ABSTRACT

Title of Document: ANALYSIS OF VARIABILITY IN CAR-FOLLOWING BEHAVIOR OVER LONG-TERM DRIVING MANEUVERS

Taehyung Kim, Doctor of Philosophy, 2005

Directed By: Associate Professor David J. Lovell
Department of Civil and Environmental Engineering

The main goal of this dissertation has been to contribute to a better understanding of car-following behavior, and more specifically, on the variability in car-following behavior that is commonly observed in naturalistic driving situations.

This dissertation includes a thorough review of the literature in this area in which some important limitations of current car-following experimental studies and models, which make them inconsistent with naturalistic driving behavior under car-following situations, were investigated. A new data collection system using an instrumented test vehicle, with a synchronized user interface and data acquisition program coupled with two separate CAN networks, GPS, inertial distance measuring instrument, and digital video, has been developed to produce a sufficient quality and quantity of data on real driving behavior.

As a result of the data collection and analysis, we developed a better understanding of various behavioral characteristics in car-following behavior: (1) there was an oscillatory (or “drift”) process in car-following behavior, which appears as a sequence of parabolic shapes in keeping desired following distance, (2) traffic hysteresis

exists in car-following behavior, which is the phenomenon that drivers' acceleration and deceleration have different speed-density curves, (3) each individual driver has his or her own driving rule, rather than keeping a deterministic and strict driving law, but following distance for individual drivers can vary over time and space under different driving maneuvers and conditions, such as traffic, geometric, or environmental conditions, (4) drivers behave differently under different driving maneuvers, although they have exactly the same (current) instantaneous states, such as speeds of the lead and following vehicles and following distances, (5) reactions of following vehicle caused by the same driving maneuvers in car-following situations repeat themselves over time and space.

It was statistically evident from the analysis that different traffic and road characteristics (e.g., vehicle type, number of lanes, location of driving lane, and traffic condition), human characteristics (e.g., gender and distraction factors), and environmental characteristics (e.g., time of day and weather) have different effects on car-following behavior.

We hope that the findings of this dissertation will provide clues to guide the construction of more realistic car-following models to help improve the realism of microscopic traffic simulators, for which car-following logic is the core, and to develop more appropriate ACC algorithms and control strategies.

ANALYSIS OF VARIABILITY IN CAR-FOLLOWING BEHAVIOR

OVER LONG-TERM DRIVING MANEUVERS

By

Taehyung Kim

Dissertation submitted to the Faculty of the Graduate School of the
University of Maryland, College Park, in partial fulfillment
of the requirements for the degree of
Doctor of Philosophy
2005

Advisory Committee:

Associate Professor David J. Lovell, Chair
Professor Gang-Len Chang
Professor William S. Levine
Associate Professor Kent L. Norman
Associate Professor Yongjin Park, Keimyung University, Korea

Acknowledgements

Thanks to God for he has done for me. The LORD is my rock, my fortress and my deliverer; my God is my rock, in whom I take refuge. He is my shield and the horn of my salvation, my stronghold.

Sincere appreciation is extended to my advisor, Professor David J. Lovell for supervising this dissertation; his time, energy and support were invaluable. His patient guidance and inspiring advice help me through many difficult moments. Very special thanks to my dissertation committee members, Professor Gang-Len Chang, Professor William S. Levine, Professor Kent L. Norman and professor Yongjin Park, for their invaluable advice and interest in my work.

I also thank Hiroshi Tsuda and his colleagues at Nissan Technical Center North America, Inc. for donating a test vehicle and an infrared range sensor for my research.

I am thankful for all transportation program students with whom I have been privileged to study. Special thanks to Soojung, Dongkeun, Eungcheol, Hyoungsoo, Dongwook, Kyeongpyo, Sungjae, Taehyeong (Tommy), Yeonjoo, Minwook, Namsuk, Sunho, Minseok, Hyunah, Deepak, Somnuk, Peter, Evangelos, Jason and other students for their contributions to me as a person and as a scholar.

Many thanks to the family members at the University Korean Presbyterian Church for their lasting friendship, sincere support and prayer: Pastor Kabsung Son, Deacon Kim family, Deacon Moon family, Deacon Shin family, Deacon Jeon, Deacon Seo, members in college group and young adult group and other family members in the church, especially for prayer supporters on Wednesday prayer meeting.

None of this would have been possible without the extraordinary support and encouragement of my parents Hyungdoo Kim and Jungsoo Baek, my parents-in-law Jungsuk Song and Youngja Lee, and my brothers and sisters. I would like to express my heartfelt thanks to my wife, Jiyoun Song and lovely two daughters, Hyelin and Hyewon, for their continuous love and encouragement when I was down and for the sacrifice and understanding during very difficult moments. It is to them that this dissertation is dedicated with much love and gratitude.

Table of Contents

List of Figures

List of Tables

Chapter 1: Introduction

Large and increasing vehicular traffic volumes and the accompanying safety concerns have increased the need for a better understanding of the dynamic characteristics of traffic flow. There have been a variety of theoretical approaches and mathematical descriptions applied to the study of traffic flow on a roadway. One such theory is normally called “car-following,” and other similar appellations have also been used. The general idea is that the motion of each car in the line of traffic depends on that of the car in front of it, at least under high density conditions. The behavior of single-lane no-passing traffic can then be described and analyzed in terms of the motions of individual cars in the line of traffic.

This dissertation focuses on research for which the central goal is a better understanding of car-following behavior, and more specifically, on the variability in car-following behavior that is commonly observed in naturalistic driving situations. Most of the empirical work in this area is several decades old, and no real improvements in methods or understanding have taken place recently either. New applications in partial traffic automation require a more careful treatment of the subject matter since the car-following logic has been the core for developing appropriate automation algorithms and control strategies. Chapter 1 of this dissertation describes the general background, the limitations of previous experimental studies and models on car-following behavior, objectives of this research, and brief descriptions of the remaining chapters of the dissertation.

1.1 Background

Over the past half century, research and field experiments to study car-following behavior have been conducted on test tracks and roadways, and then modeled to represent drivers' behavior. Car-following models form one of the main logical processes in all microscopic traffic simulation models such as INTEGRATION, CORSIM, VISSIM and PARAMICS, and in modern traffic flow theory. In recent years, the importance of a detailed understanding of such driver behavior has become more essential because an adequate description of this process has instant application in both the design and assessment of advanced driver assistance systems (ADAS), such as adaptive cruise control (ACC) which enables the driver to keep the desired following distance through the distance sensors and vehicle dynamic actuators. It is noteworthy that the establishment of an understanding of normative driver behavior was ranked as the second most important area for development out of 40 problem statements, as scored by an advanced vehicle control and safety systems (AVCSS) panel (ITS America, 1997).

However, the manner in which previous data were collected introduced biases into the models, and also tended to obscure important statistical variations of following behavior both across and within drivers, which might help explain why stochastic elements are not well-represented in current car-following models.

It is our premise that basic research to understand the underlying causal mechanisms and variability of car-following behavior is still required. Data collection techniques are much better now than they were when much of the seminal data in this field was collected. With new high-fidelity data and better understanding of detailed car-following behavior, modern traffic flow theory and the realism of microscopic traffic simulators could be improved greatly.

1.2 Limitations of Previous Studies on Car-Following Behavior

Car-following models were first proposed by Reuschel (1950) and Pipes (1953). The body of literature in this area was extended greatly by Herman et al. (1959~1967) during what may be thought of as the "heyday" of transportation science, when accomplished researchers from mathematics and physics converged on transportation as a rich area of practical research. The literature has been continuously refined up to the present with various different approaches to describing a relationship between the leader and the following vehicle(s). Additionally, a series of field experiments have been conducted, accompanied by the development of different car-following models to calibrate parameters, and to validate and support the models. Certain of these models and methods are reviewed more thoroughly later in this dissertation.

Previous empirical studies and models of car-following behavior have some important limitations. The research philosophy of most previous car-following studies was to develop models first, based on simple theories of driver responses, and then to calibrate and validate them with field data using uncertain experimental methods, as will be discussed in the Chapter 2 of the dissertation. It is difficult to ascertain whether the behavior induced by the models, applying the above research philosophy, is in any way "natural." For example, a common assumption in car-following models is that the reaction of a following vehicle at time $t + T$ depends only on the situation at an earlier time instant t. Hence, current car-following models are "memoryless" in the sense that the following vehicle's action lags the lead vehicle consistently by a constant delay. In particular, there is no dependence on the past sequence of car motions that produced the current state. In fact, for a given instantaneous state, the most natural following response might differ, depending on how that state was reached. Of course, history can always be added to the definition of state, but possibly at severe cost in terms of complexity. With careful forethought, it may be possible to capture the most salient aspects of the history and yet retain models that are tractable.

Largely, there have been two kinds of data collection methods for car-following experiments, using either video recording (or aerial film) to capture many anonymous vehicles, or wire-linked test vehicles on a test track or a roadway. In the first case, it should be noted that this type of data collection is very difficult and tedious work. One advantage is that real drivers are being observed, who are unaware that the experiment is taking place, thus, their behavior is as "natural" as can be expected. Furthermore, there are many different subjects. However, there are large experimental errors caused by the inaccuracy of the measured values of distance and spacing within each small frame of film. Hence, this method tends to produce large calculation errors in drivers' responses, such as acceleration or deceleration. In particular, driving maneuvers (or scenarios) that unfold over a greater distance than can be captured by the camera cannot be represented properly. In fact, it may be more important to investigate sequences of car motions for determining following behavior than instantaneous states because the most natural following response might differ, depending on how that state was reached. Furthermore, it is very hard to capture various human characteristics such as gender and age.

With the wire-linked vehicles, the drivers of the following vehicles (i.e., the subjects of the experiment) were members of the research team, who knew they were being observed, and who were also typically driving under specific instructions to follow the lead vehicle at a safe distance. It is reasonable to presume, therefore, that they were driving in an artificially attentive and careful manner. Moreover, they were aware of the premises of the experiments. This kind of design has the obvious weakness that it may not capture what normal drivers will do under normal conditions on a roadway.

Furthermore, this experimental design provides a very limited understanding of the variation of following behavior across different drivers. Only one (or a few) members of a diverse population are represented. Hence, most existing car-following models have been analyzed under the assumption that all drivers behave in the same way and that a deterministic relationship exists between the action of a lead vehicle and the reaction of the following vehicles. In fact, there might be various responses to the same stimuli within the same driver and across different drivers. Moreover, only certain potentially causal elements, such as relative speeds and spacings, have been studied. There are numerous other factors that may be influential, such as various human characteristics, traffic and road characteristics, and environmental characteristics.

1.3 Research Objectives

A major goal of this research is to observe and analyze the car-following behavior of subjects who do not know they are part of an experiment. We would like to investigate the stochastic effects in car-following behavior across and within drivers with distinguishable driving maneuvers that unfold over a sequence of time, as well as those caused by variability of critical factors such as human characteristics (e.g., gender and environmental conditions like telephoning or vehicle occupancy (distraction level)), traffic and road characteristics (type of vehicle, congestion level, number of lanes, and location of driving lane), and environmental characteristics (e.g., time of day and weather condition). In order to achieve this goal, the following objectives have been pursued:

- Review the literature in this area and disclose some important limitations of current car-following experimental studies and models, which make them inconsistent with naturalistic driving behavior under car-following situations.
- Develop a new data collection system using an instrumented test vehicle, which could overcome shortcomings of previous data collection methods, and a synchronized user interface program to check the status of each device and concurrently store the information transferred from each device to the laptop computer.
- Collect car-following time series data during the rush and non-rush hour periods. In particular, pay attention to *sequences of events* that may be more important to determining following behavior than instantaneous relative speeds and spacings.
- Profile and investigate the following vehicle's responses and logical processes in car-following situations. Furthermore, identify the variability in car-following behavior across and within drivers, investigate various critical causal factors affecting the driving behavior of the following vehicle, classify behavioral profiles of the following vehicles based on those factors, and distinguish stochastic differences in following behavior.

1.4 Organization of the Dissertation

The rest of the dissertation is organized as follows. An in-depth review of previous research on car-following behavior is provided in Chapter 2. Chapter 3 introduces a new data collection system using an instrumented test vehicle and the system architecture, i.e., hardware and software of the new data collection system. As a partial technical aside, this chapter also includes some geometric analysis of when the radar range sensor used in this study can be obfuscated near curves when used in its intended application as a forward-facing rage sensor for autonomous cruise control (ACC). While developing and testing the new data collection system, a preliminary survey was conducted to observe real car-following behavior under naturalistic driving conditions and furthermore to identify driving maneuvers that would be observed in car-following situations. Chapter 4 presents some findings from the preliminary survey and car-following field experiments using the new data collection system. Chapter 5 describes the findings that are observed from the data collected in the study site. Finally, some conclusions and contributions of this dissertation are offered.

Chapter 2: Literature Review

The review of the literature is divided into four sections and focuses mainly on the problems and limitations in previous experimental studies and models of car-following behavior. In the first section, the most well-known simple car-following models are described. The limitations with respect to causal mechanisms that each model has adopted to represent car-following behavior follows in the second section. The third section describes the data collection methods used in previous car-following field experiments and some biases caused by those methods. The fourth section describes the logical process of representing the following vehicle's responses. Finally, the review of the literature is summarized in the fifth section.

2.1 Seminal Models

An important contribution of this dissertation is documentation of a method to collect high-resolution vehicle behavior data using contemporary technology. The absence of such methods at the time the first car-following models were developed is evidenced by the somewhat out-of-order research methodology that tended to permeate the earliest models in this area. The general pattern was to propose an extremely simple and uniform model of driver response (such as collision avoidance or maintaining safe following distances), and then to use the necessarily crude experimental methods of the time to calibrate the small number of parameters involved in the model. What was not done, and what should be the hallmark of good research, is to collect the data first, scrutinize it carefully, and then to let ideas about possible models manifest themselves in the data. To be fair, these were extremely competent researchers, so one must conclude that the expedient nature of the methodology was dictated by the technological limitations in place. Nevertheless, it was possible in this dissertation to collect better data and to let these better speak for themselves, without the temptation necessarily to hasten to simple models.

The family of car-following models typically referred to colloquially as the "General Motors" models was based on a model first developed by Chandler et al. (1958). This was a simple linear model, in the sense that the response (acceleration or deceleration) of the following vehicle was assumed to be proportional (linear) to the stimuli (relative velocity) between the lead and following vehicles.

$$\ddot{x}_{n+1}(t+T) = \alpha[\dot{x}_n(t) - \dot{x}_{n+1}(t)] \tag{1}$$

where $\ddot{x}_{n+1}(t+T)$ is the acceleration or deceleration of the following vehicle at time $(t+T)$, $\dot{x}_n(t)$ is the velocity of the lead vehicle at time *t*, $\dot{x}_{n+1}(t)$ is the velocity of the following vehicle at time *t*, *T* is a reaction time and α is a sensitivity parameter. The only parameters in this model were the delay with which the response followed the stimulus, and the "sensitivity" or gain of the model. A series of field experiments were carried out on test tracks to calibrate these parameters. Interestingly, while the field data revealed significant variation in the sensitivity values across different drivers, the model could not accommodate this variation and it was not adequately explained. Later, a common explanation amongst other researchers was that it makes sense for the sensitivity to increase as the relative spacing decreases.

In the linear model, the sensitivity term is independent of the spacing between the lead and following vehicles. Hence, Gazis et al. (1959) developed a non-linear car-following model with a sensitivity term that was inversely proportional to the relative spacing.

$$\ddot{x}_{n+1}(t+T) = \frac{\alpha_0}{[x_n(t) - x_{n+1}(t)]}[\dot{x}_n(t) - \dot{x}_{n+1}(t)] \tag{2}$$

where α_0 is a calibration parameter. Subsequently, Edie (1961) assumed that as the speed of the traffic stream increases, the driver of the following vehicle would be more sensitive to the relative velocity between the lead and following vehicles. Hence, he introduced the speed of the following vehicle into the sensitivity term of the non-linear car-following model developed by Gazis et al. (1959).

$$\ddot{x}_{n+1}(t+T) = \frac{\alpha'[\dot{x}_{n+1}(t+T)]}{[x_n(t) - x_{n+1}(t)]}[\dot{x}_n(t) - \dot{x}_{n+1}(t)] \tag{3}$$

where α' is a dimensionless sensitivity parameter. Finally, a generalized form of car-following models was proposed (Gazis et al., 1961) that subsumes all of these aforementioned models.

$$\ddot{x}_{n+1}(t+T) = \frac{\alpha_{l,m}[\dot{x}_{n+1}(t+T)]^m}{[x_n(t) - x_{n+1}(t)]^l}[\dot{x}_n(t) - \dot{x}_{n+1}(t)] \tag{4}$$

where l and m are constants.

It should be noted that the above car-following models developed with support from General Motors assume that all drivers follow the exact same driving rules. In fact, these rules may differ with different drivers, or even for the same driver and with different conditions, and in fact, possibly even to some extent with the same driver and nearly identical situations. Therefore, it is difficult to ascertain whether the behavior induced by the above models, applying the above research philosophy, is in any way "natural." In particular, there simply are not enough modern data sets collected under appropriate experimental conditions to make this determination. Hence, a more desirable approach to the study of car-following behavior in this dissertation was first to collect large quantities of detailed data under car-following situations using modern observation techniques. Following that, the data was processed and analyzed in various ways to look for emerging patterns.

2.2 Causal Mechanisms

A number of different approaches have been adopted and developed to represent the causal mechanisms in car-following behavior. However, only certain potentially causal elements, such as relative speeds and spacings, have been considered and formalized in previous car-following models.

One of the earliest studies, by Pipes (1953), is based on the goal of avoiding collisions or maintaining safe following distances. He assumed that the movements of the various vehicles of the line obey a postulated following rule suggested by a "rule of thumb" frequently taught in driver training, which is to allow one additional length of a car in front for every ten miles per hour of speed. By the application of this postulated following rule, he proposed the following simple linear equation in which the car spacing is a linear function of speed of the following vehicle.

$$x_n - x_{n+1} = b + \tau\dot{x}_{n+1} + L_n \tag{5}$$

where x_n is the position of the front of the n^{th} vehicle, x_{n+1} is the position of the front of vehicle $n+1$, b is the minimum distance between the vehicles when stopped, τ is the time gap prescribed by the postulated traffic law, $\dot{x}_{n+1}$ is the velocity of the vehicle $n+1$

and L_n is the length of the n^{th} vehicle. For example, if the rule of thumb was 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 this equation (5) is differentiated with respect to time, the result is as follows:

$$\dot{x}_n - \dot{x}_{n+1} = \tau \ddot{x}_{n+1} \tag{6}$$

Equation (6) cannot be applied in general as a traffic law, because it only serves to keep those pairs of vehicles in equilibrium that were in that state to begin with. In fact, all linear models would suffer from this same drawback – since the derivative (equation (6), or the "following law") is independent of the constant terms of the equilibrium spacing rule (equation (5)), any initial condition would produce the same following behavior for the same speed profile of the lead vehicle, including spacings that were far too close (after a lane change, perhaps) or too distant (in which case the interaction between the vehicles might be weak or nonexistent). The behavior that drivers, finding themselves in an "out-of-equilibrium" status, might follow to return to equilibrium was not defined or studied.

From the perspective of driving in expectation of a "brick wall stop," where one imagines the lead vehicle to stop instantaneously (a frequent worst case scenario considered in these models), the spacing rule for this model seems dubious, as simple physics suggests that stopping distance should vary with the square of vehicle speed, rather than linearly. Kometani and Sasaki (1959) modified the linear model to accommodate that consideration - the car spacing is expressed by a quadratic relation of speeds of the lead and following vehicles. They introduced a time lag T (reaction time of a driver) in the model and assumed that a driver chooses his or her velocity at time $t+T$ based on the spacing observed at an earlier time t.

$$x_n(t) - x_{n+1}(t) = \alpha \dot{x}_n^2(t) + \beta_1 \dot{x}_{n+1}^2(t+T) + \beta_2 \dot{x}_{n+1}(t+T) + b \tag{7}$$

where $x_n(t)$ and $\dot{x}_n(t)$ are the position and speed of the nth vehicle at time t respectively, and α, β_1, β_2 and b are all constants.

Notwithstanding its obvious flaws, Zhang and Kim (2001) recently modified Pipes' model to reproduce both the so-called "capacity drop" and "traffic hysteresis" phenomena, which some experimenters have deduced from field data. They postulated that cars are always in one of three phases - acceleration, deceleration and coasting. The time gap, which the original model assumed to be constant, was made a function both of vehicle spacing and of which phase a driver was in. They did not, however, address the suspicion, raised by many people and significant empirical evidence, that not many people drive according to this safe following distance rule.

All General Motors car-following models, introduced in section 2.1, have the same basic form: *Response = function (stimuli, sensitivity)*, where response is acceleration or deceleration of the following vehicle and the stimuli are the relative velocity between the lead and following vehicles. The various modifications of the sensitivity term led to a generalized form of car-following models, equation (4). Most of the previous models are special cases of this generalized model with different combination of l and m. For example, equation (1) is represented by equation (4) with $l = m = 0$, equation (2) is by equation (4) with $l = 1, m = 0$, and equation (3) is given by equation (4) with $l = 1, m = 1$. Note that the magnitude of the response is directly proportional to the relative velocity at the time of observation (before the lag), and to the instantaneous velocity of the following vehicle at the time of actuation (after the lag) and with some exponent to be calibrated. This latter artifact does not necessarily agree with the physics of the problem, as fluid resistance and non-constant power curves at high speeds greatly reduce the acceleration (positive) that a vehicle can achieve. This response is inversely proportional to some power of the relative spacing at the time of observation, which is reasonable.

In most previous car-following models, the driver's absolute response was the same for acceleration and deceleration, i.e., the models were "symmetric." However, it is well-known that the capability (and, perhaps, willingness) to decelerate in a vehicle is generally greater than to accelerate. Hence, Herman and Rothery (1965) conducted car-following experiments to investigate the difference of the capability of a driver's reaction between acceleration and deceleration, and Ozaki (1993) proposed modified car-following models that have different forms of driver's responses based on the data collected on a test track and a Japanese motorway:

$$
\begin{aligned}
\ddot{x}_{n+1}(t + T_{d,a}) &= \alpha_{d,a}[\dot{x}_n(t) - \dot{x}_{n+1}(t)] \\
\alpha_d &= 1.1 * \dot{x}_{n+1}(t)^{0.9} / [x_n(t) - x_{n+1}(t)]^{1.0} \\
\alpha_a &= 1.1 * \dot{x}_{n+1}(t)^{-0.2} / [x_n(t) - x_{n+1}(t)]^{0.2} \\
T_d &= 1.3 + 0.02 * [x_n(t) - x_{n+1}(t)] + 0.7 * \ddot{x}_n(t) \\
T_a &= 1.5 + 0.01 * [x_n(t) - x_{n+1}(t)] - 0.6 * \ddot{x}_n(t)
\end{aligned}
\tag{8}
$$

where α_d and α_a are sensitivity values for deceleration and acceleration, T_d and T_a are driver reaction times for deceleration and acceleration respectively.

