	No	Do not reject
D82	16.74	27.64	-1.69	1.89	No	Do not reject
D83	84.62	86.40	-1.30	1.70	No	Do not reject
D84	82.96	84.50	-2.37	1.76	No	Do not reject
D85	97.56	97.61	-0.04	1.76	No	Do not reject
D86	29.73	31.45	-0.38	1.77	No	Do not reject
D87	42.96	44.47	-0.65	1.71	No	Do not reject
D91	61.16	58.55	6.85	1.77	Yes	Reject
D92	32.43	35.75	-1.77	1.94	No	Do not reject
D95	97.71	97.97	-0.32	1.68	No	Do not reject
D97	96.01	96.56	-1.08	1.74	No	Do not reject
D98	33.49	42.31	-1.34	1.73	No	Do not reject
D99	14.44	15.17	-0.20	1.86	No	Do not reject

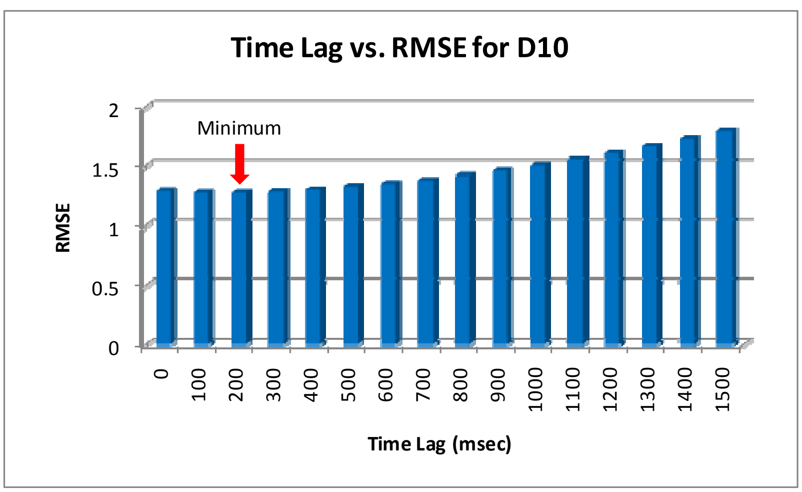
APPENDIX B: Results of t-test for Hypothesis 2

Driver No.	Lead Speed μ_L	Following Speed μ_F	*t-Stat*	$t_{\alpha, dof}$	Is *t-Stat*>=$t_{\alpha, dof}$?	Result
D100	32.96	36.87	-1.06	1.86	No	Do not reject
D102	33.68	33.89	-0.16	1.78	No	Do not reject
D106	32.37	34.10	-0.95	1.73	No	Do not reject
D107	41.27	42.61	-0.38	1.76	No	Do not reject
D108	54.36	56.95	-1.15	1.67	No	Do not reject
D109	74.65	79.26	-1.69	1.73	No	Do not reject
D112	16.87	27.52	-1.12	1.94	No	Do not reject
D113	26.48	31.13	-0.73	1.83	No	Do not reject
D114	13.68	18.52	-1.62	1.83	No	Do not reject
D115	10.57	13.83	-1.09	1.89	No	Do not reject
D116	27.06	30.22	-1.53	1.94	No	Do not reject
D117	27.38	31.48	-0.92	1.76	No	Do not reject
D118	64.91	69.66	-1.28	1.76	No	Do not reject
D120	23.04	26.02	-1.00	1.78	No	Do not reject
D121	23.08	25.44	-0.92	1.86	No	Do not reject
D122	18.30	24.83	-1.28	1.89	No	Do not reject
D123	14.90	18.18	-1.01	1.94	No	Do not reject
D124	28.65	30.48	-0.50	1.68	No	Do not reject
D125	51.49	51.65	-0.08	1.68	No	Do not reject

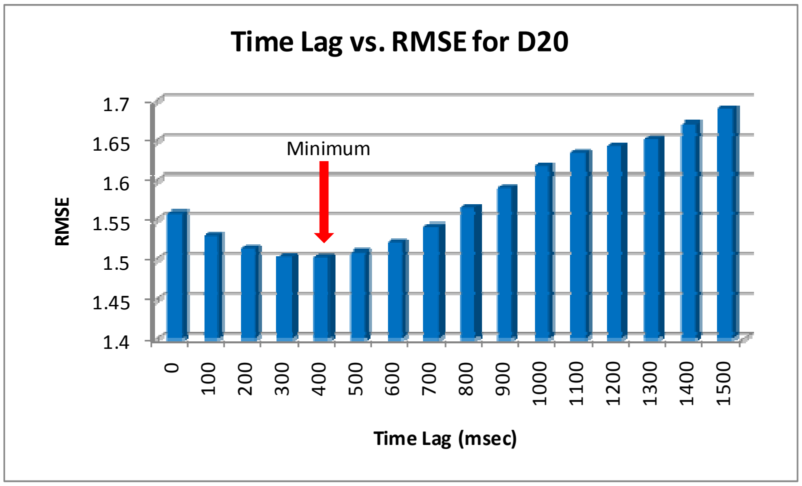
APPENDIX C: Charts for Time Lags vs. RMSE of Speeds

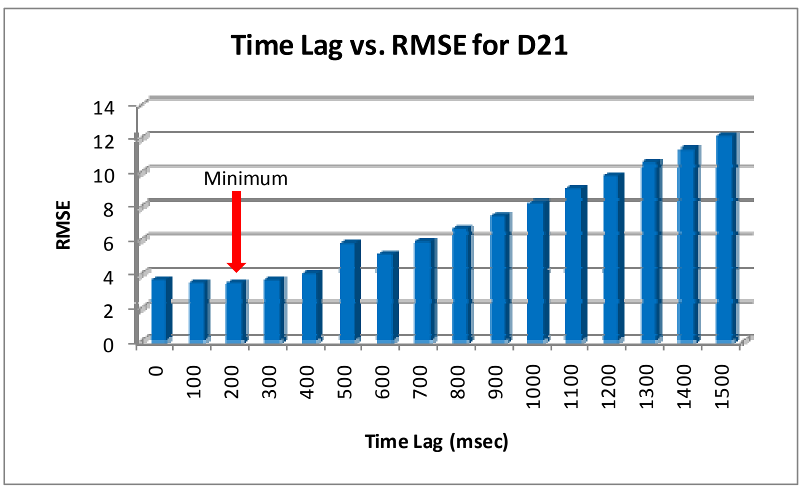


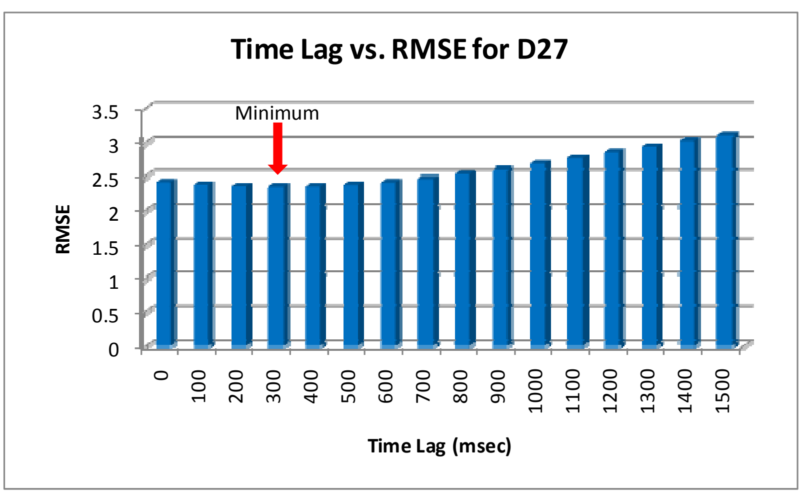




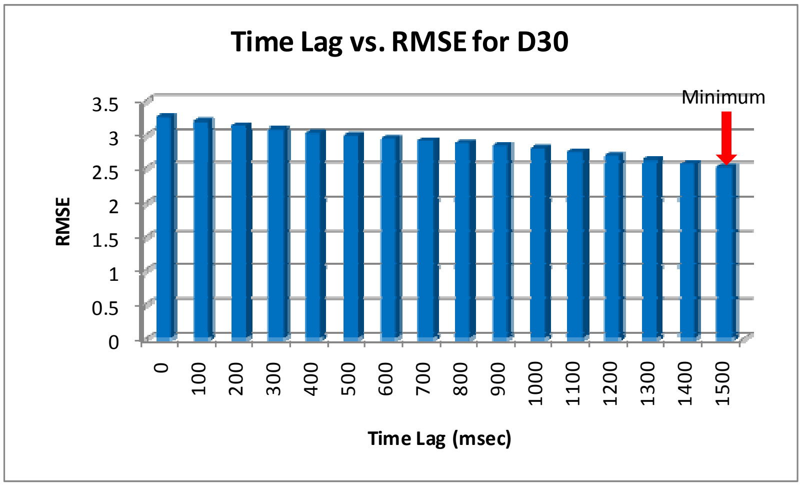
APPENDIX C: Charts for Time Lags vs. RMSE of Speeds

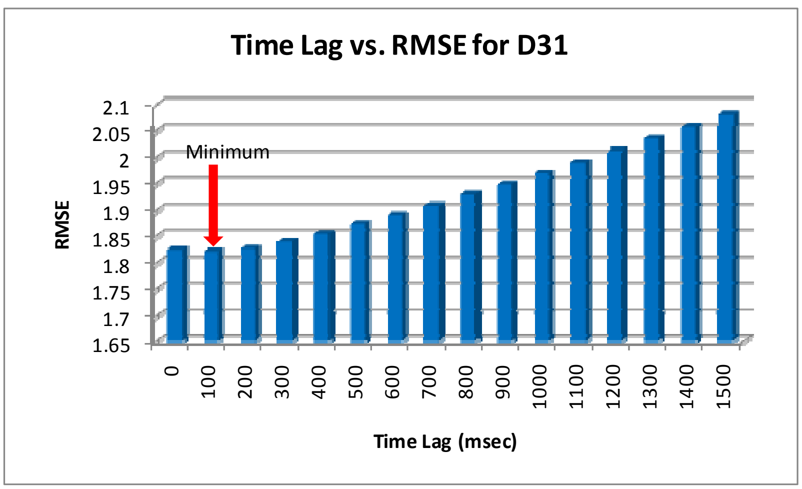


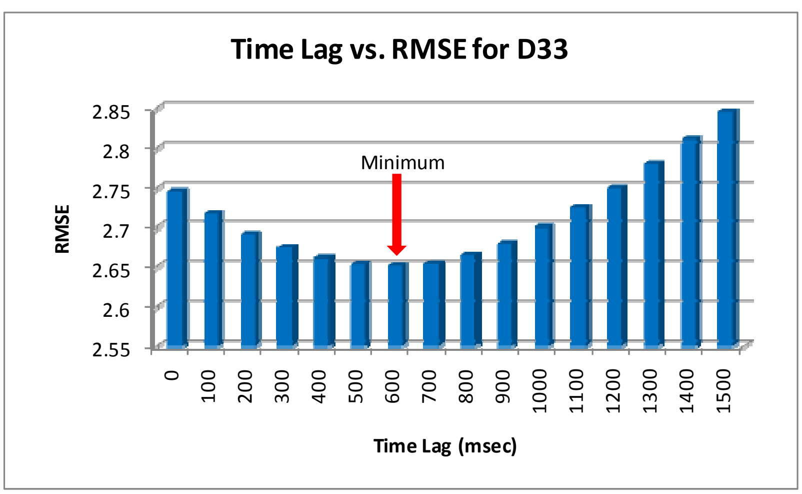




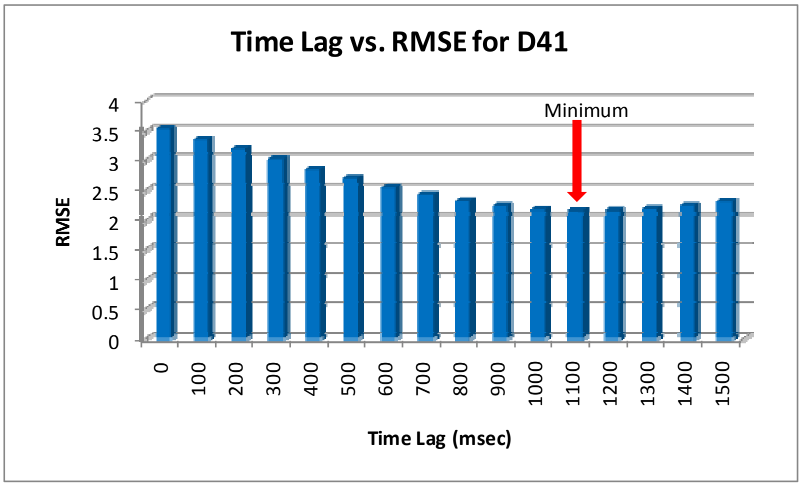
APPENDIX C: Charts for Time Lags vs. RMSE of Speeds