The series of General Motors car-following models do not consider the effect of the inter-vehicle spacing independently of the relative velocity; i.e., drivers will always accelerate if the relative velocity is positive and decelerate if the relative velocity is negative. However, in real driving, it is often seen that when the following vehicle is some reasonable distance behind the leading vehicle, the following vehicle can accelerate even if the relative velocity is zero. One might circumvent this criticism by claiming that this would not happen in high density traffic; however, due at least in part to lane-changing and a mix of vehicle types, such larger-than-average gaps frequently appear, even in rush-hour traffic. Hence, Low et al. (1998) proposed a car-following model, adding a nonlinear spacing-dependent term to the model developed by Gazis et al. (1961).

$$\ddot{x}_{n+1}(t+T) = a\frac{[\dot{x}_n(t)-\dot{x}_{n+1}(t)]}{[x_n(t)-x_{n+1}(t)]} + b[x_n(t)-x_{n+1}(t)-D_{n+1}]^3 \tag{9}$$

where a and b are positive real numbers, D_{n+1} is the desired spacing that the driver of vehicle $n+1$ attempts to achieve from the vehicle ahead. The first term on the RHS is the model proposed by Gazis et al. and the cubic term is the additional spacing-dependent term.

Gipps (1981) claimed that the parameters $\alpha_{l,m}$, l and m in the generalized form of General Motors car-following models have no obvious connection with identifiable characteristics of drivers or vehicles, and argued that the parameters in a model should correspond to obvious characteristics of drivers and vehicles. Hence, he proposed a model for the response of the following vehicle based on the assumption that each driver sets limits to his desired braking and acceleration rates, and then uses these limits to calculate a safe speed with respect to the preceding vehicle. It was assumed that the driver of the following vehicle selects his speed to ensure that he can bring his vehicle to a safe stop if the vehicle ahead comes to a sudden stop. The model has two components, which cover acceleration and braking separately. The acceleration component is as follows:

$$\dot{x}_{n+1}(t+T) = \dot{x}_{n+1}(t) + 2.5a_{n+1}T[1-\frac{\dot{x}_{n+1}(t)}{V_{n+1}}][0.025+\frac{\dot{x}_{n+1}(t)}{V_{n+1}}]^{1/2} \tag{10}$$

where $\dot{x}_{n+1}(t+T)$ is the maximum speed to which vehicle $n+1$ can accelerate during the time interval (t, $t+T$), a_{n+1} is the maximum acceleration for vehicle $n+1$ and V_{n+1} is the desired speed at which the driver of vehicle $n+1$ wishes to travel. The braking component is as follows:

$$\dot{x}_{n+1}(t+T) = b_{n+1}T + \{(b_{n+1}T)^2 - b_{n+1}[2(x_n(t) - L_n - x_{n+1}(t)) - \dot{x}_{n+1}(t)T - \frac{\dot{x}_n(t)^2}{\hat{b}}]\}^{1/2} \tag{11}$$

where $\dot{x}_{n+1}(t+T)$ is the maximum safe speed for vehicle $n+1$ with respect to vehicle n, b_{n+1} is the most severe braking that the driver of vehicle $n+1$ wishes to undertake (b_{n+1}<0), L_n is the effective length of vehicle n and $\hat{b}$ is the estimate of b_n. Finally, in any given circumstances, the speed adopted by vehicle $n+1$ is the minimum value of these two components.

An obvious critique of the above models is that they assume that all drivers follow the same driving rules. In fact, these rules may differ with different drivers, or even for the same driver and with different conditions, and in fact, possibly with the same driver and nearly identical situations. Subramanian (1996) and Ahmed (1999) extended the GM non-linear car-following model (Gazis et al., 1961) by assuming that the reaction time is a function of factors (e.g., age, gender, weather conditions, geometry, vehicle type and traffic conditions) modeled by a truncated log-normal random variable. We share with these authors the sense that there are significant stochastic components missing from other car-following models. However, there is a difference between injecting some randomness into the model, and doing so in a way that properly captures stochastic effects. For example, simply turning a constant parameter into a random variable, yet still assuming that, once sampled, it will remain the same for that driver throughout the journey, does not capture the incomplete consistency that has been observed within drivers for similar stimuli. Further, this retains the myopic character of the model and does not allow for the kind of longer-term, evolving maneuvers that we feel are a critical component of actual driving. In particular, the use of a simple study site and myopic data collection schemes prevents (unfairly) this variation from even being observed in the first place.

Kikuchi et al. (1992, 1999) also recognized that the reactions of the following vehicle to the lead vehicle might not be based on a deterministic relationship, but rather on a set of approximate driving rules developed through experience. Their approach to modeling these rules consisted of a fuzzy inference system with membership sets that could be used to describe and quantify the behavior of following vehicles. However, the logic to define the membership sets is subjective and depends totally on the judgment and approximation of the researchers. Furthermore, no field experiments were conducted to calibrate and validate these fuzzy membership sets under real driving conditions. While we agree with the premise of the paper, and seek to resolve similar issues, the methodology employed does not warrant any further explanation. Some researchers may argue over semantics, but we believe that there are no quantitative problems in fuzzy logic that cannot be solved in an equivalent manner using classical methods (Ruspini, 1996), so the use of fuzzy logic by itself does not distinguish a model from other approaches.

All of the models examined so far use only a simple set of kinematic variables, such as relative spacings and speeds, instantaneous speeds, etc., to determine subsequent behavior. In fact, there are numerous other factors besides basic kinematics that may influence car-following behavior, such as various human characteristics (e.g., gender, environmental conditions like telephoning, vehicle occupancy (distraction level)), traffic and road characteristics (e.g., type of vehicle, congestion level, number of lanes, and location of driving lane), and environmental characteristics (e.g., time of day and weather condition). We hypothesize that different types of vehicles, such as truck and auto, and different geometric and road traffic conditions might have a different impact on car-following behavior. For example, a vehicle cannot accelerate rapidly on a steep roadway, compared to level terrain, and might be more careful when driving behind a truck. Different traffic and road characteristics such as road curvature, relative speed, stream speed and the length of time in the coupled state might affect car-following behavior differently, as suggested by Rockwell (1972). Recently, Chen et al. (1995) conducted a series of experimental studies using a video recording method for environmental effects on car-following behavior, although this kind of data collection method has the obvious weakness that it may not capture various human characteristics and driving maneuvers that unfold over a greater distance than can be captured by the camera. They found that the effects of road surface conditions and weather, traffic density, and different locations are related to the differences in car-following behavior.

Unfortunately, no further studies have been made to identify numerous other factors that may be influential to car-following behavior, investigate those effects quantitatively and to incorporate their findings into car-following models that could replicate these characteristics. Hence, it is very important to identify various critical factors affecting the driving behavior of the following vehicle through extensive field experiments, investigate the relationships between those factors and the following vehicle's behavior, and categorize the range of each critical factor based on the differences of behavioral characteristics. Of course, in order to do so, empirical data must be collected and studied. The next section describes some studies that have been done in the past, as well as experimental errors and biases that should be avoided if possible.

2.3 Experimental Studies and Biases

As mentioned in the previous chapter, numerous car-following field studies have been conducted to calibrate parameters and to validate the models. One of the most extensive experiments was performed by Chandler et al. (1958), cooperating with the General Motors research team. They first conducted field experiments using wire-linked vehicles on the test track to quantify the parameter values for the reaction time and the sensitivity in the simple linear model (equation (4) with $l = m = 0$). In the experiment, eight different drivers were used in the instrumented car and were asked to follow the lead vehicle while maintaining a safe distance. Subsequently, Gazis et al. (1959) also performed experiments using wire-linked vehicles to obtain the parameter values for the sensitivity parameter and reaction time in the non-linear model (equation (4) with

$l = 1, m = 0$). It was conducted at the Holland, Queens Mid-town, and Lincoln Tunnels in New York with eleven different drivers, and at the General Motors test track. A similar three-car experiment was carried out by Herman and Rothery (1963) to investigate the effect of looking two cars ahead instead of just at the car immediately in front, and to study the appropriateness of an "asymmetric" model; i.e., one in which acceleration and deceleration responses were different in absolute value (for the same absolute stimulus).

Kometani and Sasaki (1959) performed car-following experiments with two test vehicles. A lead vehicle and a following vehicle were photographed by a camera from the top of a roadside building. Rough instructions were given to the driver of the lead vehicle concerning the magnitude and the location of intended acceleration and deceleration maneuvers, whereas the driver of the following vehicle was instructed to follow the lead vehicle, maintaining a safe spacing which he considered a minimum.

Numerous experiments were conducted afterward to modify the sensitivity term of the generalized General Motors model. Similarly, Hanken et al. (1967, 1968) developed an empirically-based model by piece-wise linear regression analysis with data from car-following experiments using wire-linked vehicles similar to those used by the General Motors research team. Aron (1988) used three instrumented vehicles with optical sensors installed on the wheels of the second and third vehicle to collect car-following data. Ozaki (1993) proposed a modified General Motors car-following model based on the data collected on a test track with a lead vehicle and two instrumented following vehicles, and on a Japanese motorway with a video camera mounted on the top of a 32-floor building. Recently, Brackstone et al. (1999) conducted car-following experiments on a three-lane motorway in the United Kingdom. In their experiments, each of seven subjects was instructed to follow an instrumented test vehicle through the test section.

In most of these experiments, the drivers of the following vehicles knew they were being observed, and most were also driving under specific instructions to follow the lead vehicle at a safe distance. Moreover, they were aware of the premises of the experiments. This kind of design has the obvious weakness that it may not capture what normal drivers will do under normal conditions on a roadway. Furthermore, this provides a very limited understanding of the variation of following behavior across different drivers. Only one (or a few) members of a diverse population are represented. Hence, most existing car-following models have been analyzed under the assumption that all drivers behave in the same way and that a deterministic relationship exists between the action of a lead vehicle and the reaction of the following vehicles. In fact, there might be various driver responses within the same driver and across different drivers. The significant variations in the value of reaction time (1.0 to 2.2 seconds) and sensitivity (0.17 to 0.74) of different drivers observed in car-following experiments performed by Chandler et al. (1958) and Gazis et al. (1959) illustrate the random fluctuations of following behavior amongst drivers.

On the other hand, Treiterer and Myers (1974) monitored the trajectories of a large number of vehicles using aerial film to calibrate parameters in the generalized General Motors model. They investigated the acceleration and deceleration phases separately. Similarly, Subramanian (1996) used the data collected by FHWA to estimate the parameters in the extended General Motors non-linear model. The data were collected using a 35-mm motion picture camera mounted on an aircraft. The film data were then reduced using a microcomputer-based digitizing system. Subsequently, Ahmed (1999) collected car-following data using standard video equipment. The length of the recorded section varied from 150 to 200 meters at different zoom levels. The video data were processed using image processing software. The drivers in the car-following experiments did not know they were part of an "experiment." However, it should be noted that this type of data collection is very difficult and tedious work and there are large experimental errors in video recording or aerial film methods caused by the inaccuracy of the measured values of distance and spacing within each small frame of film or video. Hence, it tends to produce large calculation errors in drivers' responses, such as acceleration or deceleration. In particular, driving maneuvers (or scenarios), as will be discussed in the next section in detail, that unfold over a greater distance than can be captured by the camera cannot be represented properly. In fact, it may be more important to investigate sequences of car motions for determining following behavior than instantaneous states because the most natural following response might differ, depending on how that state was reached. Furthermore, this kind of design has the obvious weakness that it may not capture various human characteristics such as gender, occupancy, and in-vehicle activities.

As reviewed above, the design of experimental studies in previous car-following models has the obvious limitation that it may not capture normal driving behavior. Hence, new data collection methods that could overcome shortcomings of previous methods should be considered. The new data collection methods need to observe and analyze the car-following behavior of subjects who do not know they are part of an experiment. Also, they should be able to capture the following behavior of a diverse population of drivers to identify and distinguish the variability in car-following behavior across and within drivers. Furthermore, the new data collection method should be designed to capture various critical factors such as human characteristics, traffic and road characteristics, and environmental characteristics affecting the driving behavior of the following vehicles.

2.4 Memoryless Process

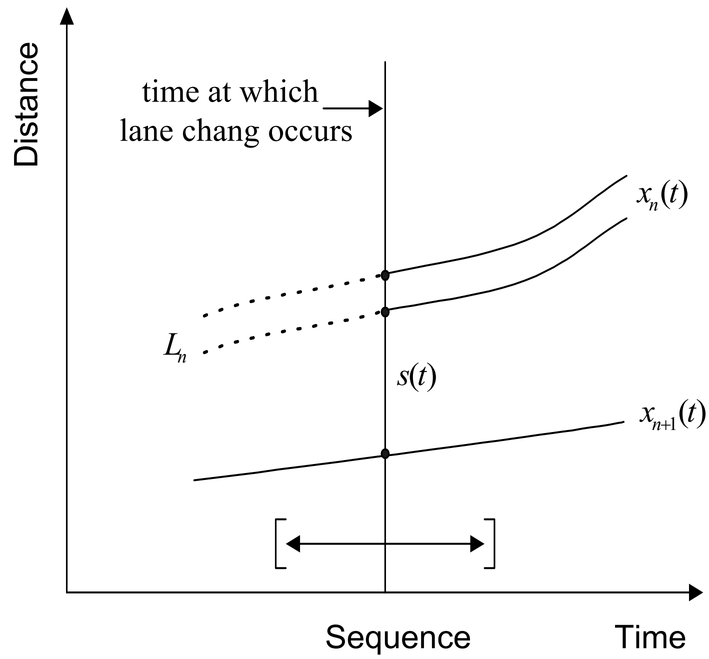
A common assumption in car-following models is that the reaction of a following vehicle at time $t+T$ depends only on the situation at an earlier time instant t. Hence, current car-following models treat the dynamic evolution of cars at a given state as a memoryless process; i.e., the following vehicle's action lags the lead vehicle consistently by a constant delay. In particular, there is no dependence on the past sequences of car motions that produced the current state (in existing car-following models, the state includes only instantaneous conditions, not historic ones).

In fact, for certain instantaneous states, the most natural following responses might differ, depending on how those states were reached. For example, a following driver might not respond promptly to maintain his or her desired distance when the lead vehicle has recently cut into the lane where the following vehicle is driving. If it is clear that the new leader can accelerate and increase the spacing unilaterally, or that an additional lane change may be imminent, the follower may choose simply to wait cautiously without taking evasive action, whereas current simple state-based models (with a myopic definition of the state) would predict a nearly immediate and probably aggressive deceleration maneuver. Figure 1 shows two examples where the same state might be produced under very different causes, and hence very different effects might be expected. In the first case, the new lead vehicle labelled *n* changes lanes in front of the subject car (vehicle labelled *n*+1), and acquires some relative position and velocity thereby. The vehicle then accelerates, prompting no response from the following vehicle to maintain his or her desired distance. In the second case, if the same spacings and speeds had resulted from a deceleration event, the follower might be inclined to decelerate immediately.

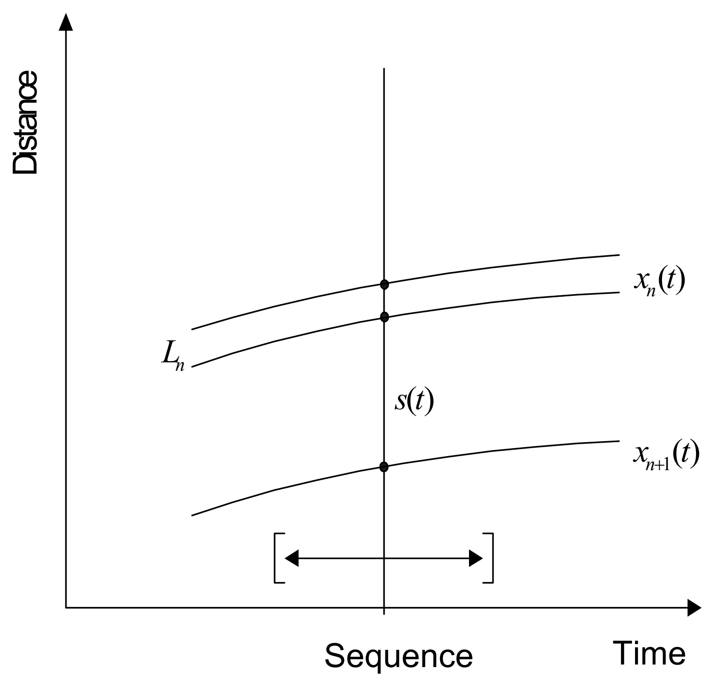
Actually, Chandler et al. (1958) first introduced the idea that the response of the following vehicle depends not only on what the relative speed was at a certain earlier instant, but rather on its time history. Hence, they extended the simple linear car-following model in which the acceleration of the following vehicle is proportional to the relative speed between the lead and the following vehicles, by adding a weighting function (Lee, 1966, called it a "memory function") that is intended to represent the way in which the following driver responds to the information he or she has received from the lead vehicle over some time interval. Therefore, the stimulus at a given time, *t*, depends on the weighted sum of earlier values of the relative speed.

$$\ddot{x}_{n+1}(t+T) = \int_{t-\Delta t}^{t} [\dot{x}_n(z) - \dot{x}_{n+1}(z)] h(z-t)\, dz \qquad (12)$$

where $\ddot{x}_{n+1}(t+T)$ is the acceleration or deceleration of the following vehicle at time $(t+T)$, $\dot{x}_n(t)$ and $\dot{x}_{n+1}(t)$ are the velocity of the lead and the following vehicle at time *t* respectively, and Δt is the interval over which memory is applied, and $h(t)$ is the weighting function defined on [- Δt ,0].



(a) Lane-changing maneuver



(b) Deceleration maneuver

Figure 1. Examples of different responses to the same instantaneous state

Lee (1966) investigated the consequences of applying several examples of possible weighting functions such as the Dirac delta function, decaying exponential function, and the Heaviside step function. Obviously, the simple linear car-following model developed by Chandler et al. (1958) is a special case of the more general theory when the Dirac delta function is used as the weighting function and the impulse occurs at time t only. However, no data collection results were shown to determine the appropriate form of the weighting function, or to confirm that this is indeed a reasonable model. Subsequently, Darroach and Rothery (1972) illustrated how one might estimate the memory function, and in the special case when it is proportional to the Dirac delta function, the reaction time and sensitivity parameters of the basic linear model, using Fourier analysis techniques. However, they did not deal with the question of the accuracy of the estimated weighting function and no further research has been made to compare it with real car-following behavior. This type of approach seems to hold some promise, at least to the extent that it attempts to resolve some of the critiques of models we have presented so far. Unfortunately, the idea of using time-series history to predict the response of the following vehicle has had rather little influence on later developments in car-following models.

2.5 Summary

Car-following logic has played a key role in all microscopic traffic simulation models to describe drivers' car-following behavior. However, as reviewed in the previous sections, current car-following experimental studies and models have some important limitations, which make those models inconsistent with naturalistic driving behavior under car-following situations. The following is a summary of the problems and limitations of current car-following experimental studies and models.

- The research philosophy of most previous car-following models was to conjure up a simple model first, and then to use field data using uncertain experimental methods to calibrate it.
- Only certain elements, such as relative speed and spacings, have been considered as causal mechanisms. As a result, limitations in the kinds and amounts of data that could be collected made it more reasonable to conjecture a simple model form, and then to use limited data to calibrate that model.
- The design of experimental studies in existing car-following models has the obvious limitation that it may not capture normal driving behavior. Furthermore, the variation of following behavior both within and across drivers is not provided.
- The current car-following models are memoryless, in that they do not consider the past sequences of car motions or events that produced a current state to determine the future state.

Chapter 3: Data Collection System

As part of this research effort, a new data collection system using an instrumented test vehicle, equipped with three sets of measurement instrumentation, has been developed and tested: (1) to observe and analyze the car-following behavior of subjects who do not know they are part of an "experiment," (2) to capture the following behavior of a diverse population of drivers to identify and distinguish the variability in car-following behavior across and within drivers, (3) to capture various critical factors such as human characteristics, traffic and road characteristics, and environmental characteristics, affecting the driving behavior of the following vehicles, (4) to identify and investigate driving maneuvers that unfold over an interval of time, (5) to easily collect a sufficient quality and quantity of data. Furthermore, a synchronized user interface program has been developed to interact with the status of each device and concurrently store the information transferred from each device to the laptop computer.

In our experiments, the instrumented test vehicle is the lead vehicle, which experiment participants drive. The driver of the test vehicle can be any normal driver who can drive legally. While the lead vehicle is driving, the following vehicle (whatever vehicle happens to be following, which we have no control over) is monitored by automatic equipment and a second experimenter. All equipment was disguised so the experimental vehicle was not a visual distraction.

The system architecture, including hardware and software, of the new data collection system is described in the first section. The second section presents a preliminary test of the rear-facing infrared radar sensor concerning the reliability of its data quality. The third section describes a somewhat tangential exercise concerning the radar range sensor, namely the dropout problem at curve transitions. This problem is relevant to our experiments for retaining track of a following vehicle around curves, but the more general application is forward-facing sensors used for ACC, so that is the context in which the analysis is presented.

3.1 System Architecture

3.1.1 Hardware

The instrumented test vehicle is an Infiniti Q45. It was modified to collect car-following data on roadway traffic and was equipped with four sets of measurement instrumentation, including an infrared radar sensor (the type normally used for ACC), a DGPS/inertial Distance Measuring Instrument, vehicle computer, and a digital video camera, as shown in Figure 2. A laptop computer was installed to store the synchronized data collected from the different devices. The test vehicle and infrared radar sensor were donated by Nissan Technical Center North America, Inc. The functions of these equipment are described briefly in Table 1.

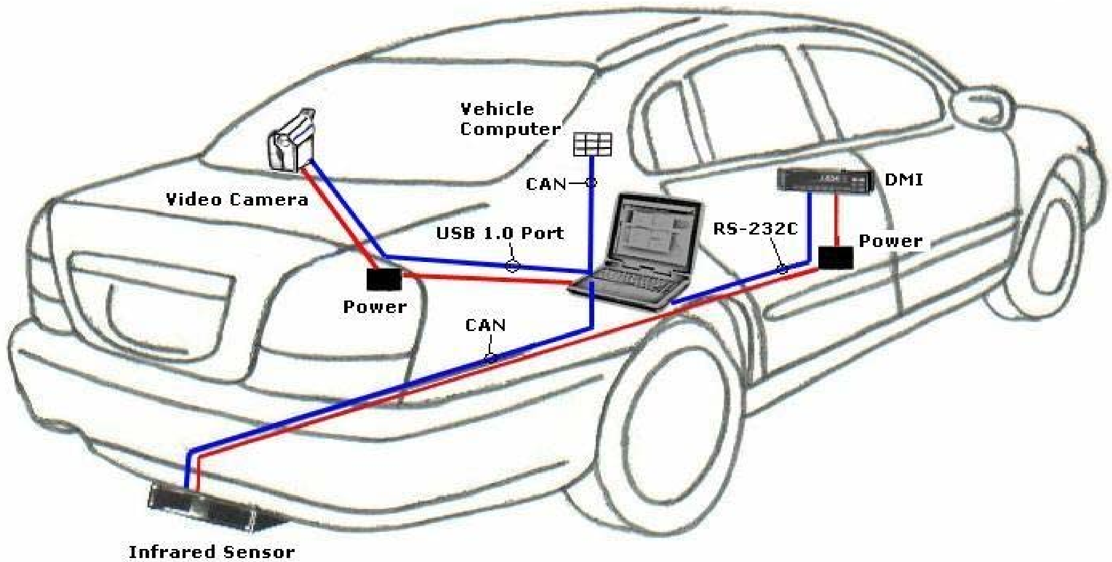


Figure 2. Test vehicle apparatus and connectivity diagram

Table 1. Functions of data collection equipment

Name	Function
Infrared radar sensor (AR211, Omron)	Measure distance, relative speed and curvature between the lead and the following vehicles. When combined with DMI information, this produces position, speed, and acceleration of the following vehicle.
Distance Measuring Instrument (SL3000DX, Sun-Lab)	Predict the position, speed, acceleration of the test vehicle (lead vehicle) integrated with Differential Global System (DGPS) and inertial navigation.
Video camera (DCR-TRV33, Sony)	Record the following driver's characteristics, such as gender and in-vehicle activities; identify and distinguish different following maneuvers; and to verify and disambiguate data from the DMI and infrared sensor.
Laptop computer	Store time-synchronized data from each device.
Vehicle Computer	Provide independent speed measurements, as well as brake pressure and status indicators necessary for the radar sensor to function properly.