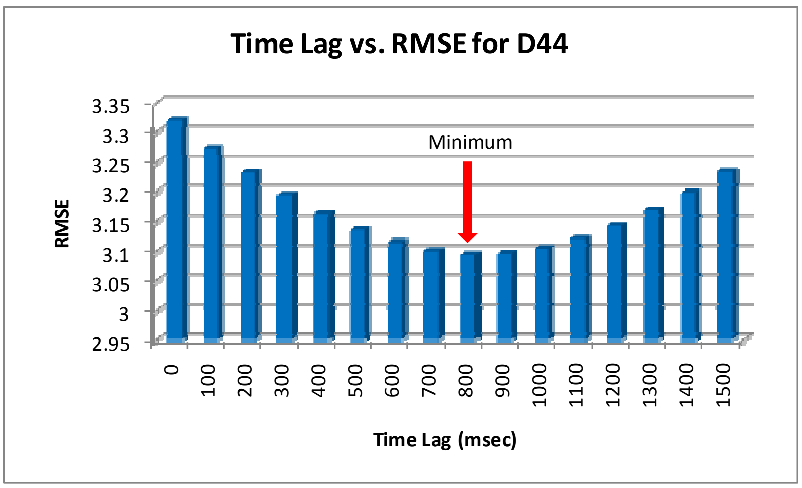


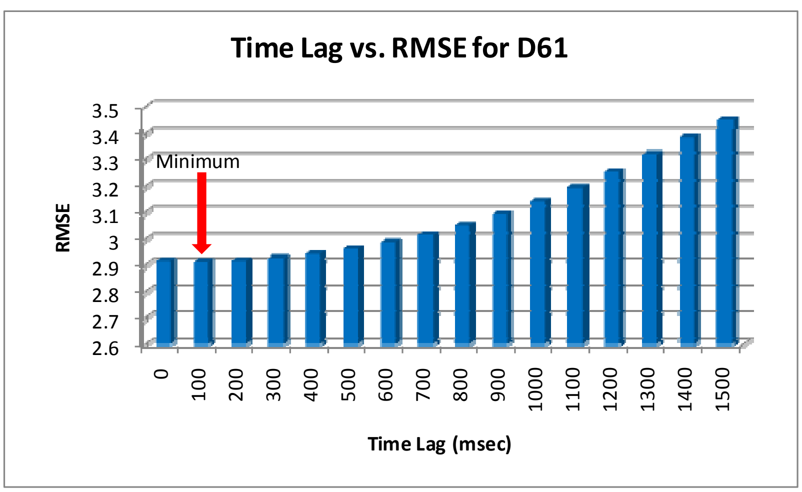




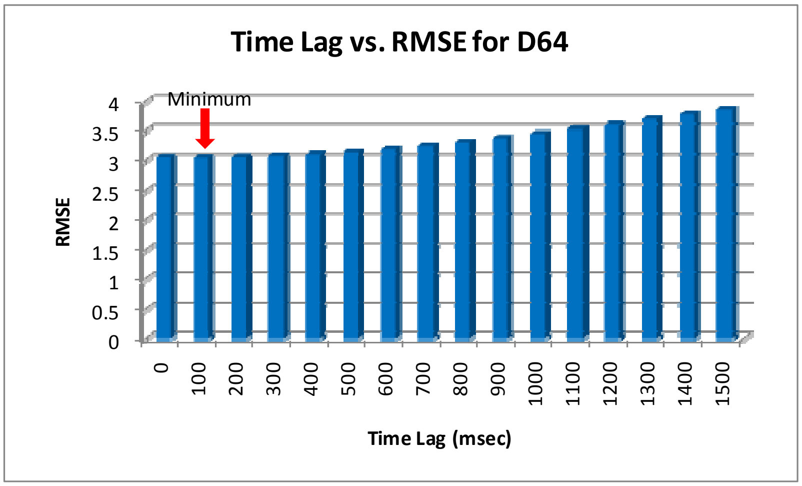
APPENDIX C: Charts for Time Lags vs. RMSE of Speeds

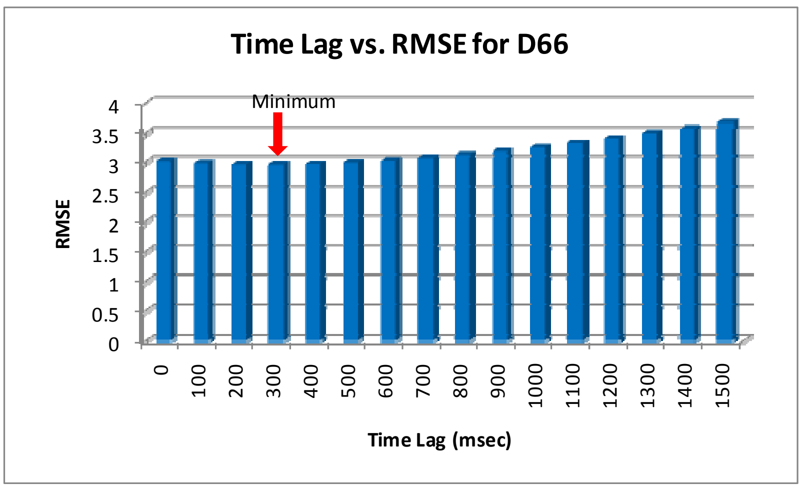


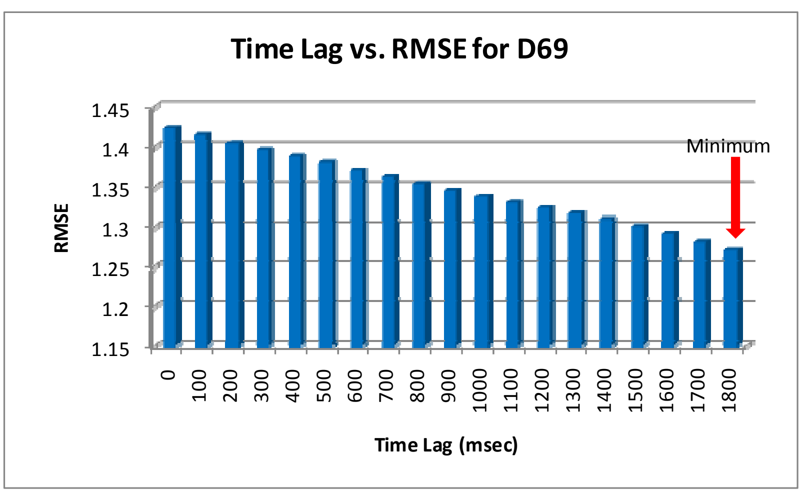




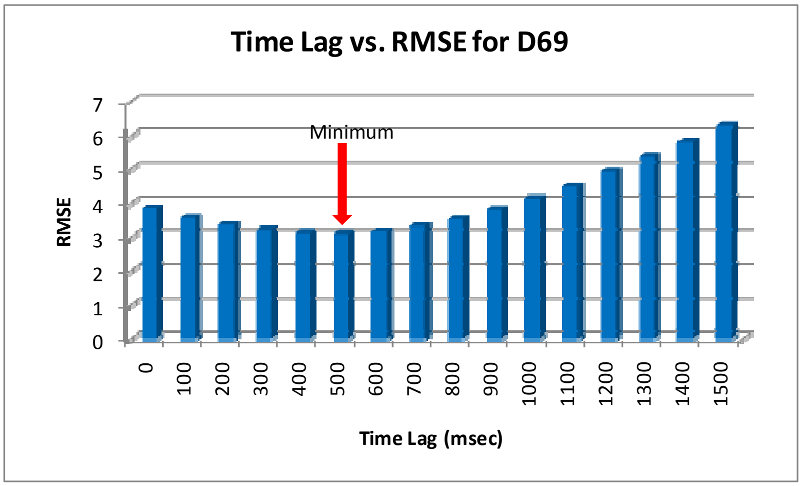
APPENDIX C: Charts for Time Lags vs. RMSE of Speeds

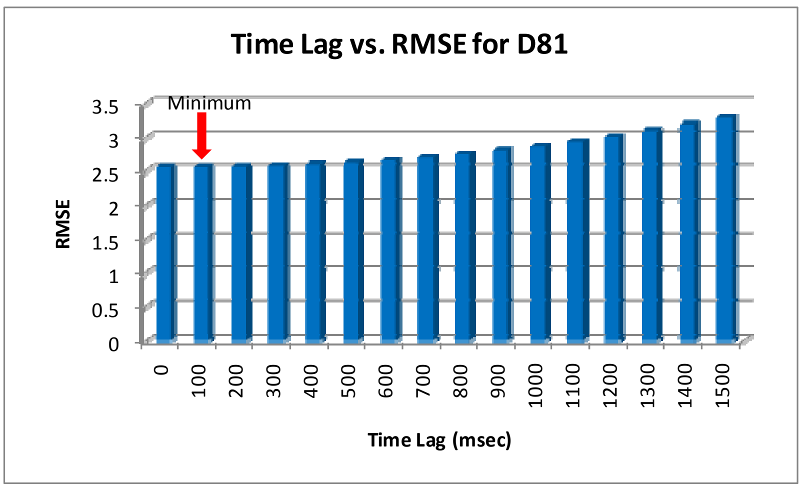


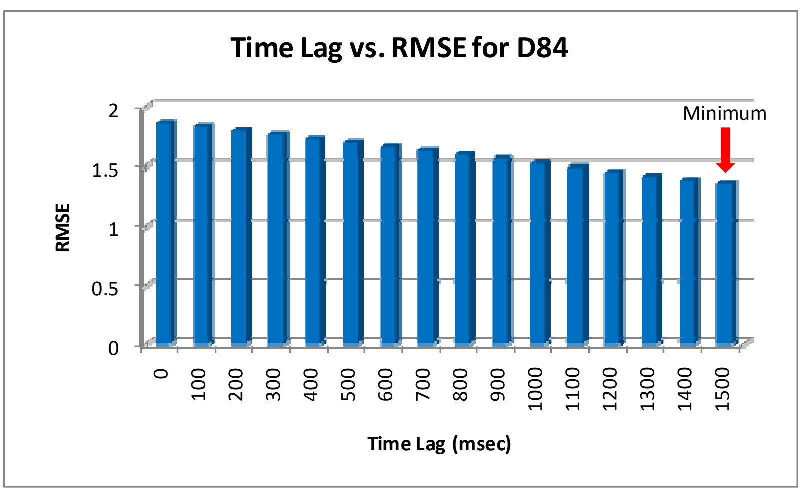




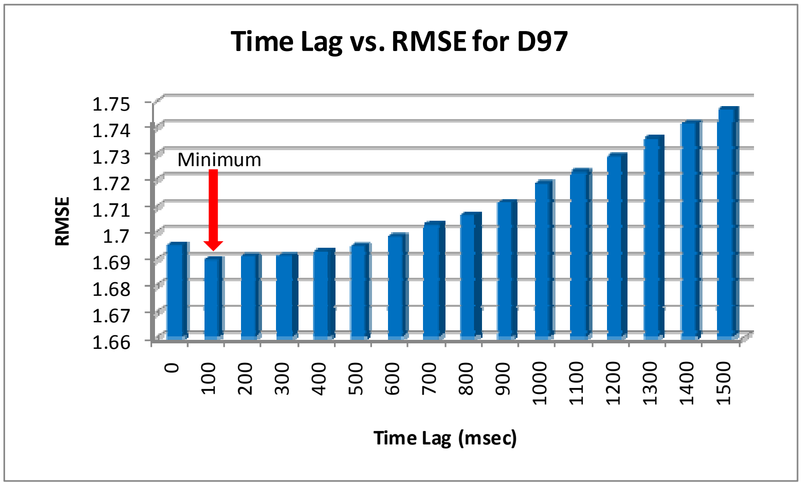
APPENDIX C: Charts for Time Lags vs. RMSE of Speeds

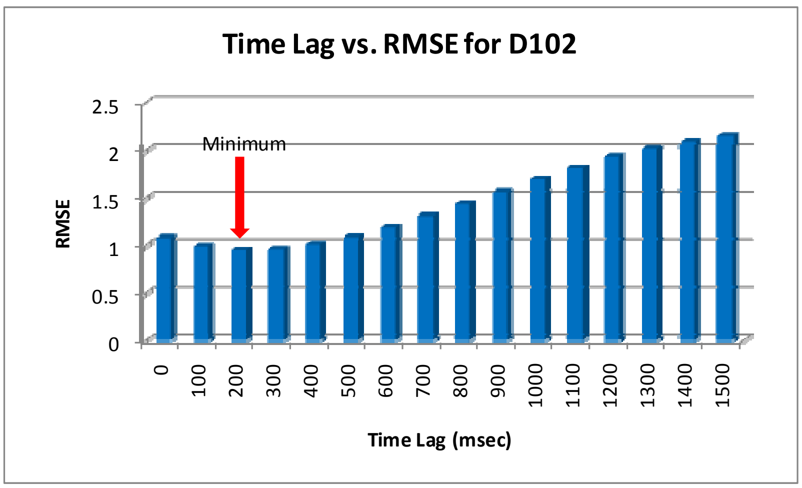


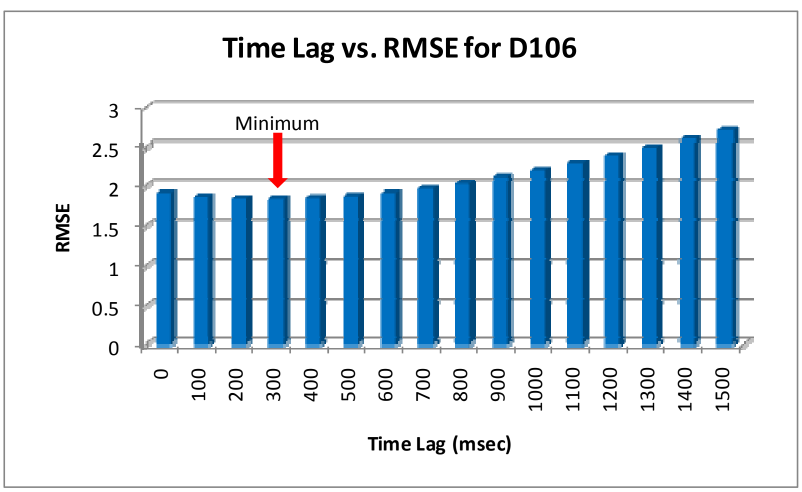




APPENDIX C: Charts for Time Lags vs. RMSE of Speeds







APPENDIX D: Actual vs. Safe Headway and Following Distance

Driver #	Mean Actual Distance (m)	Mean Safe Distance (m)	Mean Following Speed (km/Hr)	Actual Headway (sec)	Safe Headway (sec)
D1	17.89	35.70	91.64	0.90	1.60
D2	15.05	22.48	51.16	1.41	1.93
D3	18.12	27.87	62.90	1.32	1.88
D4	5.84	17.00	40.58	0.96	1.95
D5	5.93	13.85	33.67	1.17	2.02
D6	19.14	44.13	96.85	0.90	1.83
D6A	13.74	39.37	92.43	0.73	1.73
D7	6.21	29.45	69.66	0.58	1.78
D9	8.05	35.96	84.18	0.56	1.75
D10	10.41	21.81	52.21	1.06	1.85
D11	12.96	34.34	86.34	0.75	1.64
D12	9.81	19.19	45.11	1.18	1.93
D13	4.94	12.55	32.52	1.10	1.94
D14	10.96	18.91	43.82	1.31	1.96
D15	19.96	37.37	83.82	1.07	1.82
D18	8.65	14.36	34.06	1.44	2.05
D20	11.67	39.49	95.52	0.63	1.68
D21	13.06	26.30	55.16	1.18	2.04
D22	13.13	19.64	38.37	1.70	2.31
D26	16.42	35.19	78.59	0.98	1.84
D27	21.34	31.57	70.35	1.35	1.87
D28	7.08	10.97	26.63	1.63	2.16
D30	14.36	34.24	88.73	0.79	1.59
D31	24.95	39.87	95.42	1.13	1.69
D33	16.49	31.76	75.32	1.03	1.76
D35	17.76	35.42	83.21	0.98	1.75
D36	16.38	25.98	50.66	1.52	2.20
D37	11.53	25.81	54.33	1.10	2.04
D38	20.00	40.19	97.37	0.92	1.67
D39	19.55	43.17	99.43	0.89	1.74
D40	13.55	39.37	91.37	0.73	1.75
D41	15.61	34.13	80.27	0.92	1.75
D42	7.48	14.92	35.47	1.27	2.02
D43	11.34	30.86	66.67	0.88	1.94
D44	16.05	37.14	81.21	0.93	1.87
D47	12.42	38.66	93.16	0.67	1.69
D48	11.89	20.00	41.08	1.48	2.19
D50	9.65	17.79	34.54	1.53	2.38
D54	13.99	37.53	79.84	0.86	1.92
D56	7.18	40.49	92.71	0.47	1.77

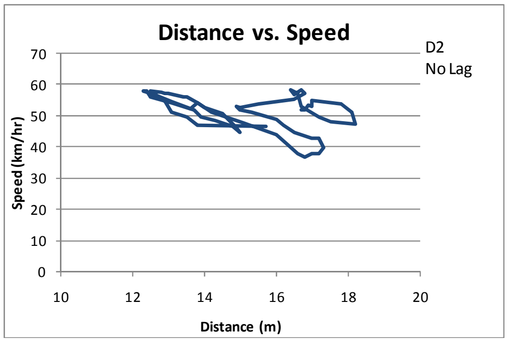
APPENDIX D: Actual vs. Safe Headway and Following Distance