1) Infrared Radar Sensor

The infrared sensor makes it possible to measure the distance and relative velocity between the leading and the following vehicle, as well as the curvature of the road, by combining tangential velocity with an internal yaw rate sensor. The sensor is identical to what is used for production adaptive cruise control (ACC)-equipped vehicles. Our model was donated for the purpose of this study by Nissan North America.

The infrared sensor has 5 beams, transmitting with a typical wavelength of 850nm. The sensor can detect relevant targets in the range of 2 to 150m in distance and -20 to 60m/s in relative velocity, with a measured accuracy of ±1.0m and ±0.3m/s respectively. It operates from 10V to 16V supply, so we simply connected it to the vehicle power bus through a fuse. The sensor has been mounted on the metal frame of the back bumper and connects to the power of 12V of the test vehicle.

Figure 3 shows the back view of the test vehicle where the infrared sensor has been mounted. The sensor was installed level to the ground, and we used a target board at various distance to calibrate the other two angular degrees of freedom. The infrared sensor originally has been developed for looking forward. In our experiments, however, the sensor was installed on the rear of the test vehicle for looking backward so that the sensor should be mounted upside-down to get appropriate returns. The sensor was not mounted upside-down, but we programmed the software, pretending that it was mounted upside-down.

The infrared sensor is a Controller-Area-Network (CAN) device, meaning that it is designed to operate as a node in the internal communications network common to certain brands of newer cars. It was important, however, not to connect the device to the in-vehicle CAN, since it was not being used for ACC purposes and would therefore confuse the vehicle. Instead, we used two independent CAN connections to our laptop computer – one coming directly from the vehicle and the other to the range sensor. A small amount of message traffic is necessary between the two to ensure proper calibration and operation – this was implemented in our software with our computer as an intermediary. The hardware used was a commercially available PCMCIA CAN interface (CANcardX) and CAN connection cable (CANcab251opto). Figure 4 shows a CANcardX with its two I/O ports and CANcab with transceiver, I/O connector and D-Sub CAN connector. Figure 5 presents brief circuitry diagram of CANcardX interfaced with test vehicle and infrared sensor. It is able to communicate at a rate of 1Mbit/second, which is adequate because the infrared sensor communicates at a rate of 500 kbit/second. It was important, however, to use a programming language that compiled into sufficiently fast code to keep up with the communications – our software is written in Visual C++.

Figure 3. Infrared sensor mounted on the back bumper of the test vehicle

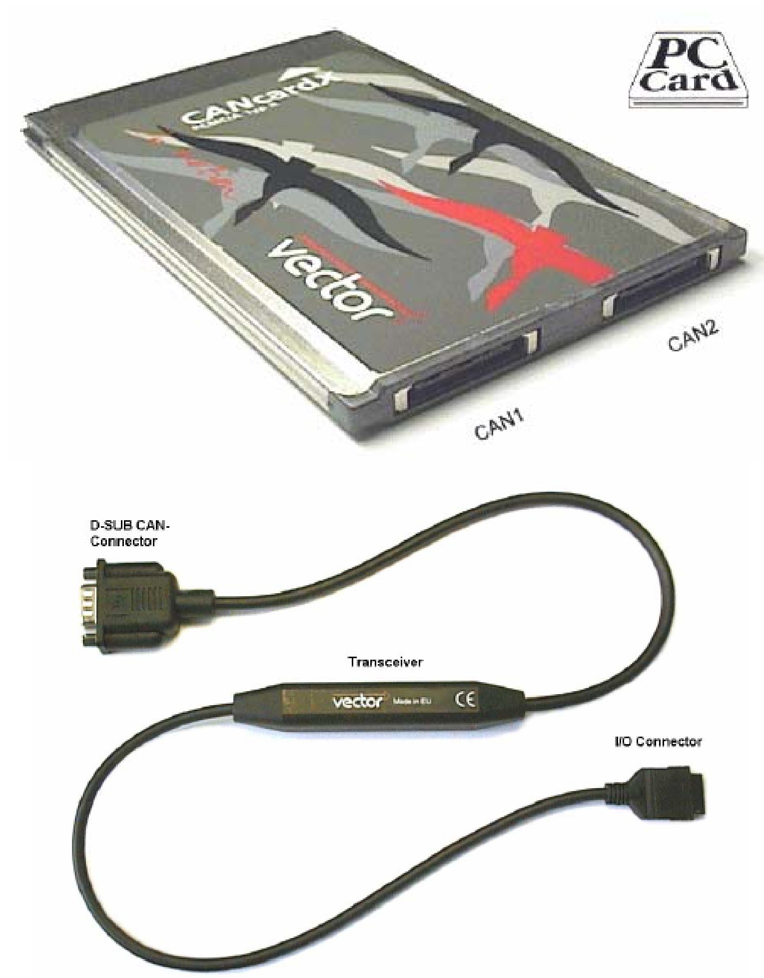


Figure 4. CANcardX with its two I/O ports and CANcab

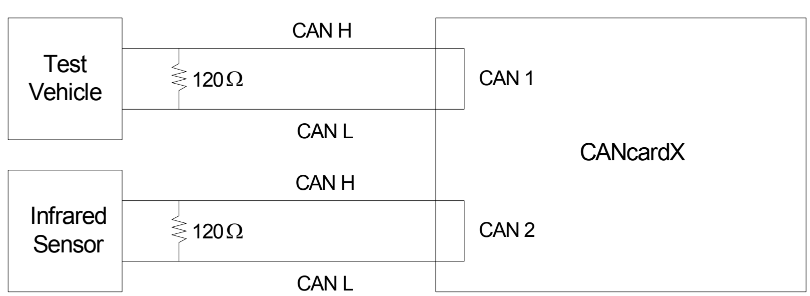


Figure 5. Circuitry diagram of CANcardX interfaced with test vehicle and infrared sensor

2) Distance Measuring Instrument (DMI)

The DMI uses a combination of inertial and GPS technologies to predict the position and speed of the test vehicle, which serves as the lead vehicle. The model we have used is SL3000DX, which is the DMI integrated with precision Differential Global Position System (DGPS) made by Sun-Lab Technologies, Inc. and is shown in Figure 6. As an added benefit, the fact that GPS is present in the data collection equipment gives us a sufficiently accurate time standard on which to base the synchronization of the 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 (CEP). The vehicle speed signal is transmitted to the DMI via Sun-Lab sensor control module – Model SCM-8. The DMI connects to the laptop computer via the RS-232 serial port and "speaks" the standard NMEA protocols common to GPS receivers. The DMI/GPS is operating from 10V to 15V DC @ 1.0A and connects to the power of 12V of the test vehicle.

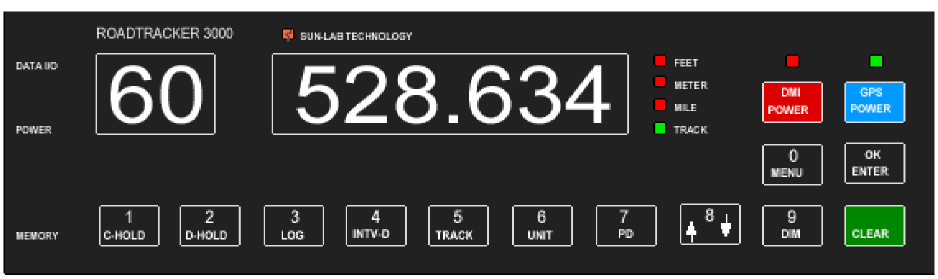


Figure 6. Distance Measurement Instrument (DMI)

3) Video Camera

The digital video camera was mounted facing backwards, and was used to monitor the driving behavior of the following vehicle and additional information such as gender and other visually noticeable conditions (for example, whether he/she was using cellular phone while driving). The video camera was used to help identify and distinguish different following maneuvers to tell when lane-changing behind the lead vehicle occurred, and also to verify and disambiguate data from the DMI and infrared sensor. The model we have used is a DCR-TRV33 made by Sony Corporation. The video camera connects to the laptop computer via the USB 1.0 port and live images are transferred to the laptop computer. The video camera has been installed next to the brake light on the back seat. The video camera was hidden in a black box and camouflaged with children's toys so as not to be a visual distraction, as shown in Figure 7.

Figure 7. Video camera hidden in a black box

4) Laptop Computer

The laptop computer stores the time-synchronized data collected from each device. It was powered from the vehicle so that experiments longer than the battery life could be conducted reliably.

3.1.2 Software

A synchronized user interface program (Visual C++) has been developed to check the status of each device and concurrently store the information transferred from each device to the laptop computer. Figure 8 shows the main screen of the user interface program. Since the infrared sensor is a Controller-Area-Network (CAN) device, we have developed our own CAN application incorporated with two separate CAN networks: the one already in the car, and a separate, small one that consists only of our laptop computer and the infrared sensor. The reasons for separating the two CAN networks are as follows: (1) there are too much data from the test vehicle, (2) the infrared sensor requires specific data not available in non-ACC car, (3) it is unwise to confuse the car with extra unexpected CAN node.

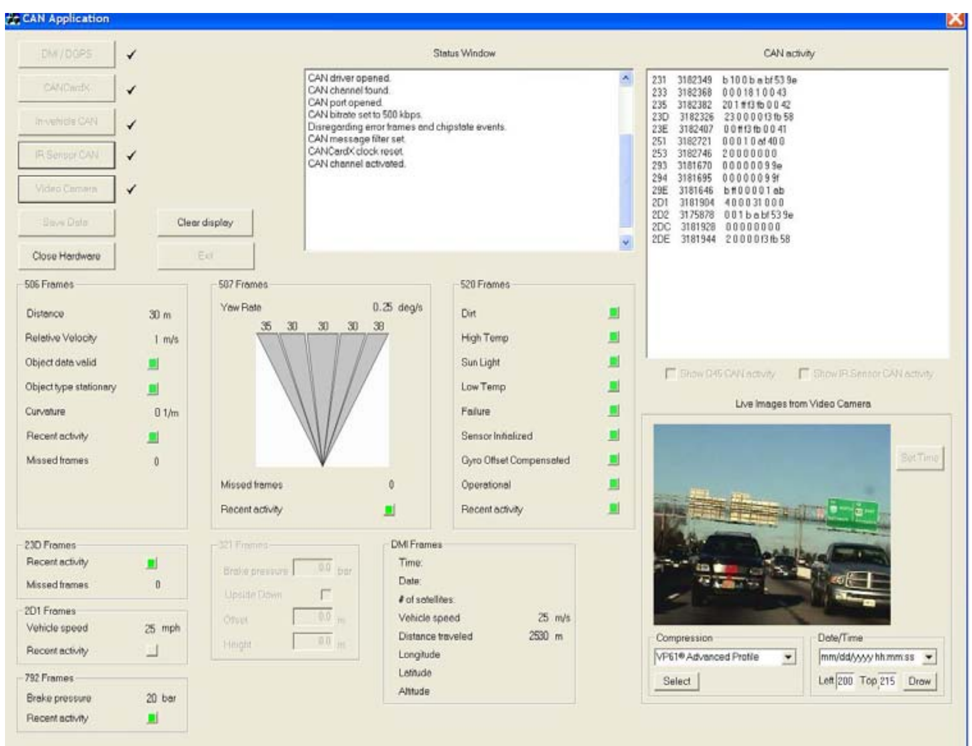


Figure 8. Main screen of user interface program

Figures 9 and 10 show the block diagram and the flow chart of the user interface program, respectively. A list of CAN data, including the transmit cycle of each CAN message, is described in Table 2. As seen in Figure 9, 23D, 2D1, and 321 CAN messages are retrieved from the test vehicle CAN and are re-transmited to the infrared radar sensor and 506, 507, and 520 messages from the infrared radar sensor are stored and processed in the laptop computer. In the diagram, the infrared sensor uses brake pressure in 321 messages for calibration of yaw rate included in the unit and judges whether vehicle stops or not, based on the brake pressure values and vehicle speed. However, since the test vehicle was not being used for ACC purposes, the 321 messages were not available. Hence, we retrieved 793 messages (equivalent to 321 messages) from the test vehicle CAN, reformatted them as 321 messages and transmitted to the infrared sensor.

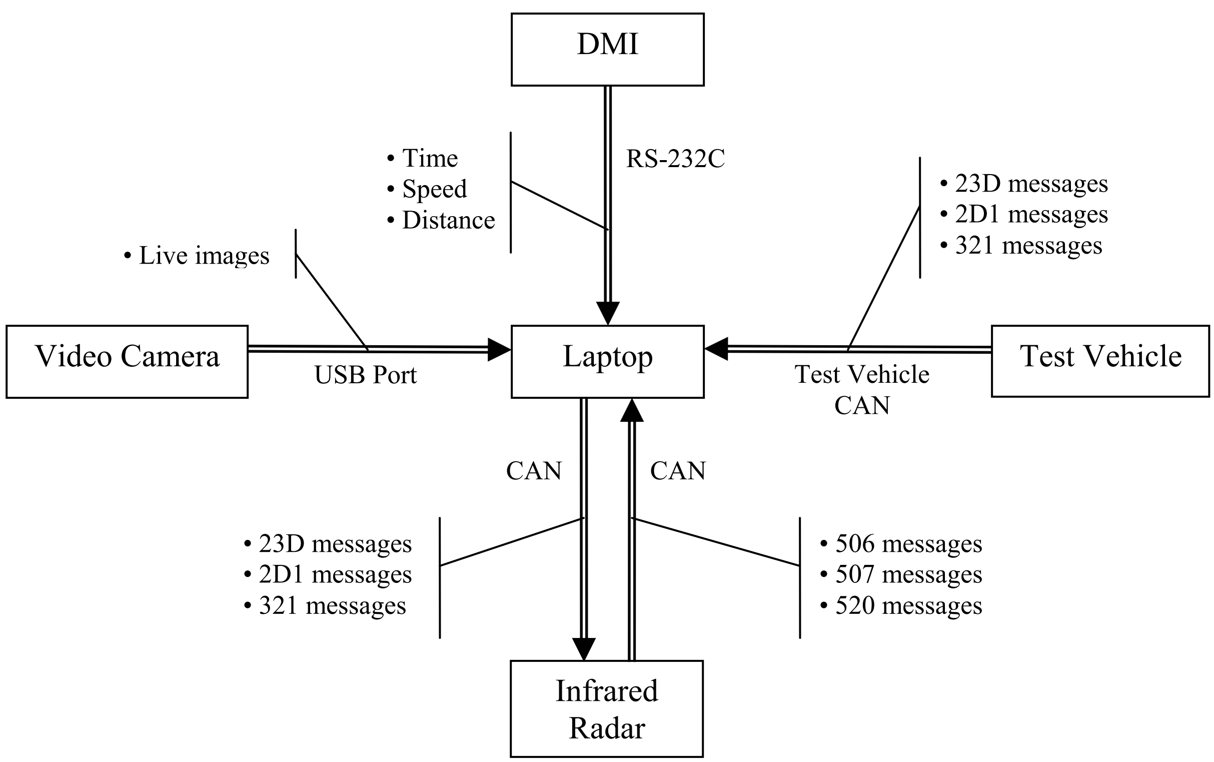


Figure 9. Block diagram of user interface program

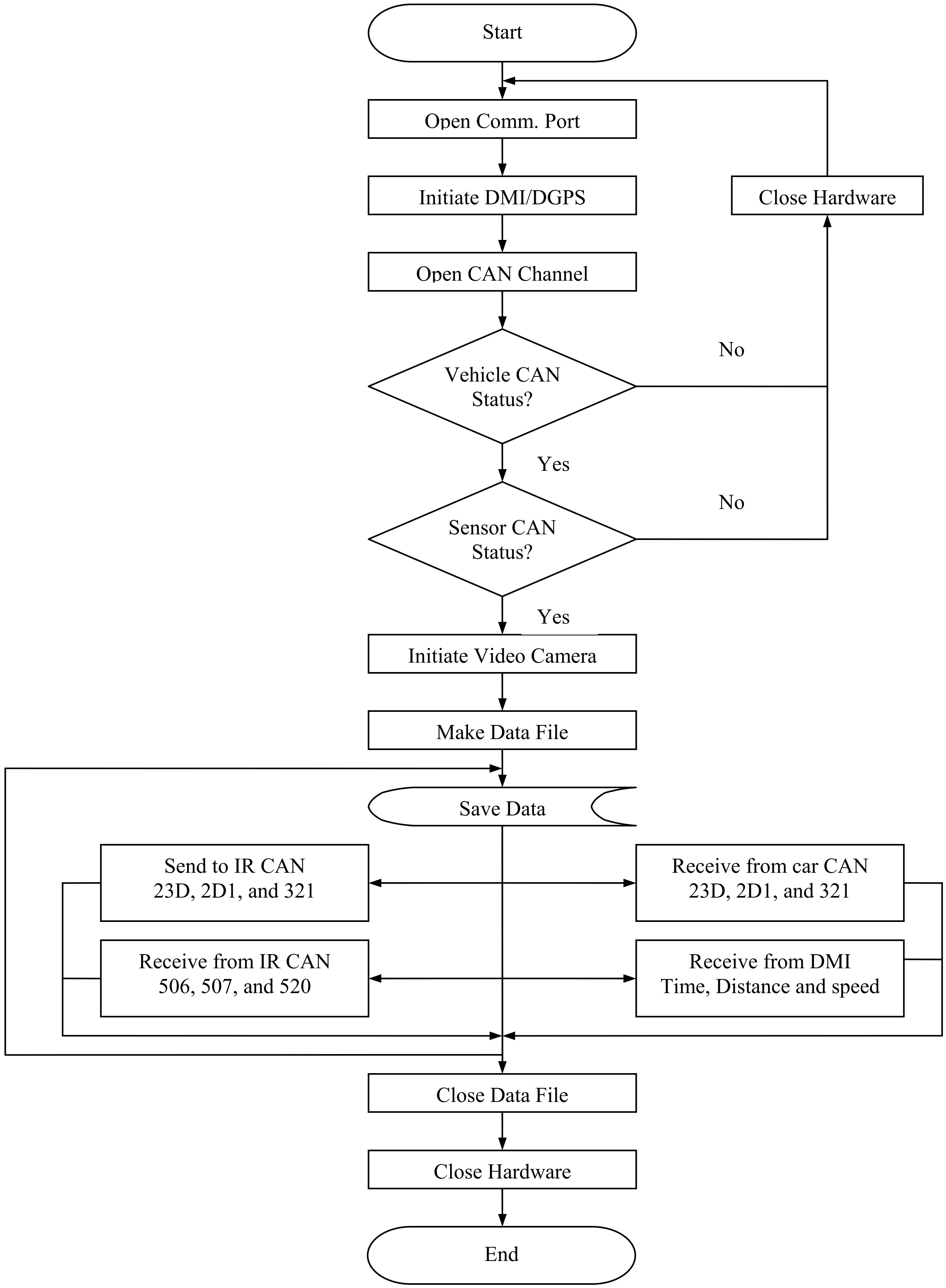


Figure 10. Flow Chart of user interface program

Table 2. CAN data explanation

ID	Name	Content	Transmit Cycle
23D	Message counter	Increases by one at every transmit cycle	10ms
2D1	Vehicle speed Configuration	Own vehicle speed Configuration of own vehicle (31hex fixed value)	10ms
321	Brake pressure Order of operation Upside down Offset Height	Brake pressure Range sensor execute measurement in accordance with this flag Range sensor is upside down or not. Offset distance between center of sensor and longitudinal vehicle center axis Height of sensor from the ground	100ms
506	Distance Relative velocity ODV OTYP Change counter Curvature Message counter	Distance of relevant target Relative velocity of relevant target Sensor detects relevant target or not. Relevant target is stationary or not. Increases by one at every timing that relevant target changes to new one Curvature estimated by range sensor Increases by one at every transmit cycle	100ms
507	Yaw rate Support_R Support_L Cut in_R Cut in_L Center Message counter	Yaw rate measured by yaw rate sensor in range sensor Distance of the nearest object detected by right side support beam Distance of the nearest object detected by left side support beam Distance of the nearest object detected by right side cut in beam Distance of the nearest object detected by left side cut in beam Distance of the nearest object detected by center beam Increases by one at every transmit cycle	100ms
520	Dirt High temp Sun light Low temp Failure Initial phase Gyro offset Operational	Performance degradation due to obstacle is diagnosed. Abnormal temperature rise of range sensor is diagnosed. Performance degradation due to sun light is diagnosed. Abnormal temperature fall of range sensor is diagnosed. Failure of range sensor is diagnosed. Sensor initialization is over and result is OK. Gyro offset is available or not. Range sensor is working and measuring normally or not. according to order of operation.	100ms

3.2 Preliminary Test of Infrared Radar Sensor

There were several issues concerning the feasibility of the data collection apparatus, particularly regarding the rear-facing infrared radar sensor. Originally, the infrared sensor was developed for looking forward and was expected to receive strong reflection from the reflectors of the rear of the lead vehicle. However, for our purposes, the sensor was installed on the rear of the test vehicle so that the sensor did not receive the strong reflection from the front of the following vehicle and the detectable distance from the sensor was reduced. Furthermore, as each vehicle class has a different frontal shape, rather than a pretty standard back, it was uncertain if the sensor beams would function properly. Hence, a preliminary test, regarding the proper height and working offset (or angle) of the sensor was conducted to investigate reliable radar returns from following vehicles and to properly design the experimental studies that need to take place in real traffic conditions. A mobile station was built to collect data for the preliminary test of the sensor, as shown in Figure 11.

Figure 11. Mobile station equipment for the preliminary test

3.2.1 Sensor configuration effect on infrared radar sensor data quality

It is very important to strategically determine certain parameters about how the sensor should be mounted, and what range it will have when data are being collected on the freeway. The range and sensitivity of the sensor change with the height at which it is mounted on the vehicle.

Field experiments were conducted for six types of vehicles, as shown in Figure 12, at different heights of the sensor (e.g., 30, 40, and 50cm) and different orthogonal distances (e.g., 5, 10, 15m, etc.) from the target vehicles. Tables 3, 4 and 5 show the comparisons between the actual distance and the measured distance from the infrared radar sensor at different heights, and distance measurement accuracy is presented visually in Figures 13, 14 and 15.