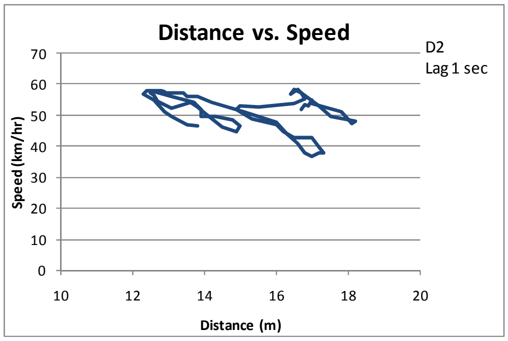
Driver #	Mean Actual Distance (m)	Mean Safe Distance (m)	Mean Following Speed (km/Hr)	Actual Headway (sec)	Safe Headway (sec)
D57	10.79	42.03	99.56	0.57	1.70
D58	10.92	33.15	78.08	0.74	1.76
D59	8.96	13.73	31.74	1.58	2.14
D60	8.11	14.24	29.92	1.67	2.41
D61	11.15	19.45	41.97	1.38	2.09
D62	7.60	12.50	28.32	1.60	2.22
D63	14.09	17.84	40.97	1.68	2.01
D64	12.60	19.65	44.58	1.43	1.98
D65	20.17	26.60	56.27	1.60	2.02
D66	8.67	11.99	26.23	1.90	2.32
D67	9.48	15.73	32.10	1.60	2.34
D68	6.49	11.02	25.23	1.64	2.47
D69	9.96	17.86	40.30	1.34	2.04
D70	9.48	17.27	41.64	1.29	1.94
D71	8.40	14.40	28.22	1.73	2.47
D72	13.18	29.20	57.64	1.11	2.11
D73	7.17	12.99	28.71	1.53	2.25
D75	8.60	12.05	29.45	1.66	2.32
D76	8.30	15.02	34.89	1.39	2.04
D77	8.96	17.92	34.86	1.50	2.32
D78	6.66	11.82	29.41	1.44	2.05
D79	9.35	16.04	34.39	1.51	2.19
D80	8.24	14.92	31.73	1.52	2.24
D81	8.23	27.60	62.82	0.76	1.86
D82	11.16	13.68	29.84	1.91	2.24
D83	14.47	39.67	86.40	0.81	1.86
D84	7.69	38.39	84.50	0.54	1.85
D85	8.83	41.42	97.61	0.51	1.71

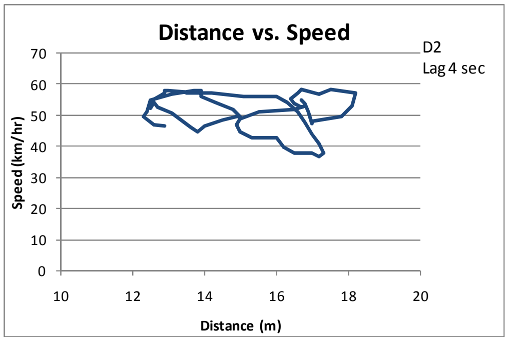
APPENDIX D: Actual vs. Safe Headway and Following Distance

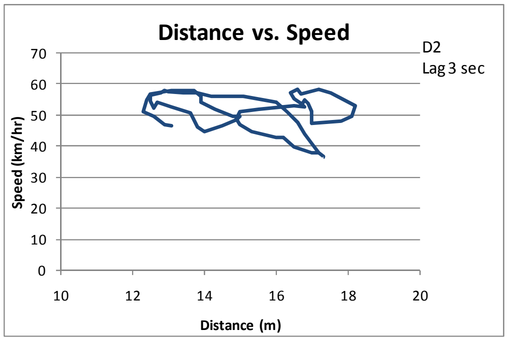
Driver #	Mean Actual Distance (m)	Mean Safe Distance (m)	Mean Following Speed (km/Hr)	Actual Headway (sec)	Safe Headway (sec)
D86	8.88	14.44	33.82	1.48	2.08
D87	12.35	20.38	44.47	1.40	2.04
D91	16.30	21.43	58.55	1.31	1.63
D92	10.62	17.62	35.75	1.58	2.26
D95	28.27	42.08	97.97	1.22	1.72
D97	13.53	41.90	96.56	0.69	1.75
D99	3.38	12.05	29.57	1.02	2.08
D100	13.58	18.48	36.87	1.81	2.30
D102	8.74	14.47	33.89	1.47	2.07
D106	10.32	15.60	34.10	1.65	2.18
D107	12.79	19.60	42.61	1.54	2.05
D108	13.13	27.41	56.95	1.11	2.03
D109	33.22	41.26	79.26	1.74	2.08
D112	8.85	11.99	30.52	1.63	2.00
D113	12.15	15.34	33.97	1.82	2.16
D114	7.69	11.27	28.80	1.61	2.03
D115	5.48	10.71	30.43	1.37	1.70
D116	13.18	15.36	37.72	1.74	2.18
D117	11.50	15.65	33.85	1.76	2.18
D118	20.01	36.78	69.66	1.28	2.12
D120	10.39	13.05	32.74	1.72	1.98
D121	9.10	12.10	30.44	1.67	2.42
D122	8.72	13.27	31.83	1.54	2.06
D123	7.25	10.97	27.93	1.66	2.01
D124	8.12	15.58	35.01	1.33	2.11
D125	15.63	22.10	51.65	1.45	1.89

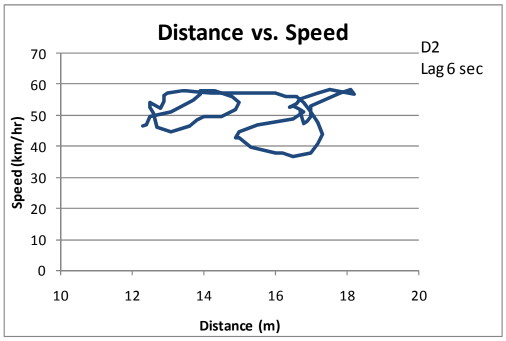
APPENDIX E: Hysteresis Loops for Various Drivers

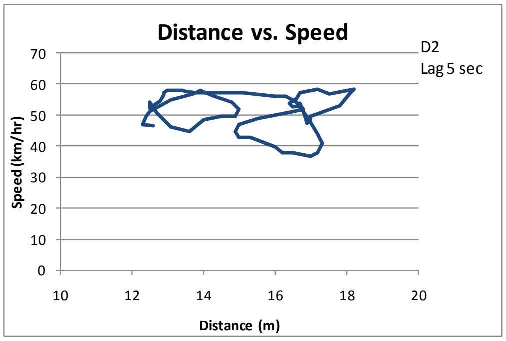


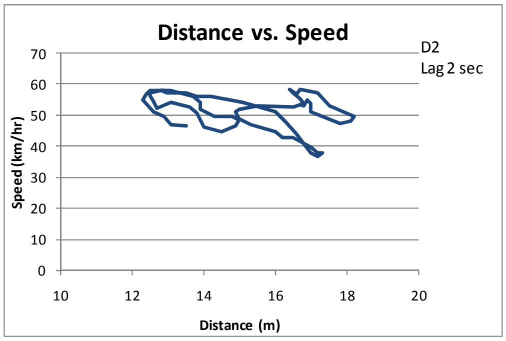


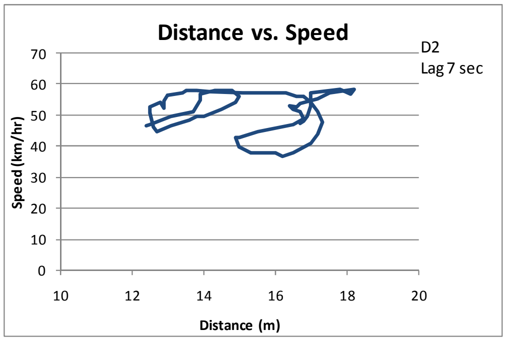












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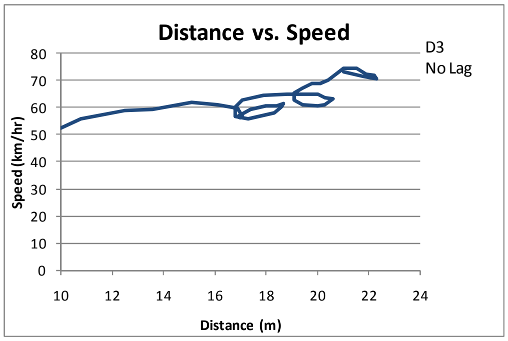

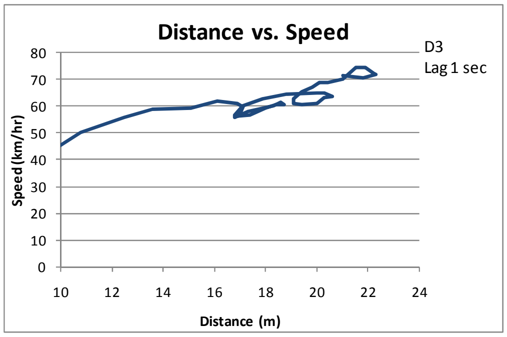

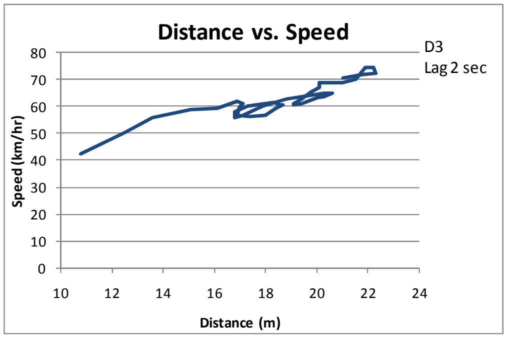

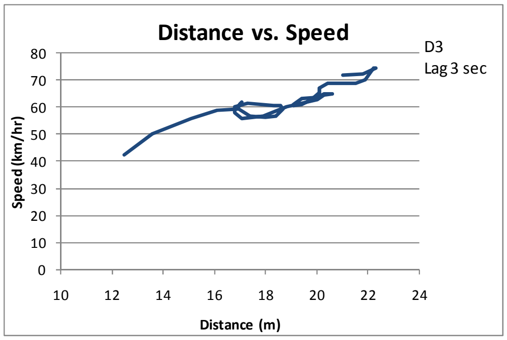

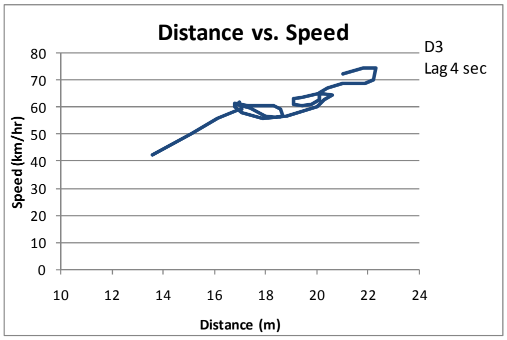

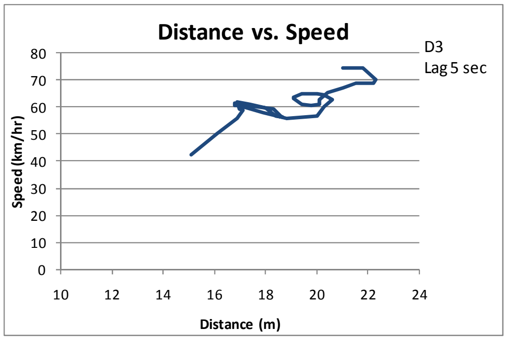

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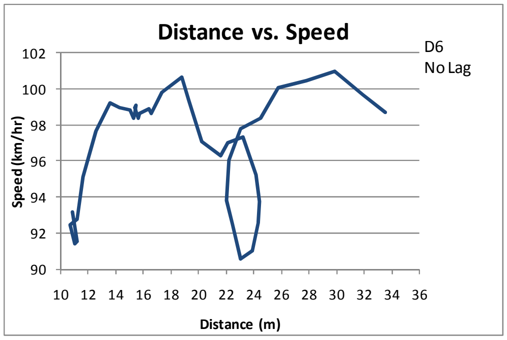