For short distances, the sensor was quite accurate. At some threshold (around 45m), however, a discrepancy appeared, meaning that the sensor was targeting a different object. It was also found that when the sensor was around 50m away from the vehicle at the sensor height of 40 and 50cm, the sensing system occasionally failed. This resulted either in a zero distance measurement, or perhaps the tracking of a nearby stationary object such as a tree. From these results, we were able to determine which distances from the lead vehicle would generate reliable radar returns from following vehicles, i.e., a limitation on traffic density conditions in designing the experimental studies, which was about 50m between the lead and following vehicles.

(1) Toyota

(2) Chevrolet

(3) Mazda

(4) Toyota

(5) Chevrolet

(6) Volkswagen

Figure 12. Six vehicles used for infrared sensor data quality

Table 3. Sensor measured distance vs. actual distance for each vehicle at height 30cm

Unit: meter

Actual distance	Measured distance from the infrared radar sensor					
	Vehicle 1	Vehicle 2	Vehicle 3	Vehicle 4	Vehicle 5	Vehicle 6
5	5	5	5	4	5	4
10	10	10	9	10	10	10
15	15	15	15	15	15	14
20	20	20	20	20	20	19
25	25	25	25	25	25	25
30	30	30	29	30	30	30
35	35	35	35	35	35	34
40	40	40	40	40	40	39
45	45	45	44	15	15	45
50	50	50	49	51	50	54

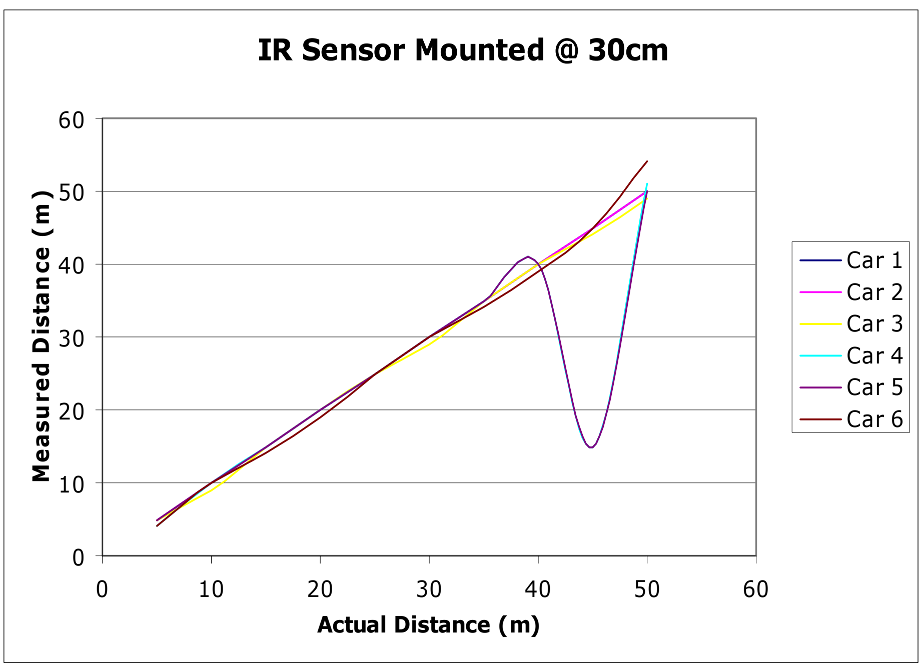


Figure 13. Distance measurement accuracy at height 30cm

Table 4. Sensor measured distance vs. actual distance for each vehicle at height 40cm

Unit: meter

Actual distance	Measured distance from the infrared radar sensor					
	Vehicle 1	Vehicle 2	Vehicle 3	Vehicle 4	Vehicle 5	Vehicle 6
5	4	5	5	5	5	4
10	9	10	9	9	10	10
15	14	15	15	15	15	15
20	20	20	20	20	20	19
25	25	25	25	25	25	24
30	30	30	29	30	30	30
35	35	35	34	35	35	34
40	40	40	39	40	40	39
45	45	45	44	45	45	44
50	65	0	49	50	50	49

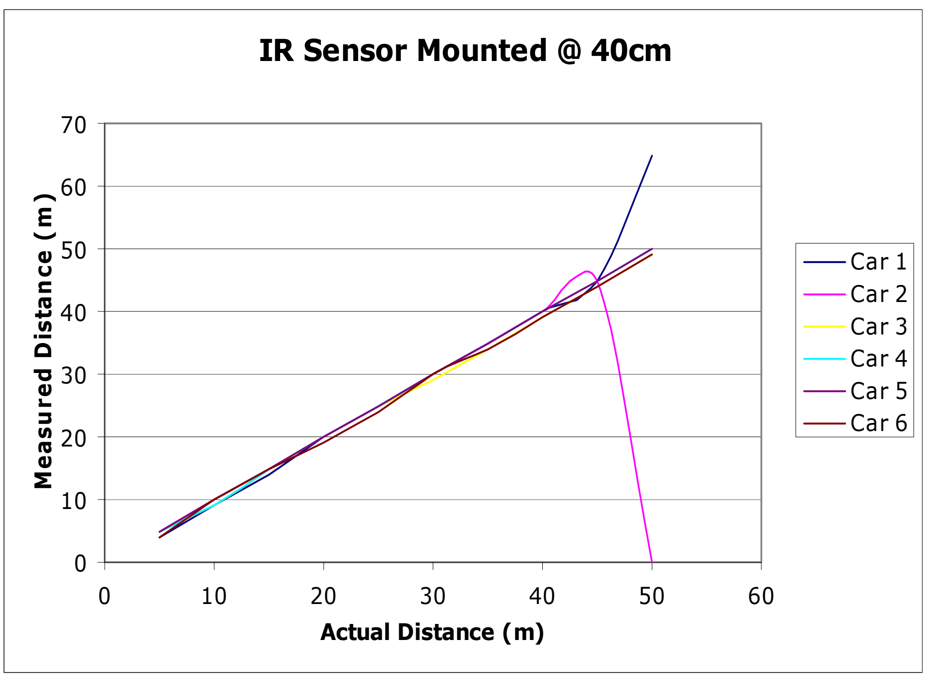


Figure 14. Distance measurement accuracy at height 40cm

Table 5. Sensor measured distance vs. actual distance for each vehicle at height 50cm

Unit: meter

Actual distance	Measured distance from the infrared radar sensor					
	Vehicle 1	Vehicle 2	Vehicle 3	Vehicle 4	Vehicle 5	Vehicle 6
5	5	5	5	5	5	5
10	10	10	10	10	10	10
15	15	15	15	15	15	15
20	20	20	20	20	20	20
25	25	25	25	25	25	24
30	30	30	30	30	30	30
35	35	35	35	35	35	35
40	40	40	40	40	40	39
45	45	45	44	45	45	44
50	65	0	49	50	50	49

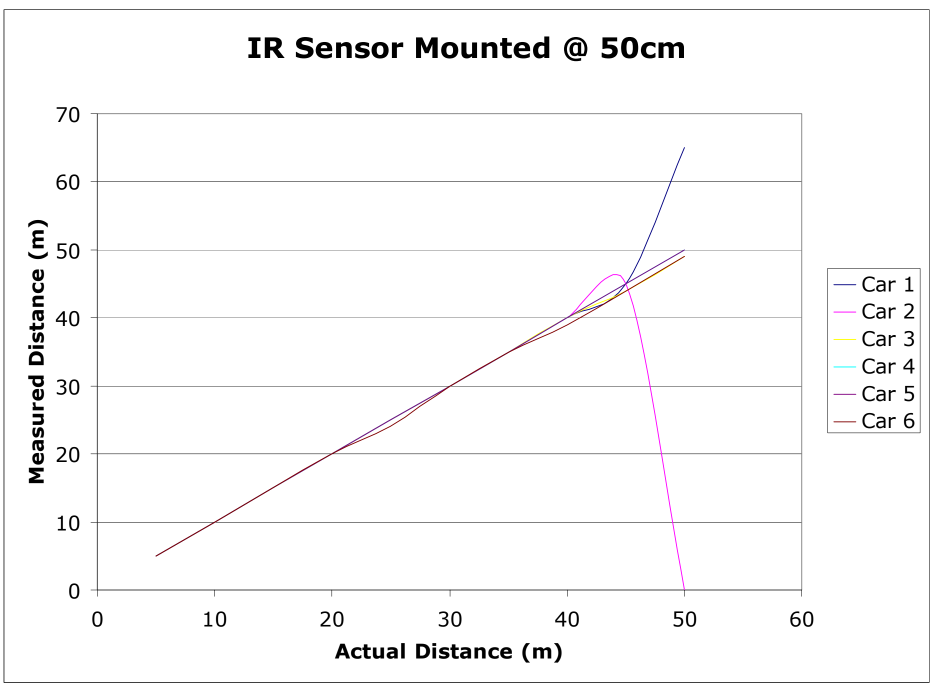


Figure 15. Distance measurement accuracy at height 50cm

In order to determine the best height at which to place the sensor, the Root Mean Square Error (RMSE) was used to calculate the error between the actual and the measured distances. From the RMSE graph shown in Figure 16, it was clearly best to place the sensor at 30cm above the ground.

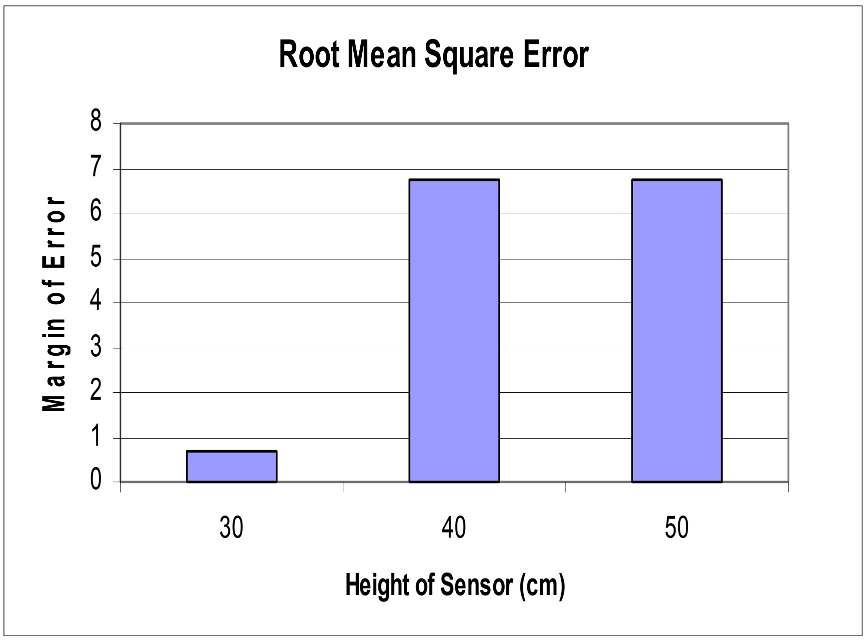


Figure 16. Comparison of Root Mean Square Error

3.2.2 Angular sensitivity of multi-beam infrared radar sensor

The infrared radar sensor is composed of five individual beams that collect data on the distance between them and any object in their paths. Schematically, they are typically shown to be adjacent and non-overlapping, with well-defined borders, as shown in Figure 17. In practice, however, this is not possible - the beams may overlap or there may be gaps between them ("underlap"). The beams may not be symmetrical; e.g., the left cut-in beam may fail to register a target at a different angle than the right cut-in beam. Each of the beams may have effective angles that vary with distance, and may have different overall ranges. Hence, it was necessary to determine the lateral and longitudinal range of each of the five beams that comprise the infrared sensor. As a result, we knew at what range (angular and distance) targets were reliably acquired in the same and adjacent lanes behind our test vehicle, which enabled us to properly design the location of the sensor on the rear bumper to get the best performance.

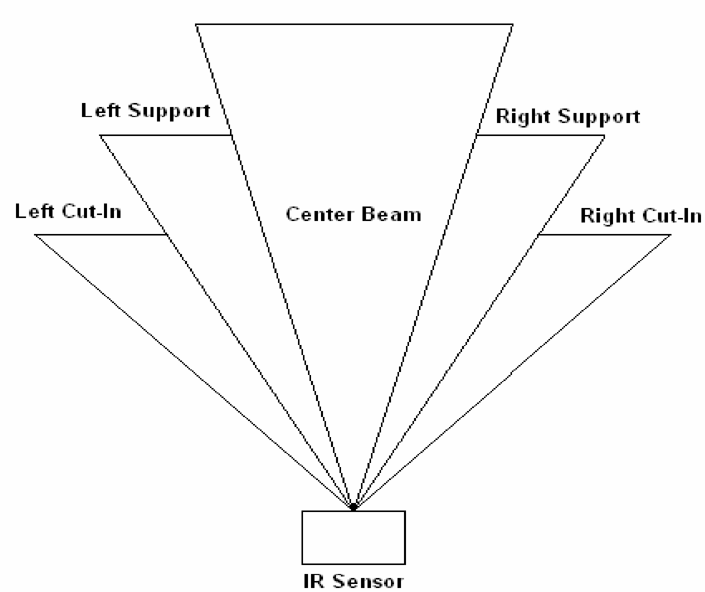


Figure 17. Schematics of five beams of the sensor

Field experiments were conducted for three types of vehicles at different orthogonal distances (e.g., 5, 10, 15m, etc.) from target vehicles. Table 6 shows one example of the working offsets and angles for each of the five beams, from left cut-in to right cut-in. In the top portion of the table, the first number gives the distance to the right for the point where the beam failed. The second number gives the distance to the left for the point where the beam failed. In the bottom portion of the table, Θ_1 represents the angle of the beam to the left of the center, while Θ_2 shows the angle of the beam to the right of the center. Figure 18 shows the shape of each of the five beams at the different distance intervals 5m to 50m.

It was observed that the beams of the infrared radar sensor were asymmetrical; each beam had a different working angle at the different distance intervals. For example, the angle of the left cut-in is smaller than that of the right cut-in. The effective beam edges were also non-linear. As the distance increased, the shape of the beams began to fluctuate. Due to the minute changes in offset failing distances for some beams, it was determined that some of the beams may overlap.

Furthermore, the results show that the failure point for the beams were similar for each vehicle tested. For instance, the cut-in beams fail at 20m, the support beams fail around 30m and the center beams fail around 50m. This conforms to the schematic diagram of Figure 17.

Table 6. One example of the working offsets and angles for each of the five beams

CAR 1										
Distance (m)	Working Offset (m)									
	Left Cut-In		Left Support		Center		Right Support		Right Cut-In	
5	1.09	0.54	0.97	0.75	0.87	0.94	0.55	1.21	0.52	1.47
10	1.55	0.68	1.26	0.75	1.02	0.82	0.95	0.98	0.92	1.58
15	1.90	0.79	1.24	1.10	1.21	1.38	1.20	1.44	0.92	1.93
20	2.27	0.79	1.40	1.17	0.98	1.76	0.68	2.11	0.20	2.49
25			2.09	0.21	1.09	0.79	0.39	1.90		
30			1.95	0.34	1.23	0.87	0.85	1.20		
35					0.99	1.43				
40					1.54	0.85				
45					0.62	0.82				
50										
Distance (m)	Working Angle (Radians)									
	Θ_1	Θ_2	Θ_1	Θ_2	Θ_1	Θ_2	Θ_1	Θ_2	Θ_1	Θ_2
5	0.215	0.108	0.192	0.149	0.172	0.186	0.110	0.237	0.104	0.286
10	0.154	0.068	0.125	0.075	0.102	0.082	0.095	0.098	0.092	0.157
15	0.126	0.053	0.082	0.073	0.080	0.092	0.080	0.096	0.061	0.128
20	0.113	0.039	0.070	0.058	0.049	0.088	0.034	0.105	0.010	0.124
25			0.083	0.008	0.044	0.032	0.016	0.076		
30			0.065	0.011	0.041	0.029	0.028	0.040		
35					0.028	0.041				
40					0.038	0.021				
45					0.014	0.018				
50										

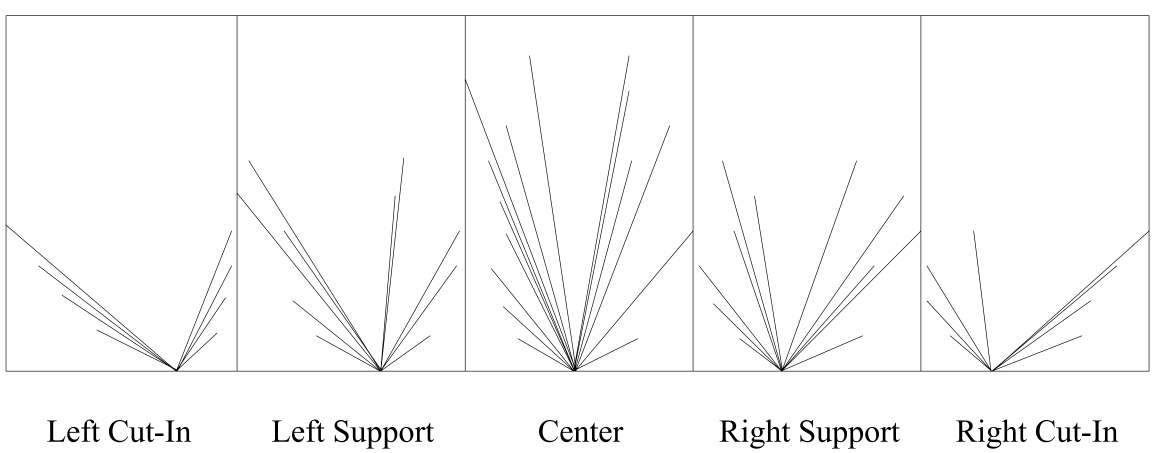


Figure 18. Lateral and longitudinal range of five beams

3.3 Dropout in Range Sensors at Curve Transitions

In our field experiments, when collecting car-following data at the transition from a tangent section to a curved section, it is possible for the instrumented test vehicle with a rear-facing infrared radar sensor to lose track of a following vehicle in car-following mode. This occurs because the test vehicle enters the curve and its path diverges from the axis of the following vehicle, yet the following vehicle is still on the tangent section. This is a temporary situation, but one that could have an impact on the quality of car-following data collected. Hence, it is very important to investigate the specific circumstances under which the infrared sensor dropouts can occur at curve transitions and that must be carefully handled when collecting car-following data using our data collection methods.

It is also an important problem for a forward-facing range sensor used in adaptive cruise control (ACC) system. One of the interesting challenges of ACC control lies in the fact that when both the subject vehicle and the target vehicle are on a curve, the target vehicle is not directly in front of the subject vehicle, as measured along its own axis. This is illustrated in Figure 19. To counter this, most ACC sensors have the ability to deflect their beams at appropriate angles. The determination of the proper angle requires an estimate of the curvature of the road being traversed, which is accomplished via a combination of an on-board yaw rate sensor and feedback from the vehicle's speed sensor. What is assumed in this calculation, however, is that the subject vehicle is currently on the curve, allowing it to measure its own lateral acceleration. During the transition from a tangent section to a curved section, however, the lead vehicle enters the curve first, and it might be possible for it to turn out of the path of the sensor beam before the following vehicle is even aware that a curve is coming (Domsch and Sandkuhler, 2000). In their report (General Motors Corporation, 2002) on a major demonstration project in the U.S., General Motors acknowledges that curve entry-exit transitions present a challenge to target acquisition and tracking in an ACC system. The issue is more complicated than simply losing track of the vehicle - from the perspective of the rangefinder in the following vehicle (if it is of the multi-beam variety equipped to take such measurements), this maneuver might just as easily resemble a lane change. As a result, if the following vehicle were traveling below its desired speed, it might interpret this as a circumstance where it would be safe to accelerate back to its desired speed. In fact, however, it would soon discover, once it was on the curve, that the lead vehicle did not change lanes, and therefore because of its own acceleration, the safe following distance had been compromised.

In this section, we present a methodology for determining the specific circumstances under which range sensor dropouts can occur at curve transitions. Examples are given using typical values of roadway and vehicle parameters. The methodological portion of this section is concerned with the issue of temporarily losing track of a lead vehicle at a curve transition from the perspective of ACC. The geometric procedure can be applied in reverse to the problem of maintaining track of a following vehicle using a rear-facing sensor.

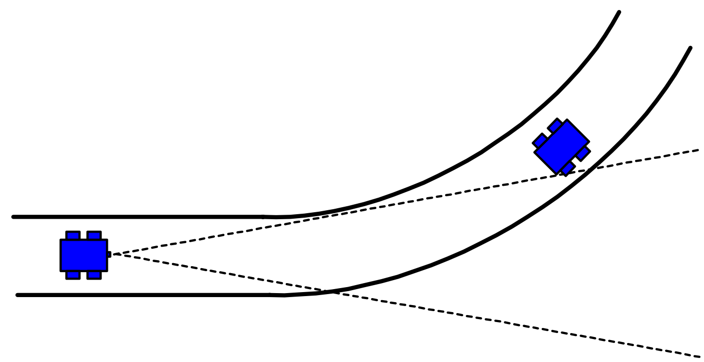


Figure 19. Target determination in circular curve section

3.3.1 Geometric derivation

In this section, we present the geometry of this situation in a way that enables us to determine, as a function of the speed of the vehicles (and therefore the safe following distance), the distance and time that the following vehicle is on the tangent, after losing track of the target vehicle, but before entering the curve where it might re-acquire. It is this interval that is most dangerous, and it might be wise not to attempt to accelerate during this time, in an ACC application. In our application, we avoided drawing conclusions from the data under these circumstances. Presumably, similar computations are being made internally for some of the more robust ACC systems; the details of their operations are not provided in the open literature, however.

It is assumed that the horizontal alignment consists only of a smooth series of connected tangent sections and circular curves. While clothoid spirals are also used frequently for curve transitions, they do not lend themselves to closed-form geometric calculations (Lovell, 1999). Furthermore, their effect is to reduce the rate of change of curvature and spread it over a longer distance, giving a following vehicle more time to enter the curve and become aware of the new circumstances. Thus, the worst-case scenario is a direct tangent-to-circular arc transition, so spirals will not be considered in this section. Figure 20 shows the geometry of tangent and circular curve sections. In the derivation that follows, coordinates are shown in vector representation for conciseness.

The origin of the coordinate system in the figure is at the point PC, which is the point of curvature, or transition from the tangent to the circular curve. The circular arc has radius *r*. The safe following distance between the two vehicles is given by *d*, which is then partitioned into $d = d_a + d_l$, where d_a is the distance along the arc of the center of the vehicle travel lane, and d_l is the remaining distance, which is apportioned to the tangent. While *d* might be given exogenously, we will also show an example where it is a commonly used function of the vehicle speed *v*.

The included angle Δ, on the circular arc, between its start and the location of the lead vehicle, is given by

$$\Delta = \frac{2d_a}{2r + l_w} \tag{13}$$

where l_w is the lane width. Throughout this analysis, all angles are given in radians.