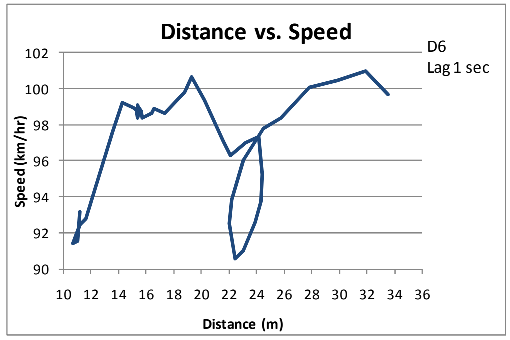

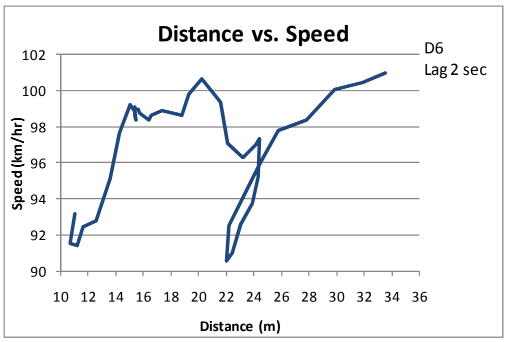

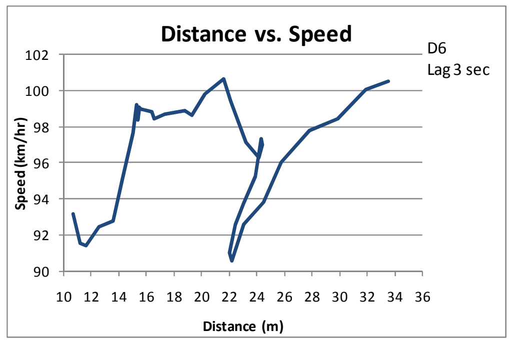

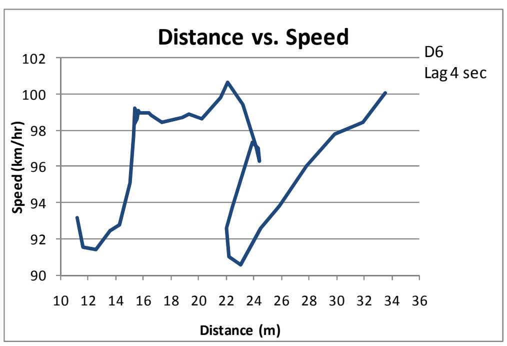

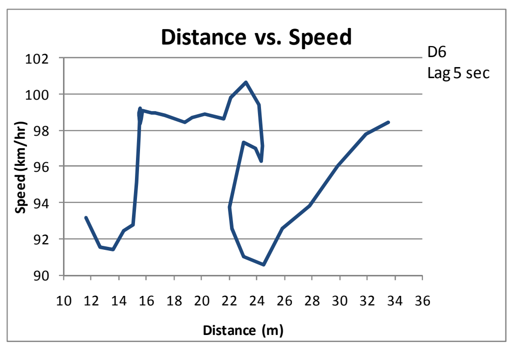

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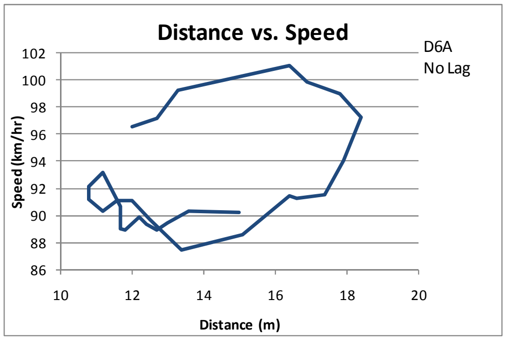
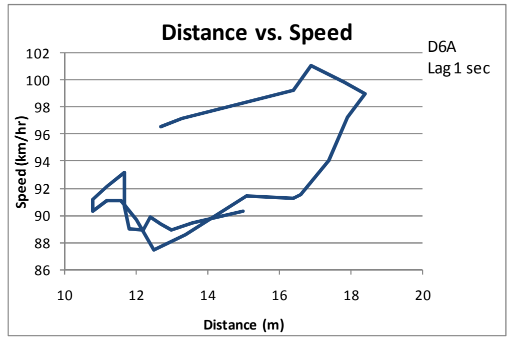
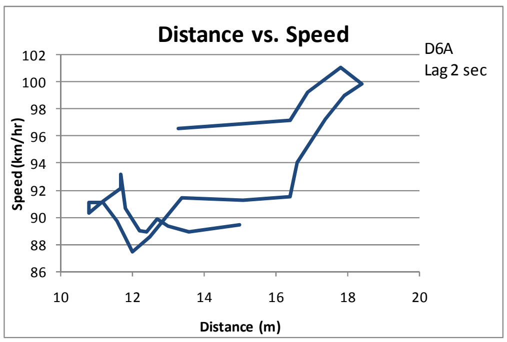
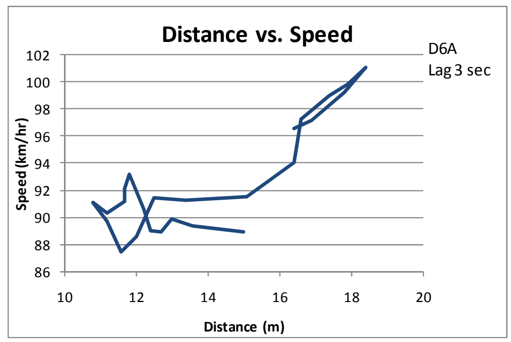
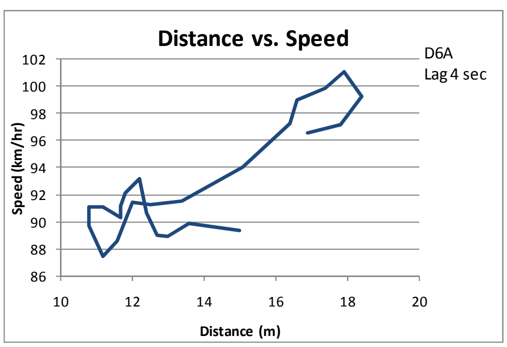
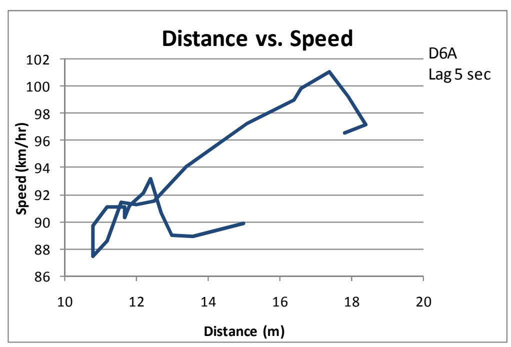