The point **A** is the middle of the driving lane at the curve transition; it is given by

$$\mathbf{A} = \begin{bmatrix} \frac{l_w}{2} & 0 \end{bmatrix}^{\mathrm{T}} \tag{14}$$

The point **B** is the middle of the driving lane at the rear of the lead vehicle. To find this point, first we find the length c, of the chord AB:

$$c = 2\left(r + \frac{l_w}{2}\right)\sin\frac{\Delta}{2} = \left(2r + l_w\right)\sin\left(\frac{d_a}{2r + l_w}\right) \tag{15}$$

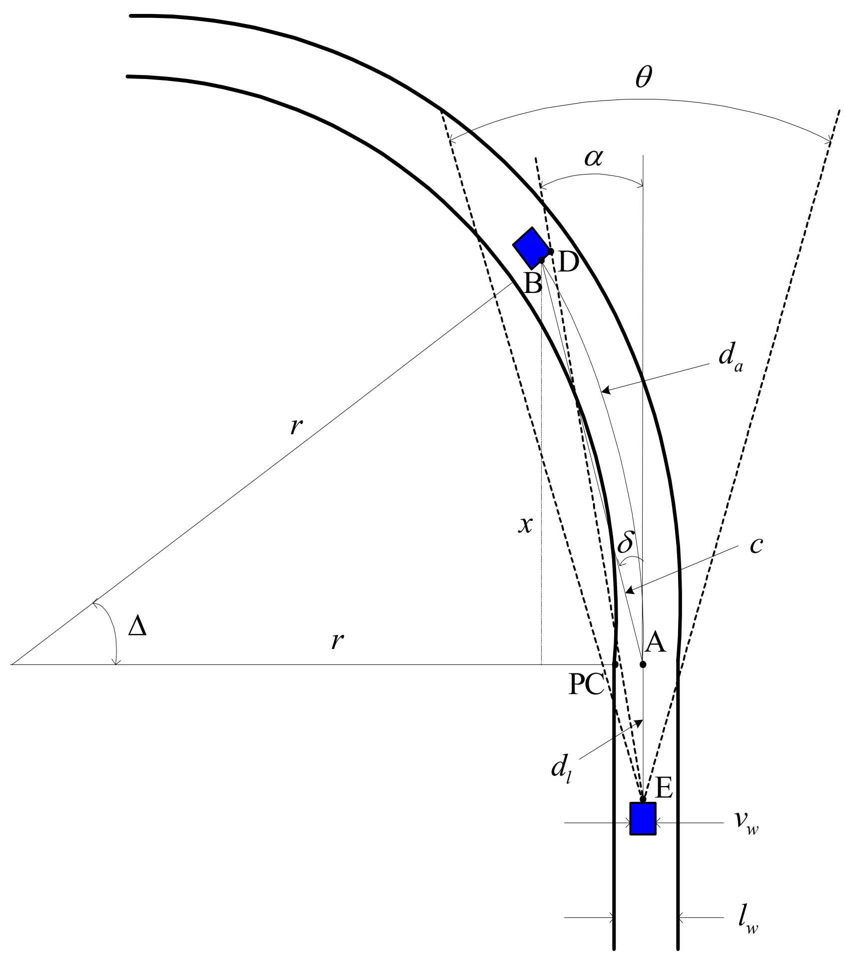


Figure 20. Geometry of tangent and circular curve sections

The point B is then determined by

$$\mathbf{B} = \mathbf{A} + cR(\delta)\begin{bmatrix} 0 & 1 \end{bmatrix}^{\mathrm{T}} \tag{16}$$

where $R(\delta)$ is the transformation matrix that effects a counter-clockwise rotation about the origin through an angle of δ radians (for examples of this form of vector algebra for highway design purposes, see (Lovell et al., 1999, 2001), and is given by

$$R(\delta) = \begin{bmatrix} \cos\delta & -\sin\delta \\ \sin\delta & \cos\delta \end{bmatrix} \tag{17}$$

and δ is the deflection angle (measured in radians, counter-clockwise from the positive abscissa) of the line that is tangent to the circular curve. This can also be written

$$\delta = \cos^{-1}\left(\frac{x}{c}\right) \tag{18}$$

where

$$x = \left(r + \frac{l_w}{2}\right)\sin\Delta \tag{19}$$

Hence $R(\delta)$ is given by

$$R(\delta) = \begin{bmatrix} \cos\left(\cos^{-1}\left(\frac{x}{c}\right)\right) & -\sin\left(\cos^{-1}\left(\frac{x}{c}\right)\right) \\ \sin\left(\cos^{-1}\left(\frac{x}{c}\right)\right) & \cos\left(\cos^{-1}\left(\frac{x}{c}\right)\right) \end{bmatrix} = \begin{bmatrix} \frac{x}{c} & -\sqrt{1-\frac{x^2}{c^2}} \\ \sqrt{1-\frac{x^2}{c^2}} & \frac{x}{c} \end{bmatrix} \tag{20}$$

Simplifying and combining then yields

$$\mathbf{B} = \begin{bmatrix} \frac{l_w}{2} \\ 0 \end{bmatrix} + cR(\delta)\begin{bmatrix} 0 \\ 1 \end{bmatrix} = \begin{bmatrix} \frac{l_w}{2} - c\sqrt{1-\frac{x^2}{c^2}} \\ x \end{bmatrix} \tag{21}$$

Removing the intermediate variables *c* and *x* then leaves

$$\mathbf{B} = \begin{bmatrix} \frac{l_w}{2} - \sqrt{\left[\left(2r+l_w\right)\sin\left(\frac{d_a}{2r+l_w}\right)\right]^2 - \left[\left(r+\frac{l_w}{2}\right)\sin\left(\frac{2d_a}{2r+l_w}\right)\right]^2} \\ \left(r+\frac{l_w}{2}\right)\sin\left(\frac{2d_a}{2r+l_w}\right) \end{bmatrix} \tag{22}$$

Assuming that the edge of the sensor beam is effective all the way to the right rear corner of the vehicle (point **D** in Figure 20), that point is derived as follows:

$$\mathbf{D} = \mathbf{B} + R\left(\Delta - \frac{\pi}{2}\right)\frac{v_w}{2}\begin{bmatrix} 0 \\ 1 \end{bmatrix} \tag{23}$$

where v_w is the assumed width of the lead vehicle. This is less likely to be true in rear-facing situations when the aerodynamic shape of the front of the following vehicle produces less clear radar returns. The transformation matrix $R(\Delta - \pi/2)$ can be simplified:

$$R\left(\Delta - \frac{\pi}{2}\right) = \begin{bmatrix} \cos\left(\Delta - \frac{\pi}{2}\right) & -\sin\left(\Delta - \frac{\pi}{2}\right) \\ \sin\left(\Delta - \frac{\pi}{2}\right) & \cos\left(\Delta - \frac{\pi}{2}\right) \end{bmatrix} = \begin{bmatrix} \sin\Delta & \cos\Delta \\ -\cos\Delta & \sin\Delta \end{bmatrix} \tag{24}$$

Hence the coordinate of the right rear corner of the lead vehicle in terms of basic parameters is given by

$$\mathbf{D} = \begin{bmatrix} \frac{l_w}{2} - \sqrt{\left[(2r + l_w)\sin\left(\frac{d_a}{2r + l_w}\right)\right]^2 - \left[\left(r + \frac{l_w}{2}\right)\sin\left(\frac{2d_a}{2r + l_w}\right)\right]^2} + \frac{v_w}{2}\cos\left(\frac{2d_a}{2r + l_w}\right) \\ \left(r + \frac{l_w}{2} + \frac{v_w}{2}\right)\sin\left(\frac{2d_a}{2r + l_w}\right) \end{bmatrix} \tag{25}$$

The other point of interest is then the point **E**, which is the front middle of the following vehicle. This can be given as

$$\mathbf{E} = \begin{bmatrix} \frac{l_w}{2} \\ d_a - d \end{bmatrix} \tag{26}$$

With the knowledge of the two points **D** and **E**, we can determine the angle α between the center axis of the following vehicle and the right rear corner of the lead vehicle. More importantly, if we equate that angle to $\theta/2$, we are determining the angle at which the lead vehicle departs the sensing region of the range sensor. Thus,

$$\tan\frac{\theta}{2}=\frac{\left|\frac{l_w}{2}\right|+\left|\frac{l_w}{2}-\sqrt{\left[\left(2r+l_w\right)\sin\left(\frac{d_a}{2r+l_w}\right)\right]^2-\left[\left(r+\frac{l_w}{2}\right)\sin\left(\frac{2d_a}{2r+l_w}\right)\right]^2}+\frac{v_w}{2}\cos\left(\frac{2d_a}{2r+l_w}\right)\right|}{\left|d_a-d\right|+\left|\left(r+\frac{l_w}{2}+\frac{v_w}{2}\right)\sin\left(\frac{2d_a}{2r+l_w}\right)\right|} \tag{27}$$

In this equation, the quantities l_w and v_w, can be assumed to be constant values determined *a priori*. For particular circumstances, a value of r can be chosen, although from the perspective of the ACC control logic, it must be expected that a range of curve radii can be encountered. The speed is not known ahead of time, and that has an impact on both the curve radius r and the following distance d. Nevertheless, we posit that the most appropriate use of (27) is to choose values for all of these parameters, as well as for the sensor angle θ, and then solve for d_a. Knowing d_a, one can then also determine $d_l = d - d_a$, which is the distance over which the car must travel after having lost the range signal, until it enters the curve and can then bend its sensor beam and re-acquire. It is clear from Figure 20 that a front-facing and rear-facing sensor would experience the same yaw, but that the appropriate direction to bend the beam is opposite. This can be corrected for the rear-facing sensor either by treating velocity as negative, or (as we have done), pretending that the sensor is mounted upside-down, so it makes this correction itself. Combined with the speed, this gives the time during which the vehicle is vulnerable to conditions outside the expectations of the sensing system. Equation (27) cannot be solved for d_a in closed form; in the examples that follow, we used the non-linear root finder in Matlab to solve the equation numerically.

3.3.2 Example

In this example, we solved for d_a as a function of v, assuming that some of the other parameter values can be fixed, and the remaining variables can be chosen also to be single-valued functions of v. For example, we chose as standardized parameter values l_w = 12 feet, and v_w = 7 feet. In the latter case, this is the design vehicle width for a typical passenger car (AASHTO, 2001). We chose θ = 10 degrees = 0.1745 radians, which is the included angle for the center beam of the Omron AR211 unit used in Nissan ACC systems. Finally, we chose r = 800 feet. This last choice was arbitrary but acceptable; the same analysis can be conducted with any other value.

The safe following distance maintained between vehicles when the ACC is in following mode can be represented by the car-following stopping distance, which includes perception/reaction and braking distance and is given in consistent units by

$$d = vt + \frac{v^2}{2g(f+G)} \tag{28}$$

where t is the perception-reaction time for ACC system, which typically has a value of the order of 0.5 s (Rajamani and Zhu, 2002). This is a much shorter reaction time than is expected in manual driving, which is typically around 2-3 seconds (Roess et al., 1998). The denominator of the 2nd term of the right hand side of (28) contains all modifiers to the effect of gravity, including the coefficient of friction f and the grade of the road G in dimensionless form. If we assume g is 32.2 ft/sec^2, f is 0.30, G is zero and v is 73.33 ft/sec (approximately 50 mph) for both vehicles in this example, then (28) yields $d \cong$ 314.5 feet. By moving all terms of (27) to one side of the equality, we turn the problem of solving for d_a into a root-finding exercise, which Matlab can do with standard numerical techniques. For the values given in this example, this yields $d_a = 221.5$ feet. Thus, $d_l = d - d_a =$ 93 feet. At the speed of 73.33 ft/sec, this means that the vehicle is "driving blind" for approximately 1.27 seconds. At least for the values given in this example, it seems wise to suggest that the ACC control unit pause at least a second or two before accelerating to the driver's desired speed, in order to distinguish between a situation where it is in fact safe to do so because the previously obstructing vehicle has left the lane in question, and a case where it only appears to be safe because of the effects of road curvature.

3.3.3 Sensitivity analysis

In this section, we show how d_l varies with marginal changes to other parameters such as the included angle of sensor, the radius of circular curve and vehicle speed, using as our nominal state the data from the analysis. Because of the number of dimensions involved, we cannot hope to completely characterize the behavior of (27) with this analysis, but it can serve to illustrate the shape of its partial derivatives, and reinforce the reasonableness of these relationships.

The relation between d_l and θ is approximately linear in this range of values, as shown in Figure 21. Sensors with included angles between 4 and 12 degrees are considered. As the angle of sensor increases, the d_l decreases which means that the blind time is decreasing. However, we have to make sure that increasing the sensor angle increases the likelihood of false readings from adjacent lanes, particularly at curves.

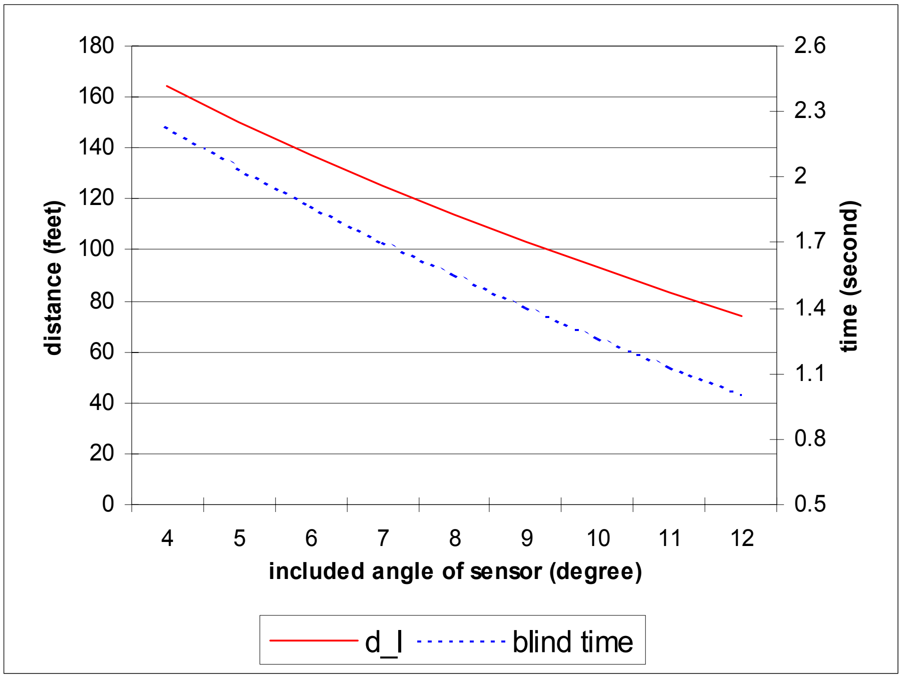


Figure 21. Effect of the range sensor included angle

While we chose a specific value of the curve radius *r* for the example, it is also fair to say that it depends in some measure on the speed *v*, which is presumably within the range of the design speed for the facility in question. It is not reasonable, however, to tie equation (27) to a specific relationship between speed and curve radius, since the vehicles are not necessarily traveling at the design speed, and because any such relation only gives a minimum value of the curve radius anyway. Beyond that, ample room is left for trading off curve radius versus superelevation, and designers can always choose larger-than-necessary curve radii to improve comfort, aesthetics, and other considerations. Figure 22 shows how a range of curve radii affects the computation of d_l. All radii are greater than the minimum required for a speed of 50mph. With the same speed, but decreasing curvature, the lead vehicle does not deviate from the following vehicle's axis as drastically, so the blind time decreases.

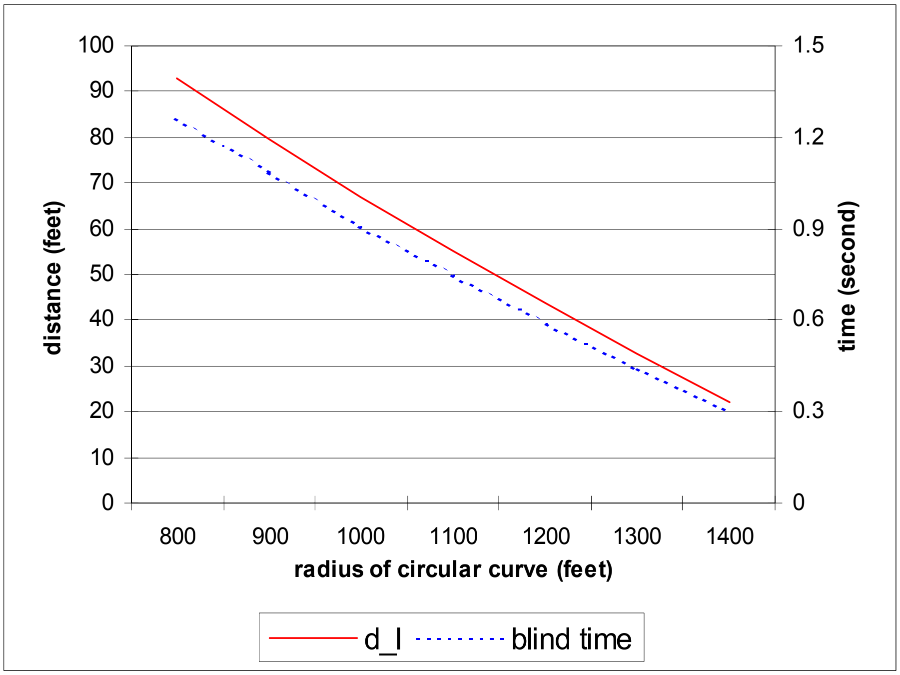


Figure 22. Effect of curve radius

Figure 23 shows how d and d_l are affected by v, via equations (27) and (28), together with factors to transform speed to the more customary units of miles per hour. We chose the minimum curve radius for each speed range and safe following distance as increasing functions of velocity. Intuitively, blind time should decrease with curve radius, but increase with stopping distance. It is clear from this figure that the latter effect is more pronounced, so the blind time increases. Of course, there are limits to the range of the range sensor.

None of the highway design standards are set in stone. They are all derived from assumptions about human driving behavior. The main point of ITS is that machines might do more and humans less. Hence, we should be on the lookout for situations where our design criteria should evolve, as a higher level of automation is present. In this section, we have described a condition that must be carefully handled when collecting car-following data using the methods of this dissertation, but that also informs ITS applications such as ACC. As such systems become more prevalent, it will be useful to periodically re-evaluate the assumed models of driver behavior and adjust them if machines do things differently.

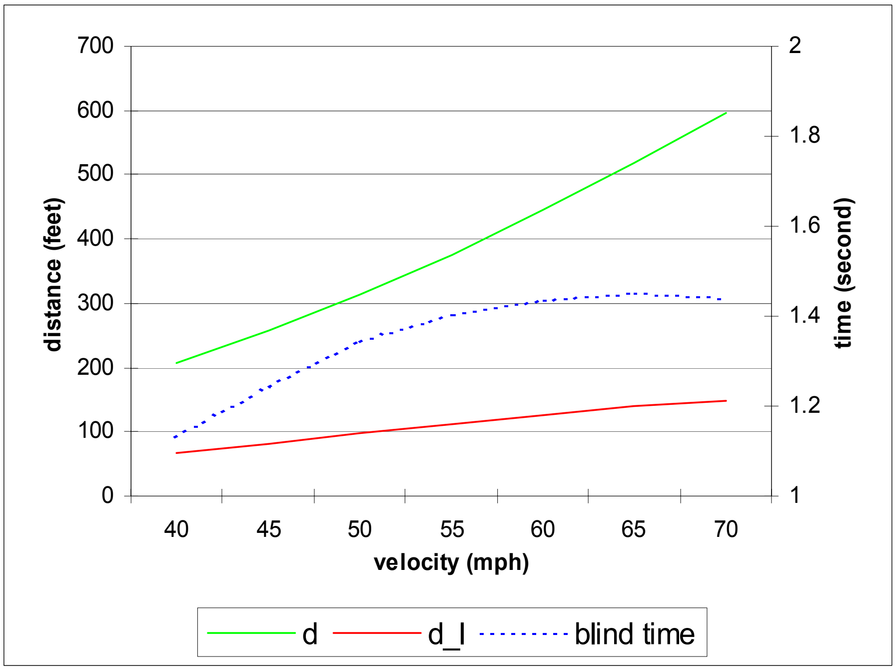


Figure 23. Effect of the velocity of the lead vehicle

Chapter 4: Data Collection

As discussed in the literature review, previous car-following experiments may not capture normal car-following behavior. Moreover, the driving behavior exhibited by the previous models may be artificial due to the biases of experimental studies. For the study of car-following behavior, the main key would be how precisely we can capture real car-following behavior under naturalistic driving, in which following vehicles do not know they are under observation. While developing and testing the new data collection system, a preliminary survey was conducted to observe real car-following behavior on roadways and to identify some driving maneuvers and evidence that would be observed in congested traffic conditions. Some findings from the preliminary survey are described in the first section. The second section presents field measurements on car-following.

4.1 Preliminary Survey

The preliminary survey was mostly conducted on I-295 in Maryland near the Washington D.C. area, which has two lanes for each direction during the morning and afternoon peak hours. A video camera was installed on the back of the test vehicle to record following vehicles' behavior and observe various following maneuvers. The driver of the test vehicle drove normally.

Through the preliminary survey, we were able to observe a diverse population of members and following maneuvers such as acceleration, deceleration, and lane-changing in reaction to the test (lead) vehicle. Also, although all possible maneuvers were not investigated in the preliminary survey, it was found that various following maneuvers that are common under real car-following situations were identified and distinguished. Figures 24 and 25 show typical examples that were observed repeatedly under congested traffic conditions. Figure 24 shows a case in which a vehicle cut in between the lead and following vehicles. The following vehicle did not respond promptly even when the new lead vehicle cut in to the driving lane, probably because the new lead vehicle performed another lane change in the same direction almost immediately. The driver of the following vehicle stayed at his previous speed without taking any aggressive reaction. Figure 25 shows a similar maneuver of the following vehicle to a different action of the new lead vehicle. In this case, the new leader cut in to the driving lane of the following vehicle and stayed in the lane. However, the follower did not respond evasively, but drove carefully without making any immediate deceleration.

In both cases, traditional car-following models would have predicted an aggressive response to the loss of spacing in front of the following vehicle. The scenario in Figure 24 is simply a situation the model was not designed to accommodate. Given the brevity of the interruption and considering a typical reaction time, omitting such a case from models might not be a huge mistake, but this should be checked. The scenario in Figure 25 is more problematic, as the myopic scope of existing models offers no explanation for the lack of a response from the follower.

It was observed that car-following behavior was affected by several factors such as human characteristics (e.g., environmental conditions such as telephoning or vehicle occupancy, which contributes to a distraction level), and traffic and road characteristics (e.g., type of vehicle or geometric condition). For example, when a driver of the following vehicle was telephoning or talking with his companions, as shown in (a) and

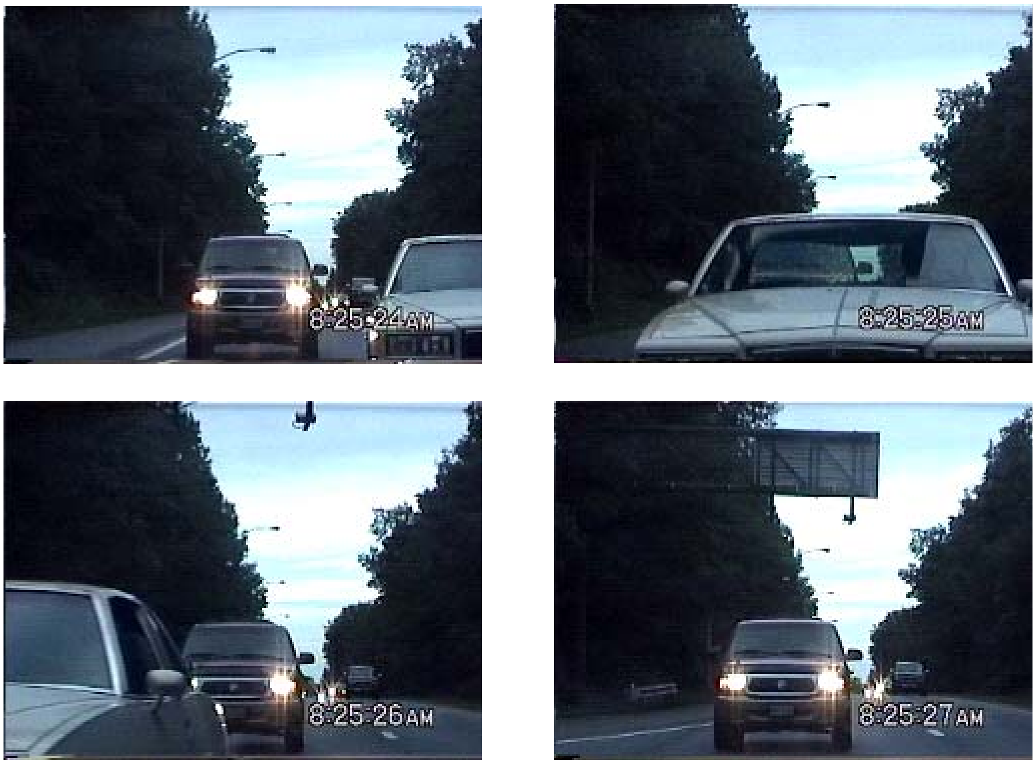


Figure 24. The new lead vehicle cuts in and leaves

Figure 25. The new lead vehicle cuts in and stays

(b) of Figure 26, he did not concentrate on his driving and responded slower than normal to the action of the lead vehicle. It was also observed that the following behavior of trucks, shown in (c), was different from that of autos. He had relatively longer following distances and slow responses to the change of the lead vehicle, compared to autos.

From the preliminary survey, we had better understanding for real car-following behavior under naturalistic driving situations. In addition, it gave us some insights into how to design data collection plan, such as the data to be observed, including some important causal factors which can affect car-following behavior and strategies to better capture driver human characteristics using a digital video camera.

(a) Distraction by other occupants

(b) Distraction by in-vehicle activities such as telephoning

(c) Following behavior of truck

Figure 26. Several factors affecting car-following behavior

4.2 Field Measurements on Car-Following

The car-following data collection was undertaken during rush and non-rush hour periods in December, 2004 and March, 2005 on freeways, including I-495 and I-295, which mostly have four lanes and two lanes for each direction, respectively, near the Washington D.C. area.

The following parameters were measured or calculated for each car-following time series:

- Duration time spent in car-following situation
- Following distance between the lead and following vehicles
- Driving distance, speed and acceleration of the lead vehicle
- Driving distance, speed and acceleration of the following vehicle
- Relative speed between the lead and following vehicles
- Time gap between the lead and following vehicles
- Human characteristics of the driver of following vehicles such as
    - Gender (e.g., male or female)
    - In-vehicle activities like talking, telephoning, and eating
    - Vehicle occupancy as distraction level
- Traffic and geometric conditions such as
    - Following vehicle type (e.g., auto or truck)
    - Road type (e.g., I-295 or I-495)
    - Number of lanes (e.g., 2 lanes or 4 lanes)
    - Location of driving lane (lane 1 or lane 2)
    - Traffic condition (e.g., traffic density – low or heavy)

- Environmental conditions such as
    - Weather (e.g., dry or wet)
    - Time of day (e.g., day or night)
    - Day of week

4.2.1 Baseline statistics

This section shows summary of baseline statistics that somehow characterize the data collected through the field measurements. A more detailed analysis is described in the next Chapter. A total of 387 car-following situations in which each of these represents an individual following vehicle, were attempted over ten days (12/09, 12/13-12/17, 3/15-3/18) and finally 301 car-following time series were successful for data analysis. A number of 167 (55%) time series were collected under uncongested traffic condition, while 134 (45%) under congested traffic condition, as shown in Figure 27.

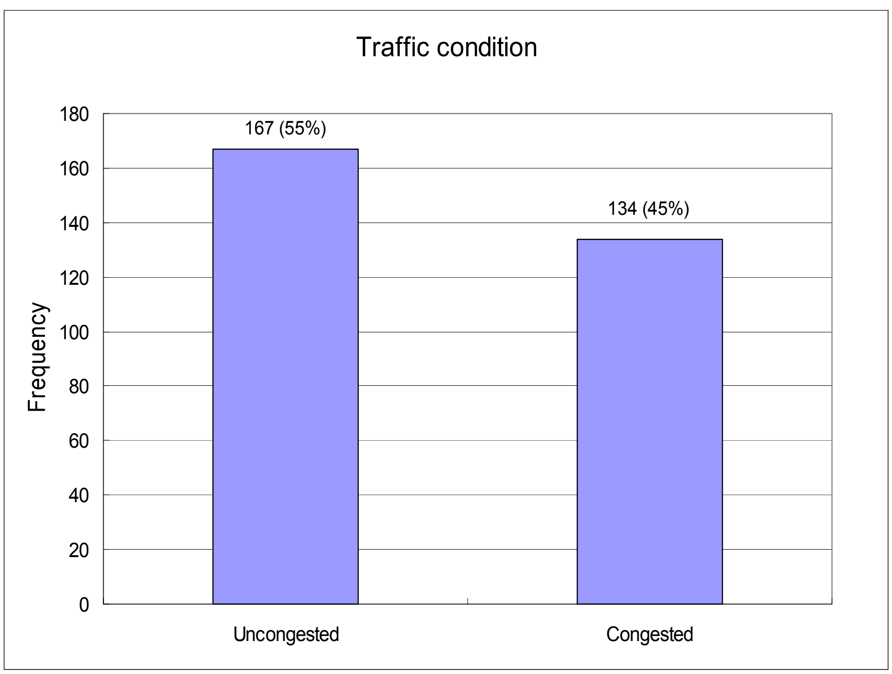


Figure 27. Frequency histogram by traffic condition

Figure 28 shows a frequency histogram of duration times that each individual vehicle spent in car-following situation for all 301 car-following time series. We observe that the number of duration times between 60 and 90 seconds exceed 55% of the total, i.e., the number was 174 (58%). The minimum, average, and maximum duration times were 24, 99 and 492 seconds.

In order to investigate causes of terminating the car-following situation for each time series, we classified the possible causes into 7 cases as follows;

- Case 1: lane changing of following vehicle
- Case 2: cut-in of new lead vehicle
- Case 3: too far following distance
- Case 4: lane changing (or exit) of lead vehicle
- Case 5: infrared sensor capability degradation caused by sunlight, headlight at night and adverse weather such as rain
- Case 6: dropout of infrared sensor in curve sections
- Case 7: complete stop of following vehicle under heavy congested condition

Figure 29 shows the number of terminations of the car-following situation by each case. It was observed that Case 1, lane changing of the following vehicle was represented by a number of 94 (31% of total data) and Case 4, lane changing or exit of lead (test) vehicle followed next as 74 (25%) because the lead (test) vehicle sometimes changed lanes to investigate the difference of car following behavior by each lane.

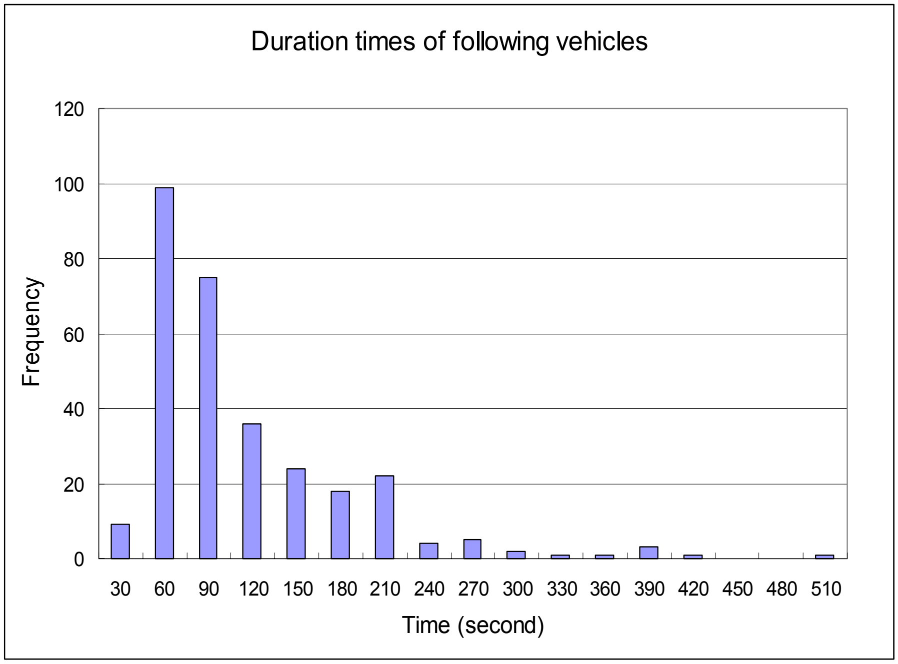


Figure 28. Duration times spent in car-following situation

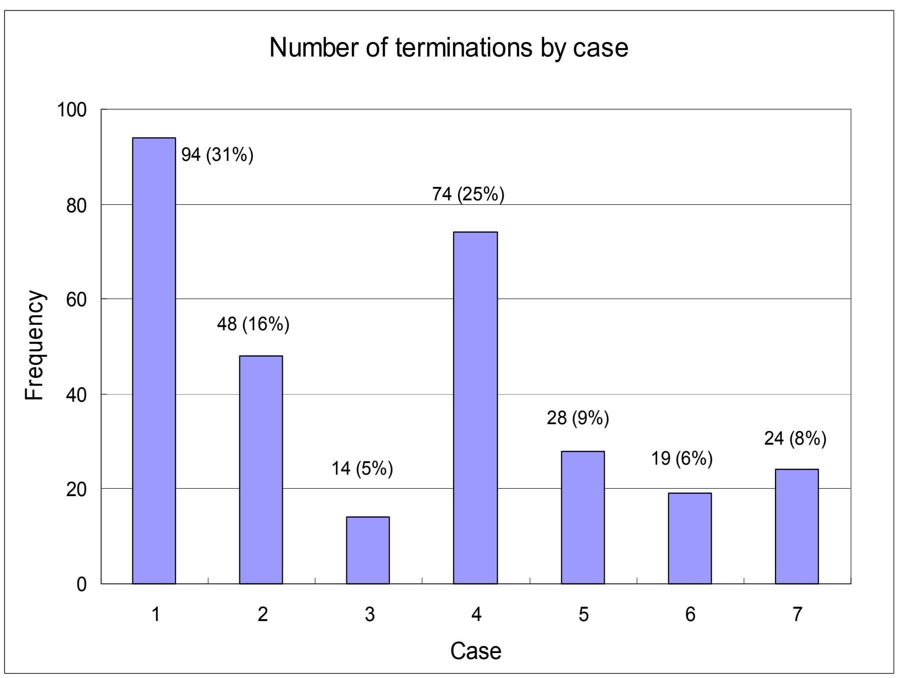


Figure 29. Termination of car-following situation by case

Figure 30 presents a relationship between speed and following distance for a total of 301 car-following time series. Although there are significant variations in following distances along the whole speed range, there is a clear trend that the following distance increases as speed increases, which is expected. In addition, it is more evident from Figure 30 that following distances show more variability in higher speed ranges than lower speed ranges. The reason could be that when driving at low speeds, it is easier for drivers to estimate the distance to the lead vehicle and keep the desired following distance because of the shorter inter-vehicle distance. However, at high speeds, it becomes more difficult for drivers to accurately estimate the distance and keep the desired following distance because of the larger distance and the higher speed involved. This would result in drivers making more errors in estimating the distance, and would increase the variability of the distance gaps. Another factor to consider is that the data include vehicles who recently became followers after a lane change, but who might have settled into a longer following distance in a steady state. Thus, the separation deemed appropriate for lane changes may not vary as much with speed, particularly from behind, if the driver fully expects to relax that distance once the lane change is completed.

A detailed understanding of driver behavior in choosing inter-vehicle separation has become more essential for both the design and assessment of advanced driver assistance systems such as adaptive cruise control and stop/go control. Time gap (the difference in passage time between the rear bumper of one vehicle and the front bumper of a following vehicle) and headway (the difference in passage time between the front bumpers of two consecutive vehicles) are two measures that are widely used to assess such driver behavior. In this study, time gap was used for the analysis since the time gap can be easily regenerated with following distance and the speed of the following vehicle, obtained by the instrumented test vehicle.

Figure 31 shows a relationship between time gap and following vehicle speed for a total of 301 car-following time series. Time gaps were relatively stable within 3 seconds at high speeds, but there were significant variations from 1 to more than 20 seconds in time gaps at low speeds. Moreover, the variation of the time gaps decreased drastically as speed increased along the whole speed ranges. There are relatively fewer data points past 90 km/h, so no solid inferences can be drawn from this section of the plot. This result indicates that considerable care must be taken in determining a desirable threshold in longitudinal driver assistance systems, since many current models have been adopted with constant time gap during adaptive cruise control (Wang and Rajamani, 2004). It seems that it is a reasonable assumption to adopt the constant time gap for car-following at high speeds, but it is not quite true at lower speeds.

Figure 32 shows a distribution of time gaps. It was shown that time gaps between 1.0 and 1.5 seconds represented about 60% of total number of time gaps and an average time gap was 1.59 seconds in the data.

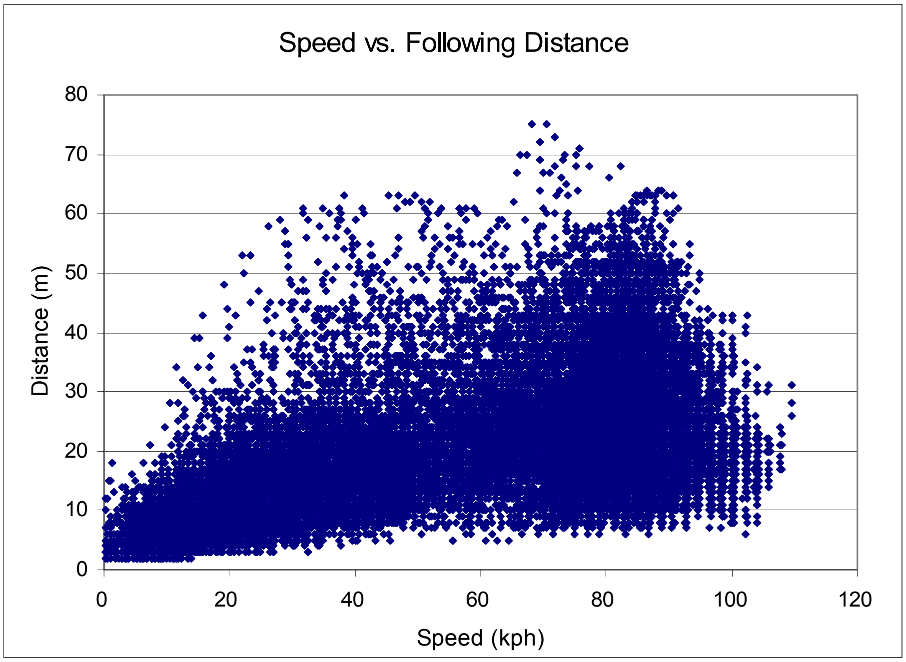


Figure 30. Speed vs. following distance for all car-following time series

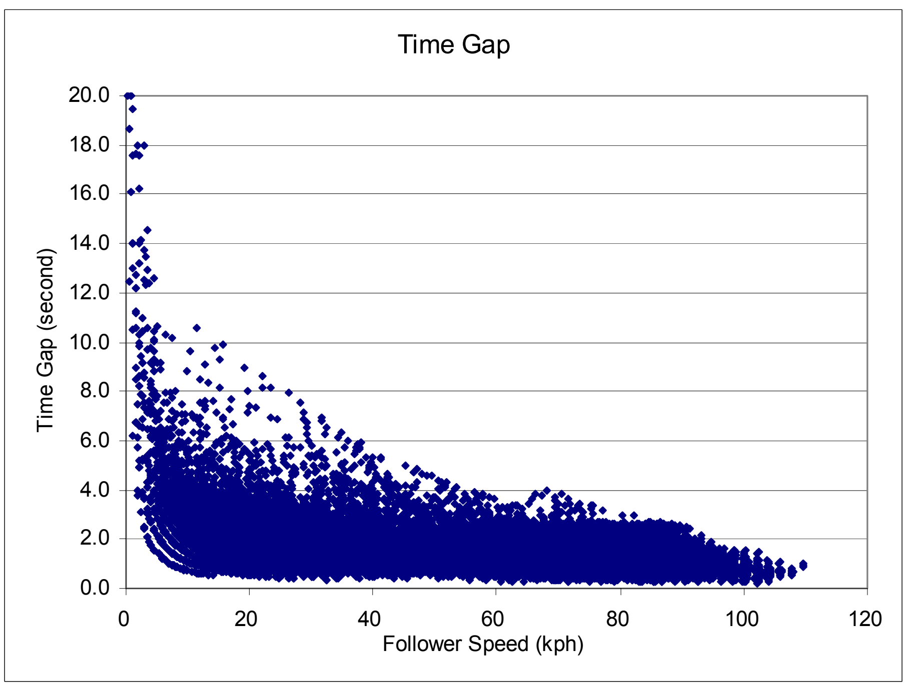


Figure 31. Relationship between time gap and speed

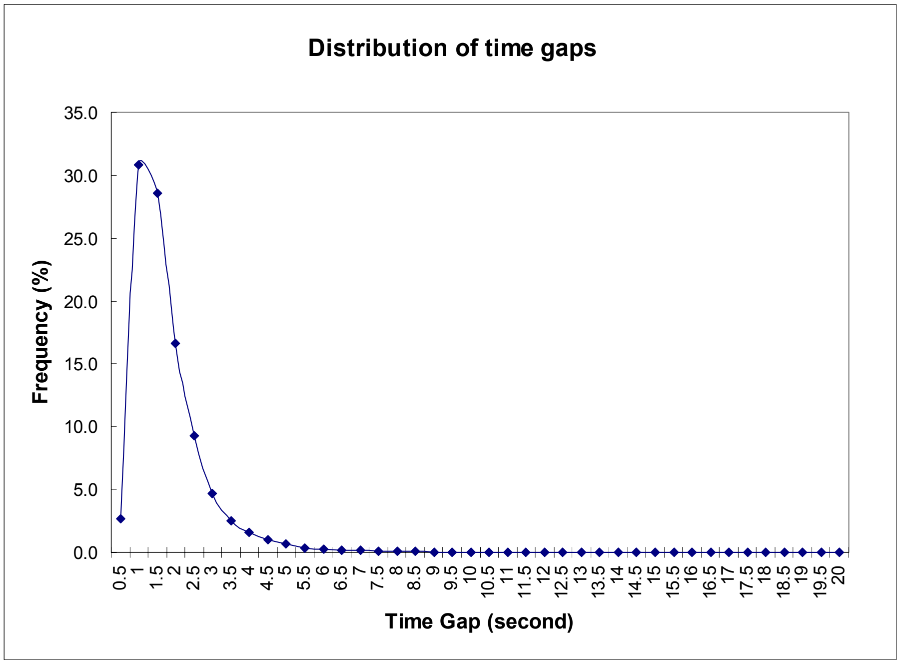


Figure 32. Distribution of time gaps

In our field experiments, we tried to collect as many causal factors that affect car-following behavior as possible. In order to distinguish the difference of car-following behavior by vehicle type, we classified the vehicle type as auto and truck. To keep thing simple, we classified pick-up trucks, minivans, and SUVs as auto, while heavy trucks like semi-trailer and buses as truck. Figure 33 shows a frequency histogram of each vehicle type in the data collected. As shown in the figure, the auto and the truck represented the number of 269 (89%) and 32 (11%) of all the data, respectively.

We classified the data according to location of driving lane, such as lane one or lane two (from right to left lanes) on I-295, to investigate the effect of different location of driving lane on car-following behavior. Figure 34 presents the number of frequency according to the driving lanes in the data collected. Especially, lane four on I-495 (mostly 4 lanes on each direction) has relatively small frequency, compared to other lanes.

The data were also classified, according to human characteristics of following drivers, such as gender and several distraction factors (e.g., occupancy and in-vehicle activities like telephoning or smoking), to identify the effect of those factors on driving behavior of following vehicles. We extracted the information related to the human characteristics from video data, recorded by digital video camera. However, sometimes, it was difficult to notice the inside of following vehicle and distinguish the number of people or in-vehicle activities, especially from video data recorded at night or under cloudy weather condition. Hence, only a number of 102 time series that one can notice the inside of following vehicle and distinguish the gender and in-vehicle activities were extracted. A number of 72 (71%) people were male and 30 (29%) were female, as shown in Figure 35.