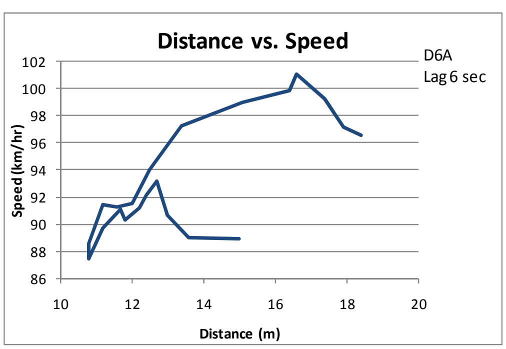


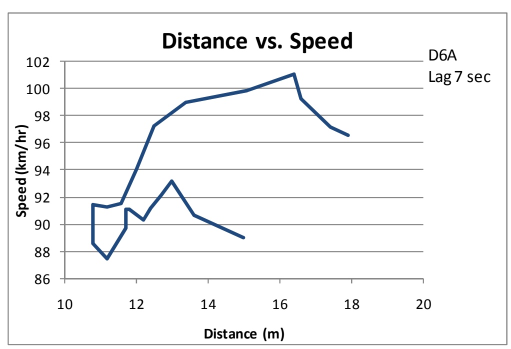




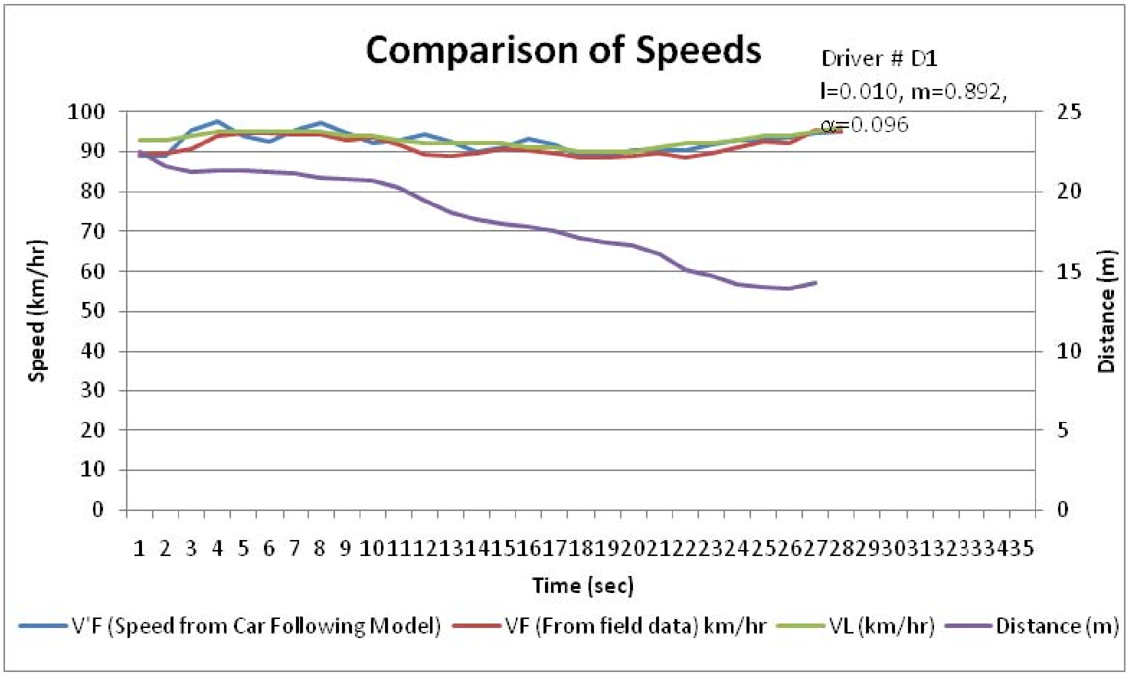


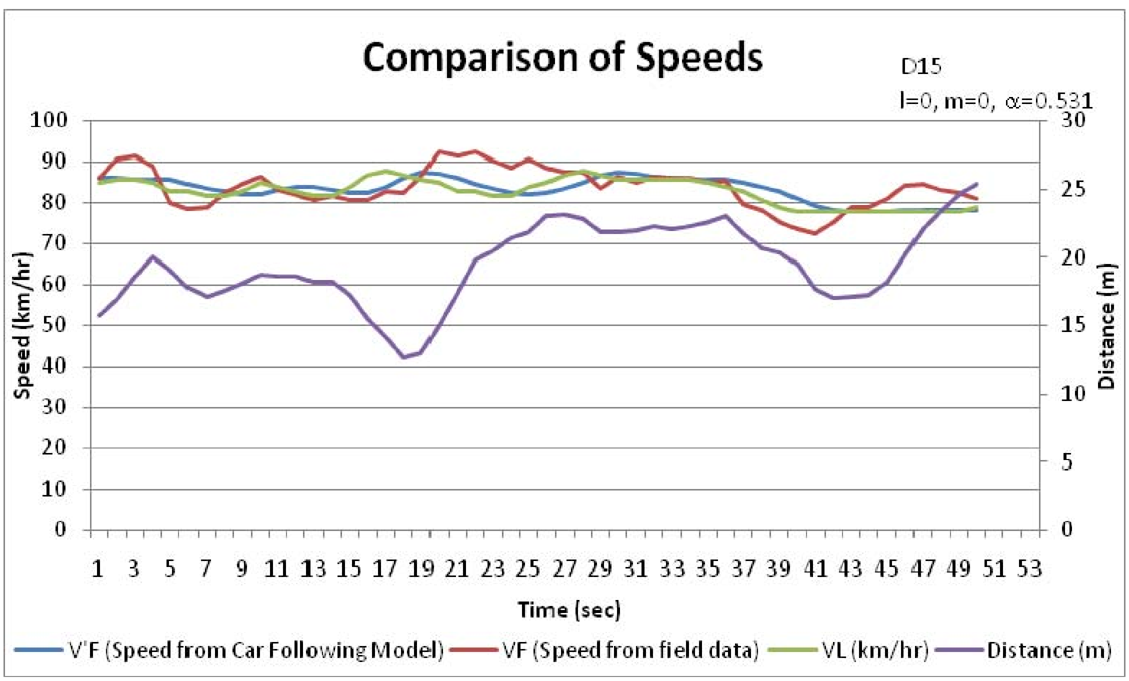




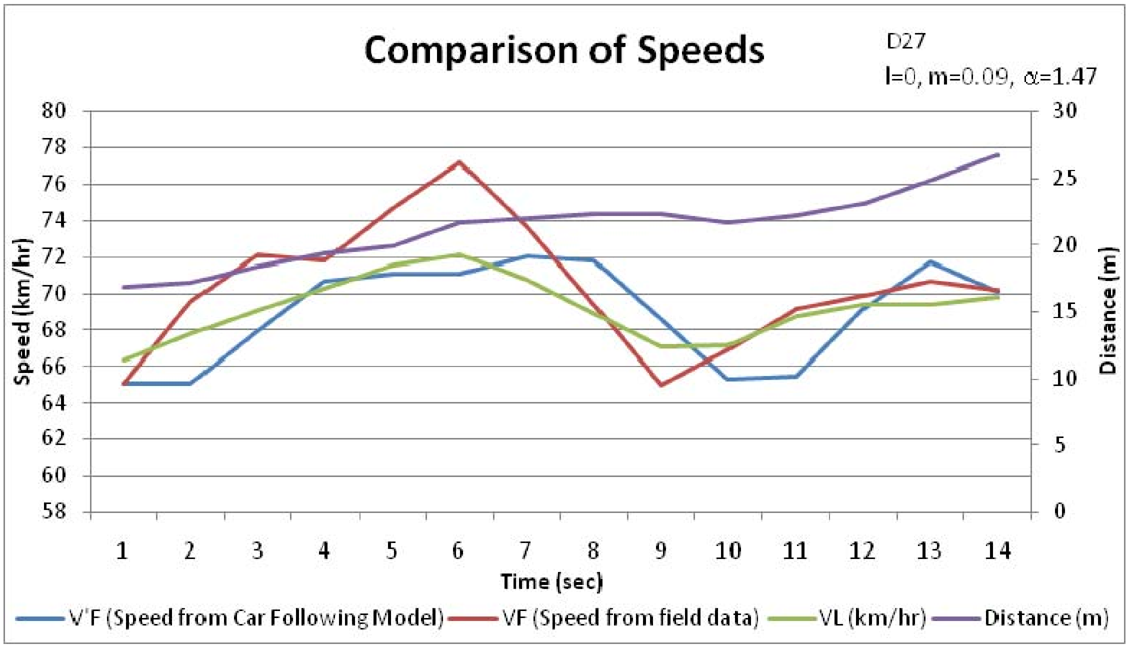


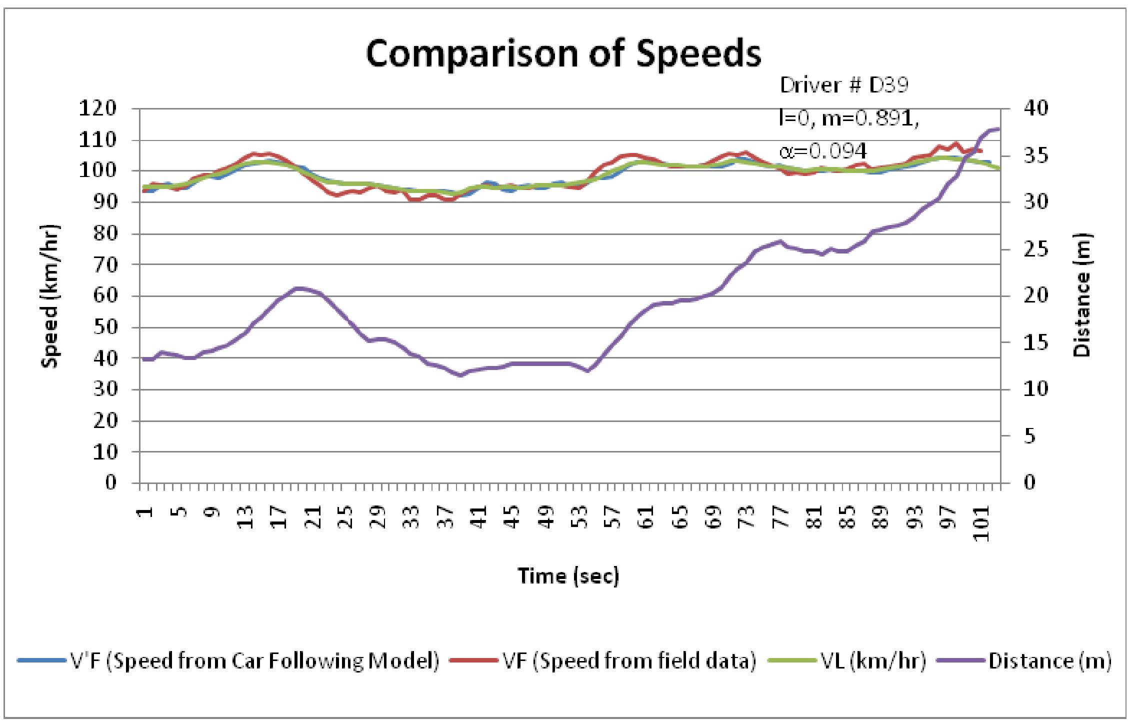
APPENDIX F: Actual vs. Car-following Model Speeds





APPENDIX F: Actual vs. Car-following Model Speeds





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