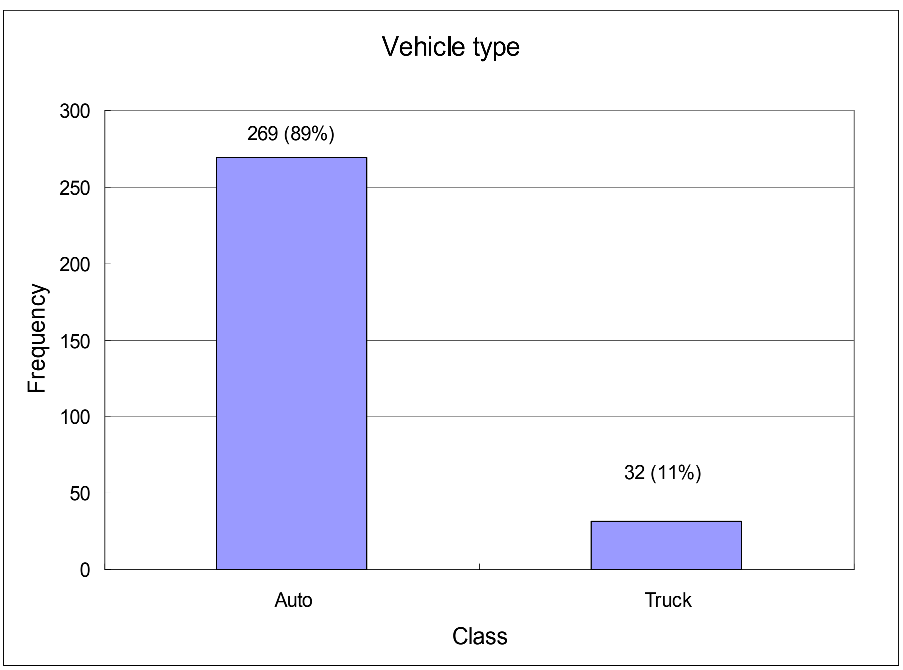


Figure 33. Frequency histogram by vehicle type

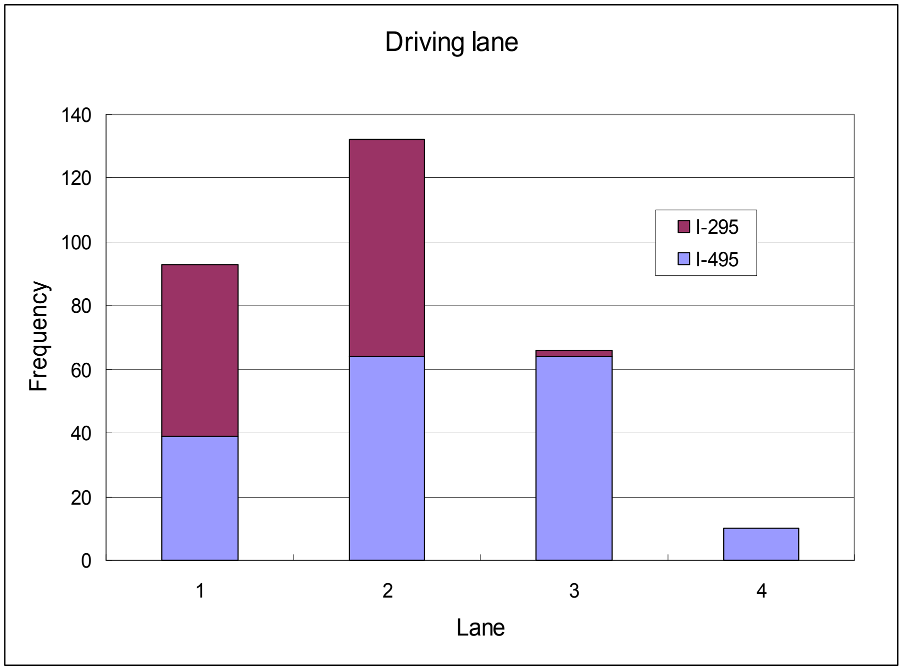


Figure 34. Frequency histogram by driving lane

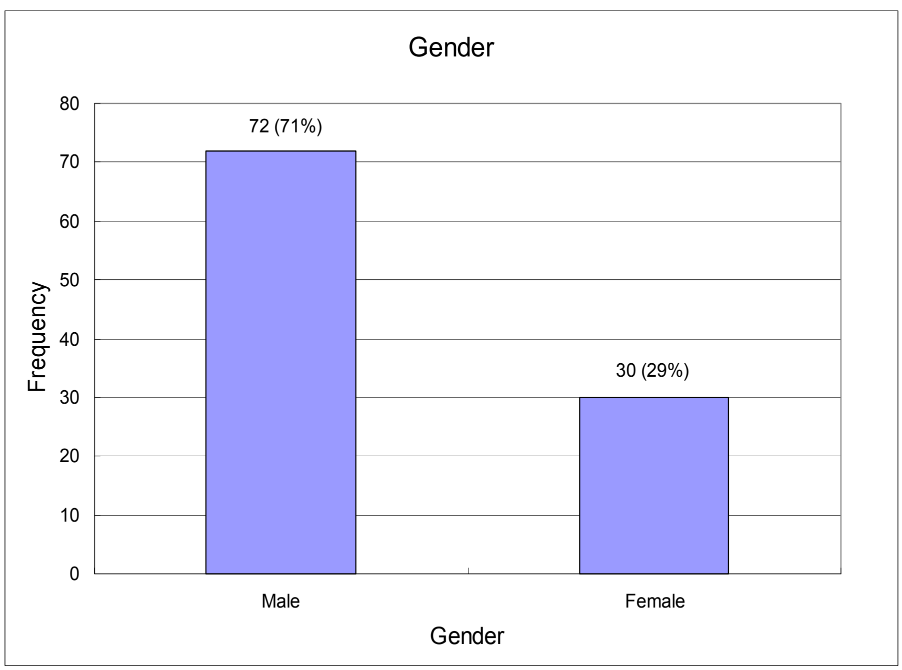
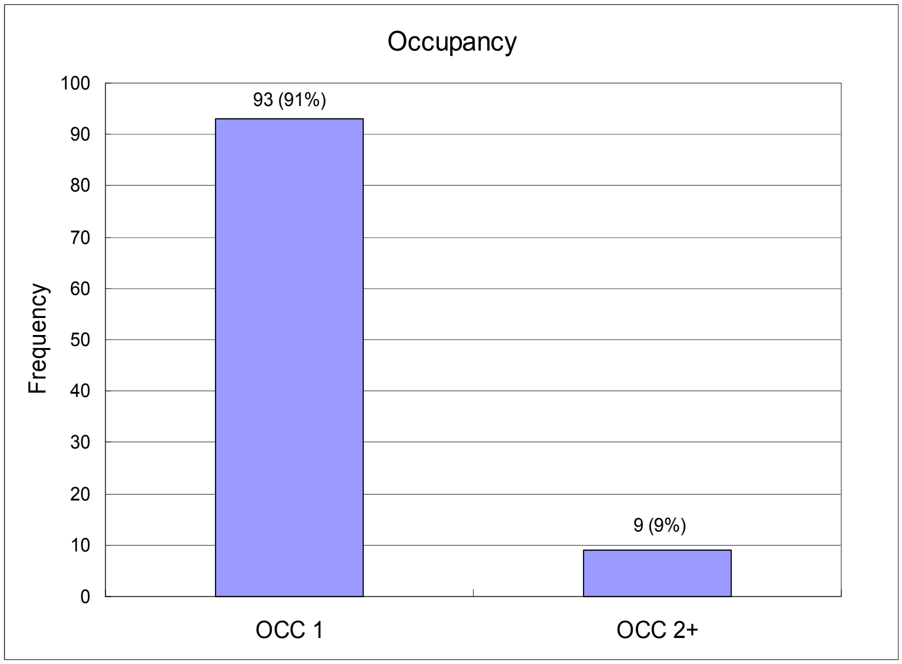


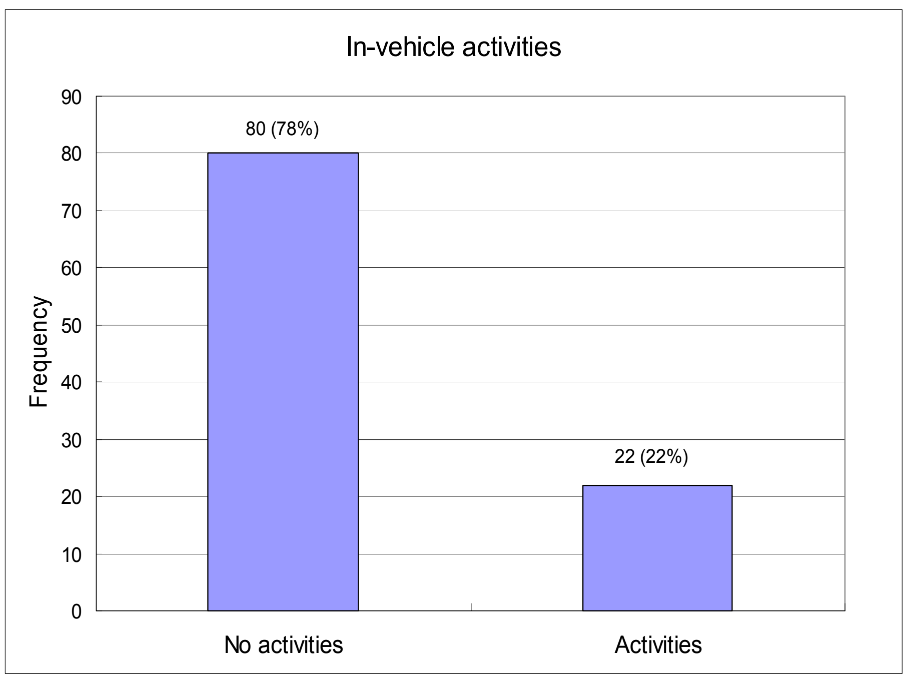
Figure 35. Frequency histogram by gender

Figure 36 shows two frequency histograms, classified by the number of people in following vehicles (or occupancy) and in-vehicle activities. In the first case, the data (102 time series) were categorized into two groups as occupancy one and more than one. As shown in the figure, more than 90% of the total following vehicles had an occupancy one, while only 9 vehicles (9%) had occupancy more than one. In the second case, the data was divided by cases with in-vehicle activities (e.g., telephoning, smoking or taking coffee) and cases without in-vehicle activities. A number of 80 (78%) drivers drove without any in-vehicle activities, while 22 drivers (22%) drove with in-vehicle activities that had different effects on car-following behavior, which was described in detail in the next Chapter.

We classified the total data (301 time series), according to various environmental conditions such as time of day (e.g., day or night) and weather conditions (e.g., dry or wet), to investigate any potential differences in car-following behavior under different conditions. It should be noted that the performance of infrared sensor was drastically reduced when data collection was conducted under bad weather condition like rain because water drops stuck on the window of infrared sensor. Therefore, some of data points in time series were missing or had unreasonable values. As a result, only small numbers of time series (only 3 cases) under rainy condition in the data were appropriate for data analysis, as shown in Figure 37. A number of 298 time series (99%) were collected under dry condition, while 3 time series (1%) were collected under wet condition.



(a) Classification by occupancy



(b) Classification by in-vehicle activities

Figure 36. Frequency histogram by distraction factors

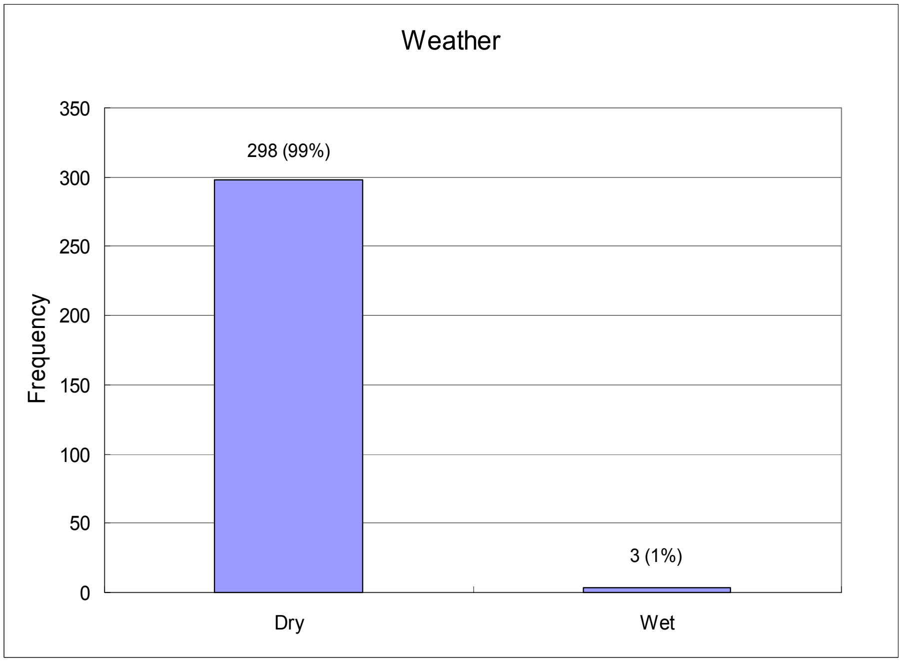


Figure 37. Frequency histogram by weather condition

In addition, when sunlight hit on the window of the infrared sensor, the infrared sensor had a possibility of performance degradation. Especially, night time data collection worked poorly because the headlights of the following vehicle interfered with the infrared sensor, just as sunlight. Therefore, some of the data in various time series collected at night were missing or had unreasonable values. Hence, relatively small numbers of time series were available, compared to those at daytime. Figure 38 shows a frequency histogram between day and night. A number of 263 time series (87%) were collected at day time, while 38 time series (13%) were collected at night time.

The extent of car-following time series data collected over ten days is briefly summarized in Table 7 and the detailed information of car-following data set for each day is shown in Appendix A.

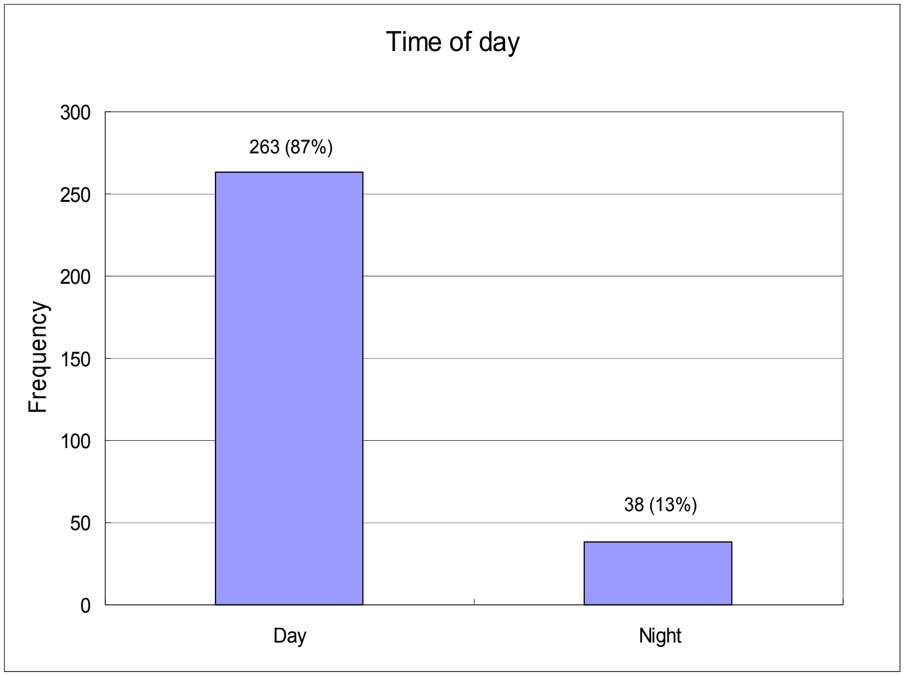


Figure 38. Frequency histogram by time of day

Table 7. Car-following time series data collected over ten days

Date	# of cases	Avg. Durat -ion (sec.)	Vehicle type (cases)		Road type (cases)		Driving lane (cases)				Traffic condition (cases)		Weather (cases)		Time of day (cases)		Day of week
			Auto	Truck	I-295	I-495	1	2	3	4	Uncong -ested	Cong- ested	Dry	Wet	Day	Night	
12/9	4	62	1	3	-	4	1	2	1	-	1	3	1	3	4	-	Thur.
12/13	9	174	8	1	9	-	4	5	-	-	9	-	9	-	9	-	Mon.
12/14	10	82	9	1	4	6	5	4	1	-	5	5	10	-	10	-	Tue.
12/15	11	87	9	2	4	7	5	6	-	-	7	4	11	-	11	-	Wed.
12/16	14	89	13	1	5	9	3	7	4	-	12	2	14	-	14	-	Thur.
12/17	36	88	34	2	19	17	6	17	13	-	32	4	36	-	36	-	Fri.
3/15	33	128	32	1	5	28	8	10	12	3	15	18	33	-	17	16	Tue.
3/16	57	104	55	2	21	36	22	19	13	3	21	36	57	-	57	-	Wed.
3/17	57	90	51	6	27	30	20	26	9	2	34	23	57	-	35	22	Thur.
3/18	70	95	57	13	30	40	19	36	13	2	31	39	70	-	70	-	Fri.
Sum	301	99	269	32	124	177	93	132	66	10	167	134	298	3	263	38	-

Chapter 5: Data Analysis

The data analysis for these experiments, including data handling, archiving, and reduction, was a very demanding task, particularly since information was collected from a set of synchronized measurement instruments. Basically, time series data were extracted from the laptop computer (to which is connected the DMI, the infrared radar sensor and vehicle computer) and video camera. The data collected by the DMI and infrared radar sensor were regenerated to calculate the speed, acceleration or deceleration, and spacing between the lead and following vehicles, as shown in Figure 39. These data were used, in conjunction with video records and the judgment of the experimenters, to define a set of distinguishable following maneuvers.

The data from the video camera were extracted, to capture the duration of time spent in car-following situations, and the following drivers' characteristics such as gender, in-vehicle activities (e.g., whether he or she was using cellular phone), vehicle occupancy (perhaps a proxy for distraction level), and type of vehicle. With the data from the video camera and additional information such as type of roadway, geometric condition, congestion level, and weather condition, etc., we have investigated and attempted to distinguish the relationships between those factors and the following vehicle's behavior under various maneuvers, and to categorize the range of each critical factor based on the differences of behavioral characteristics.

Research findings from the data analysis are described in the following sections.

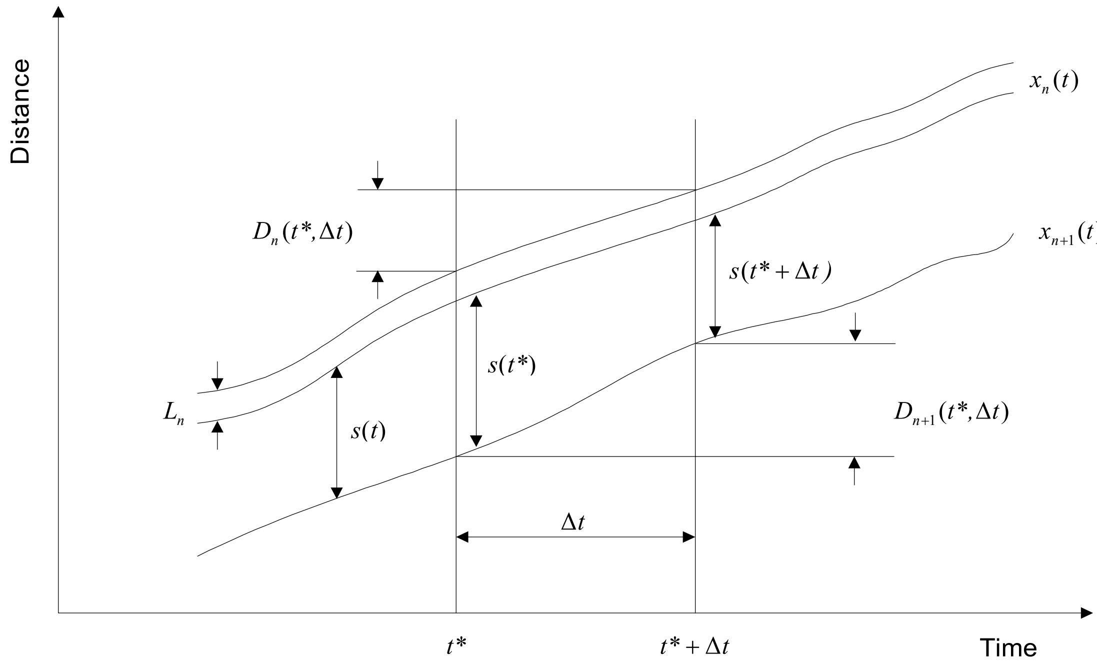


Figure 39. Generation of car-following data

$$s(t^*) + L_n + D_n(t^*,\Delta t) = D_{n+1}(t^*,\Delta t) + s(t^*+\Delta t) + L_n \tag{29}$$

$$D_{n+1}(t^*,\Delta t) = s(t^*) - s(t^*+\Delta t) + D_n(t^*,\Delta t)$$

$$\dot{x}_n(t^*+\Delta t) \cong \frac{D_n(t^*,\Delta t)}{\Delta t},\ \dot{x}_{n+1}(t^*+\Delta t) \cong \frac{D_{n+1}(t^*,\Delta t)}{\Delta t} \tag{30}$$

where $x_n(t)$ = position of the lead vehicle at time t

$x_{n+1}(t)$ = position of the following vehicle at time t

$s(t)$ = spacing between the lead and the following vehicle at time t (which can be obtained from the infrared sensor)

$D_n(t^*,\Delta t)$ = driving distance of the lead vehicle during time interval [t^*, $t^*+\Delta t$] (which can be obtained from the DMI installed in the lead vehicle)

$D_{n+1}(t^*,\Delta t)$ = driving distance of the following vehicle during time interval [t^*, $t^*+\Delta t$]

L_n = length of the lead vehicle

Δt = time increment

5.1 Behavioral Analysis

5.1.1 Oscillatory (or "drift") process in car-following

Illustrative examples of a single car-following time series under congested condition are displayed in Figures 40 to 42. This is the case of No. 8 collected on December 14, 2004 in the Appendix A. In the course of this 176-second sample, the following vehicle remained behind the test vehicle. We observe that the following distance varies from 3 meters to 15 meters, and the speed of the lead and following vehicles from 4 m/s ($\approx$ 14 km/h) to 15 m/s ($\approx$ 54km/h), as shown in Figures 40 and 41, respectively. Figure 42 shows that there is an oscillatory (or "drift") process in keeping the desired following distance. This pattern is typical of the majority of leader-follower interactions captured in these experiments. One way to describe these data chronologically is as follows; a driver slowly approaches the lead vehicle until he is close to his desired following distance and the relative speed is zero. However, he is not able to do this accurately because he is not able to perceive small speed differences and it is very hard to control his speed sufficiently well. As a result, the driver decelerates slightly to regain the desired following distance, and the spacing again increases. When the driver finds himself drifting away from the desired point, he accelerates and tries again to achieve the desired spacing and the whole oscillatory process, which appears as a sequence of parabolic shapes, is repeated, as shown in Figure 42. Some details of the oscillatory process vary, depending on driver characteristics, vehicle types and conditions in traffic and geometry and so on.

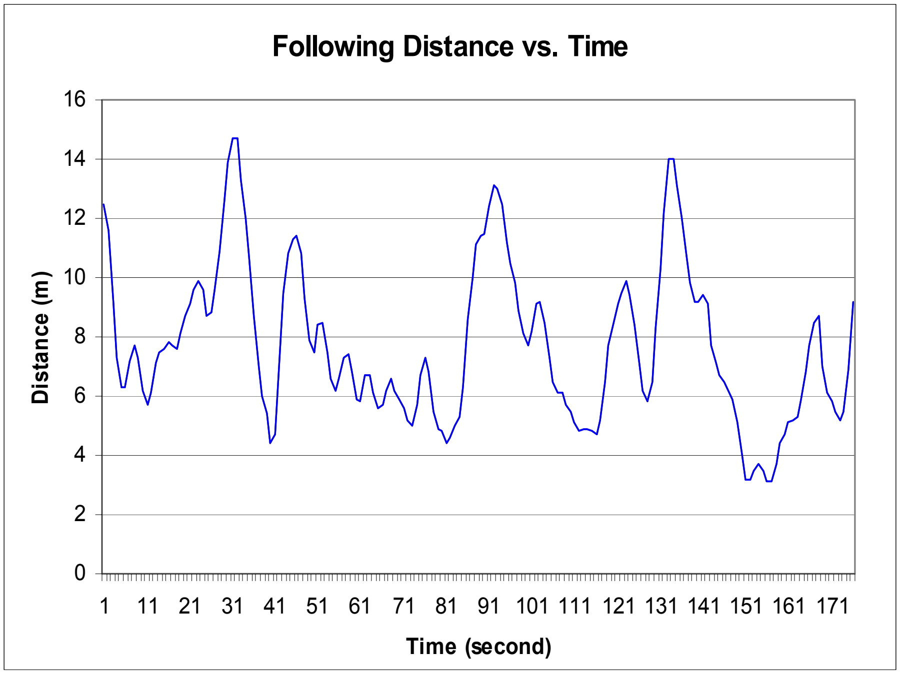


Figure 40. Following distance over a car-following time series

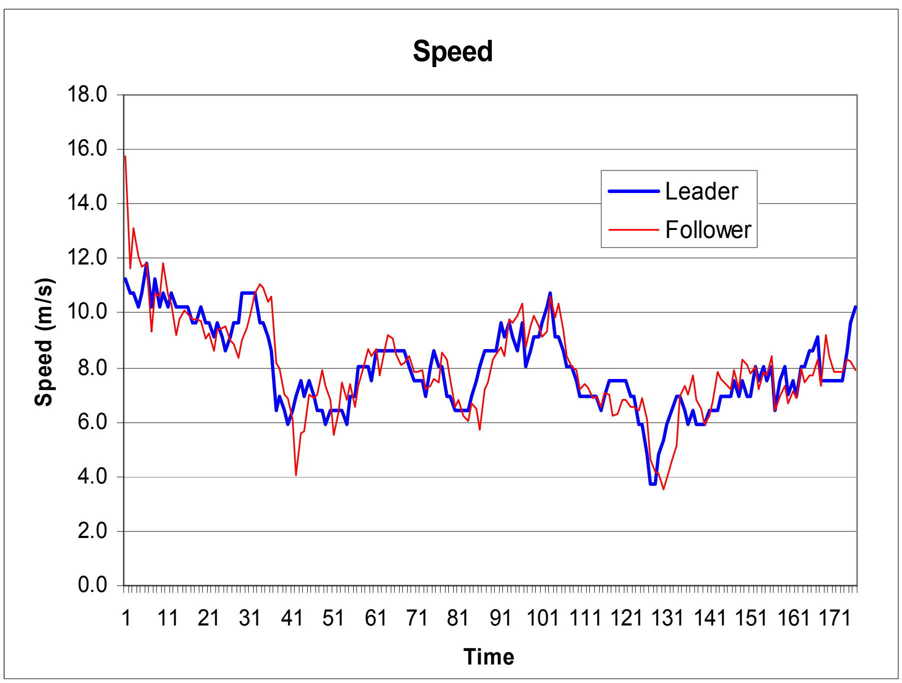


Figure 41. Speed of the lead and following vehicles

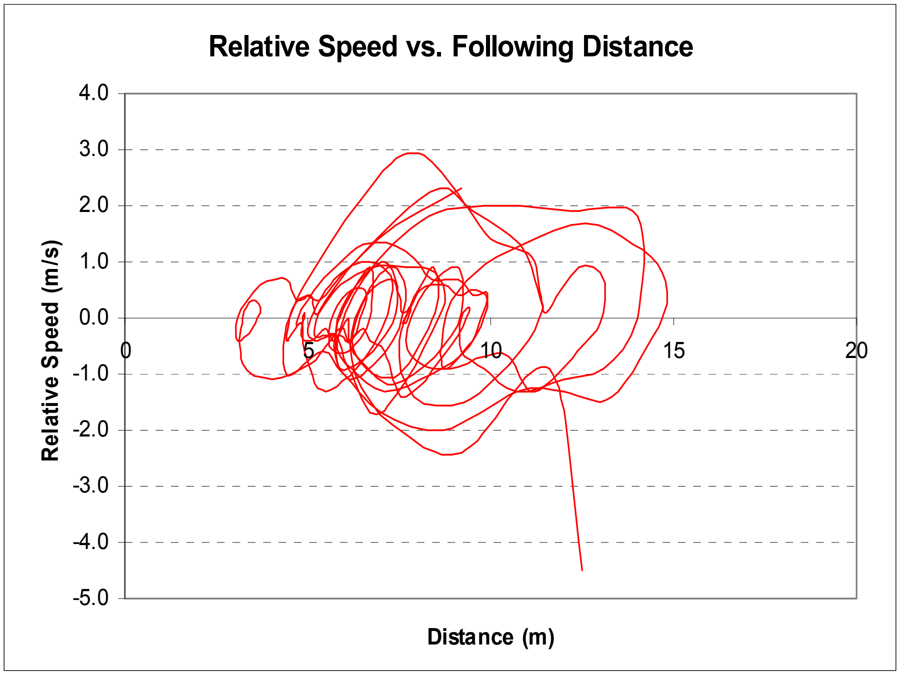


Figure 42. Trajectory of an oscillatory process in car-following behavior

5.1.2 Traffic hysteresis phenomenon in car-following

Traffic hysteresis is a phrase used to describe the phenomenon that the acceleration and deceleration processes have different speed-density curves, which are asymmetric; the phase trajectories therefore form a hysteresis loop. It should be said that this does not capture exactly the definition of the word hysteresis in the fields from which it was borrowed, but the existence of a different return trajectory seems to be common enough ground to cause a lot of researchers to use the phrase. It was first recognized theoretically by Newell (1965) and he hypothesized that drivers respond to certain stimuli differently in different traffic phases, i.e., acceleration and deceleration. He proposed a model that contained the hysteresis loop. After that, some researchers explored traffic hysteresis using bivariate relationship plots (e.g., speed-density plot), obtained from experimental data or simulation results (Treiterer and Myers, 1974, Zhang, 1999, Zhang and Kim, 2005). It is clear from Figure 43 that there are patterns that might be coined "hysteresis loops" in this car-following time series, after plotting following distances (between the lead and following vehicles) with speeds of the following vehicle. This time series is the case of No. 23 collected on March 18, 2005 in the Appendix A.

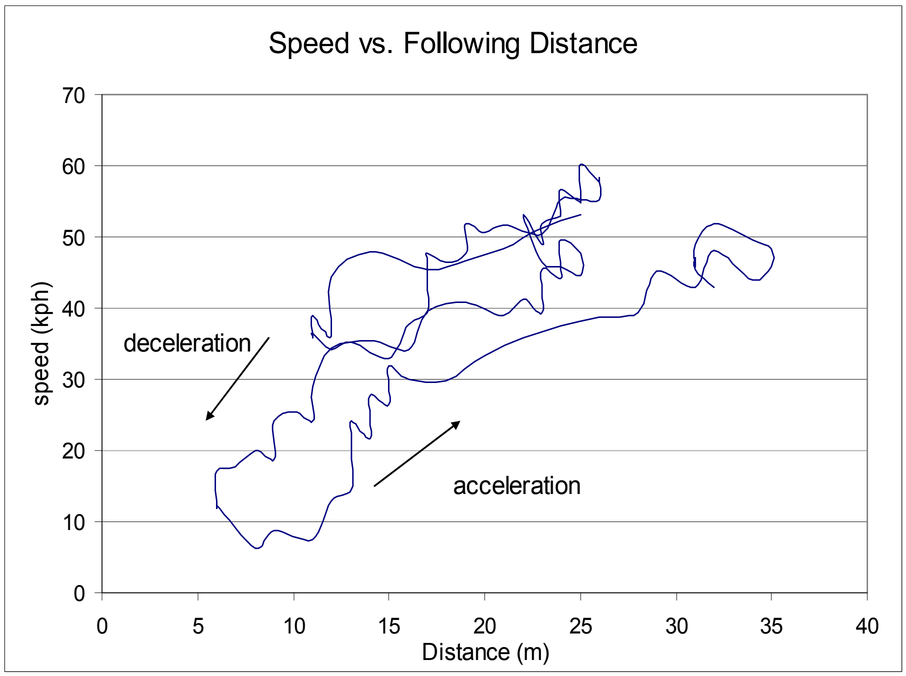


Figure 43. Traffic hysteresis phenomenon

5.1.3 Variability in following distance

From the results of the baseline statistics in Chapter 4, we found that the following distance between the lead and following vehicles increased as speed increased, although there were significant variations in following distances along the whole speed range. This section presents that there are stochastic characteristics in following behavior across different drivers and even within the same driver.

1) Following distance across drivers

Figure 44 shows the relationship between following distance and speed for five randomly chosen auto drivers (No. 12, 15, 16, 23, and 25 in the Appendix A) under congested conditions on March 16, 2005. Car-following time series were divided into 5 km speed intervals in which each data point is an average value for the speed interval. As we may expect, the following distances consistently increase as speed increases for all five drivers. What is interesting is that there are significant variations in following distances across different drivers as shown in Figure 44. It is more evident at higher speed ranges than at lower speed ranges. This finding suggests that the desired following distance is an individual driver characteristic and that what drivers believe to be safe following distances vary. This analysis confirms that every individual driver has his or her own driving rule, rather than keeping a deterministic and strict driving law.

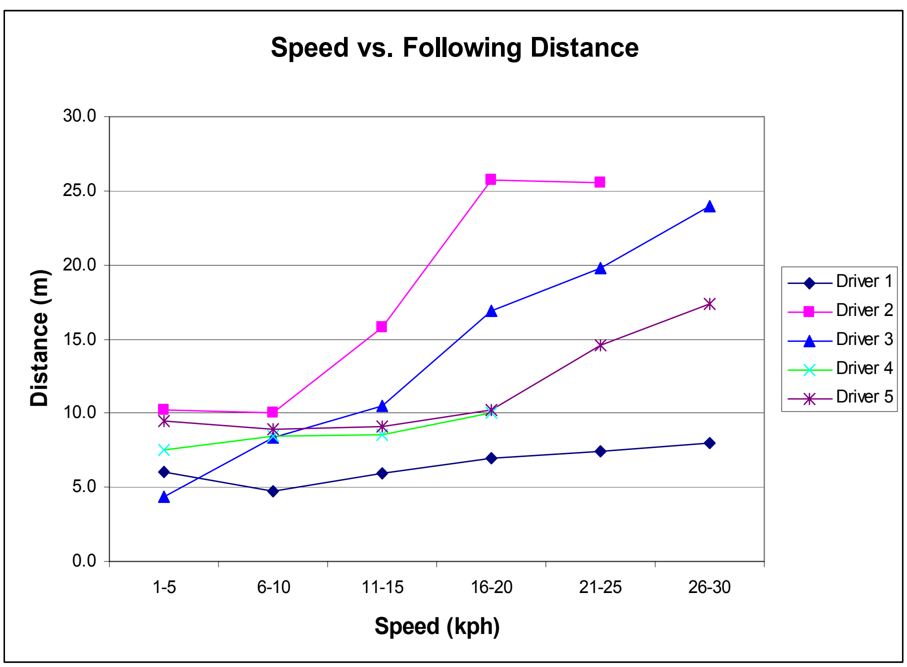
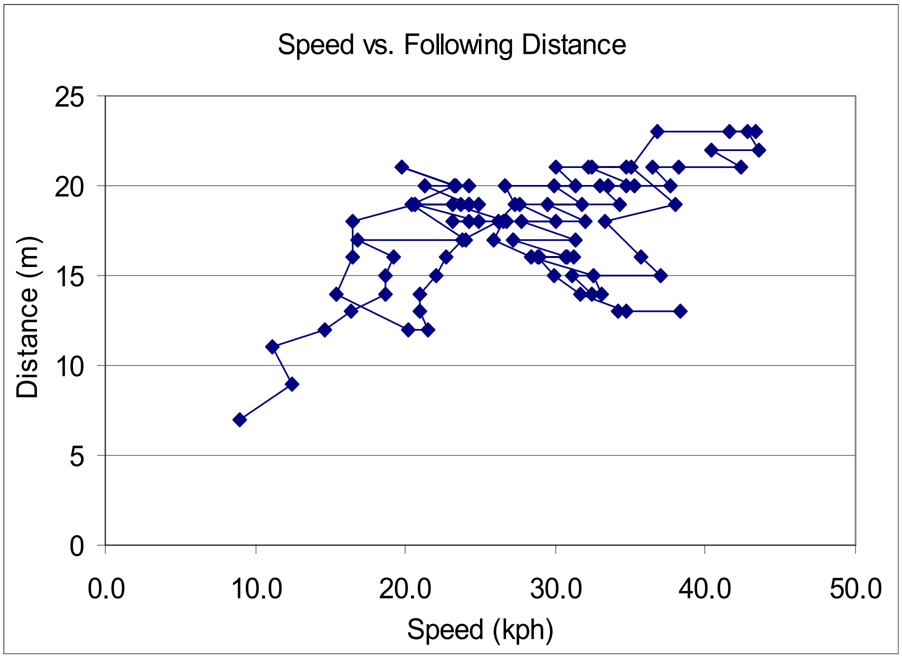


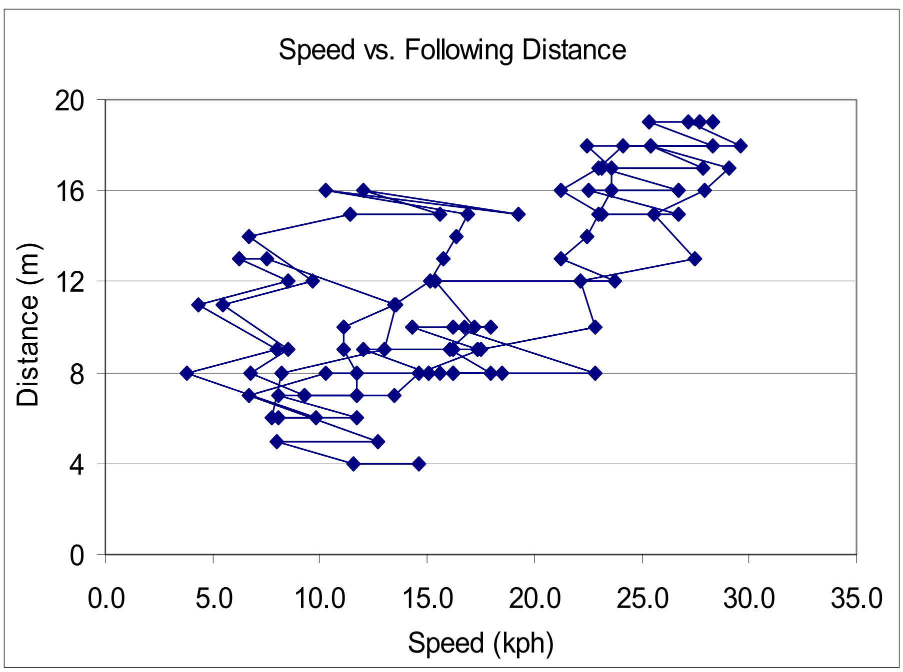
Figure 44. Variability in following distance across drivers

2) Following distance within the same driver

We observed in the previous section that an individual driver has his or her own driving rule, rather than keeping a deterministic and strict driving law. It has been also shown that drivers tend to retain their personalities, in the sense that each driver tends to maintain his driving attributes, and in some instances, drivers return to their attributes after being forced by a traffic disturbance to alter them temporarily (Cassidy and Windover, 1998). Figure 45 shows the relationship between following distance and speed within the same driver for two time series data (No. 25 for auto driver and No. 42 for truck driver on March 16, 2005 in the Appendix A). The following distance varies from 4 to 16 meters at the speed of 11 km/h in the case of auto and 12 to 21 meters at 20 km/h for truck. This result indicates that although an individual driver has his own driving behavior or attribute, the following distance may differ over time and space under different driving maneuvers and conditions, such as traffic, geometric, or environmental conditions.



(a) Auto case



(b) Truck case

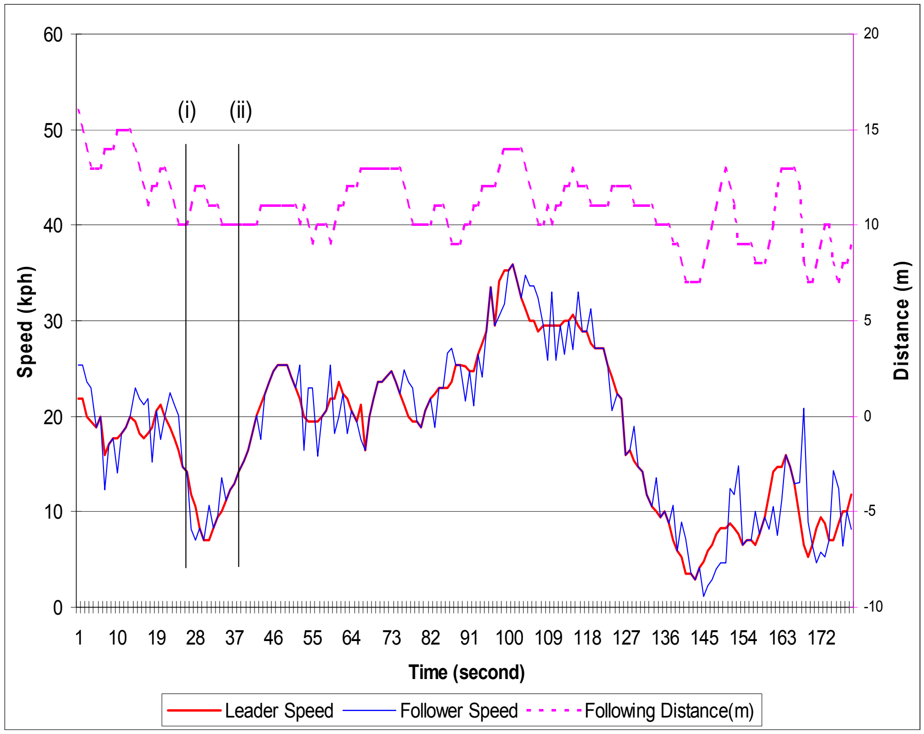
Figure 45. Variability in following distance within same driver

5.1.4 Natural driving behavior with historical state aspects in car-following

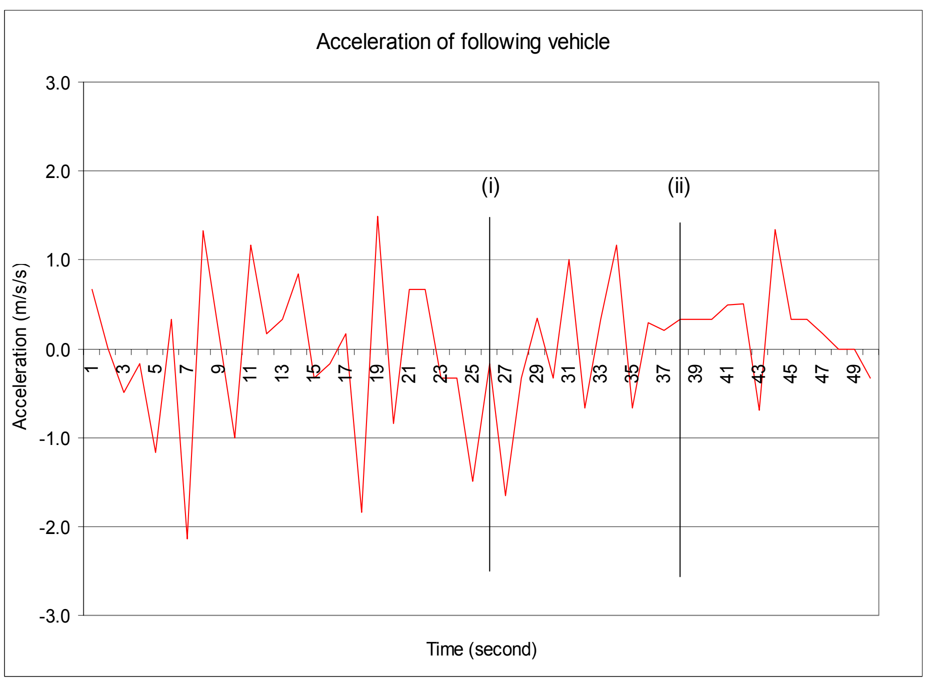
As discussed in the literature review in Chapter 2, a common assumption in car-following models, representing the following vehicle's responses, is that the reaction of a following vehicle lags the lead vehicle consistently by a constant delay. That situation we call the "current state," and note that these models assume that there is no dependence on the past sequences of car motions that produced the current state. Thus, one might call this process "memoryless." It is our hypothesis that, for certain instantaneous states, the most natural following responses differ, depending on how those states are reached. This section shows from the field data analysis that there is variability in following vehicles' reactions with the same instantaneous states under different driving maneuvers and also discloses that common following driving maneuvers exist in car-following under naturalistic driving situations.

1) Variability in following vehicle's reactions under different driving maneuvers

Drivers behave differently under different driving maneuvers, although they have exactly the same (current) instantaneous states, such as speeds of the lead and following vehicles and following distances. Figure 46 shows two examples for a single car-following time series (No. 32 on March 18, 2005 in the Appendix A), where the same instantaneous states were produced under very different causes (or driving maneuvers), and hence very different effects to the following vehicle were generated. As shown in Figure 46 (a), for both cases (i) and (ii), the same leader speeds (14.1 km/h), follower speeds (14.1 km/h), and following distances (10 m) were produced under very different driving maneuvers: the former is a deceleration event and the latter is an acceleration event. From the perspective of traditional car-following models with a myopic definition of the state, the reactions of the following vehicle at the next time should be the same. However, the reactions of the following vehicles that incorporate more history into the definition of state were totally different, as shown in Figure 46 (b), which only contains the acceleration (or reaction) profile of the following vehicle until 50 seconds to illustrate more clearly. In the first case (i) in Figure 46 (b), the following vehicle decelerates with respect to the current state, which was produced under a deceleration event. In the second case (ii) in Figure 46 (b), the following vehicle accelerates nearly immediately because the same spacing and speed resulted from an acceleration event. This result indicates that individual drivers don't follow a deterministic or a fixed driving rule, and it is more important to investigate sequences of car motions for determining following behavior than instantaneous states.



(a) Same instantaneous states under different driving maneuvers

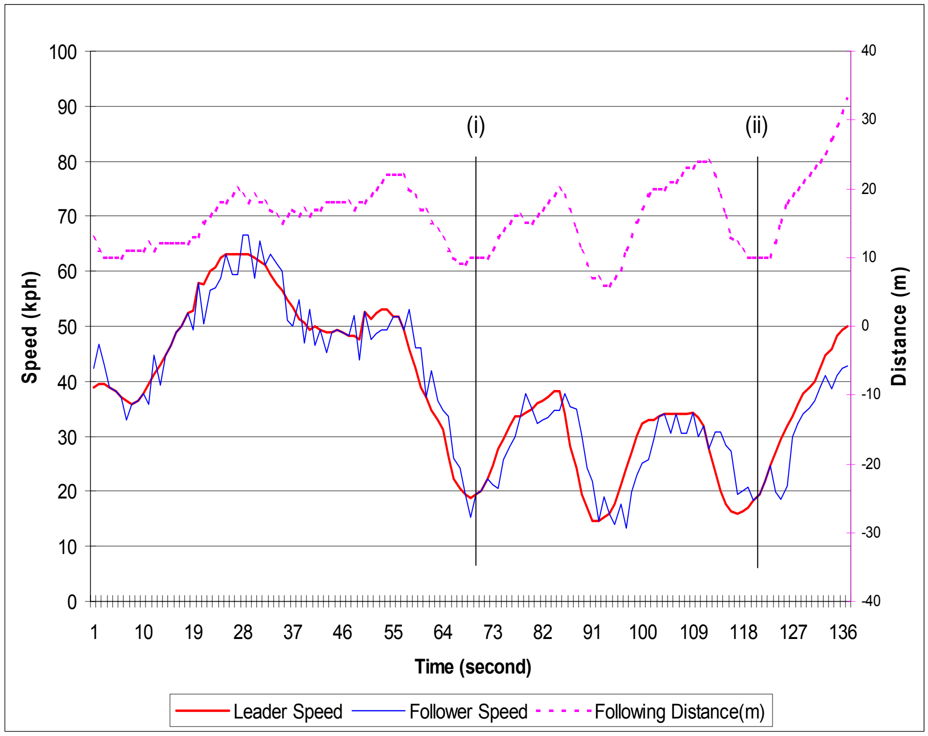


(b) Different reactions of the following vehicle

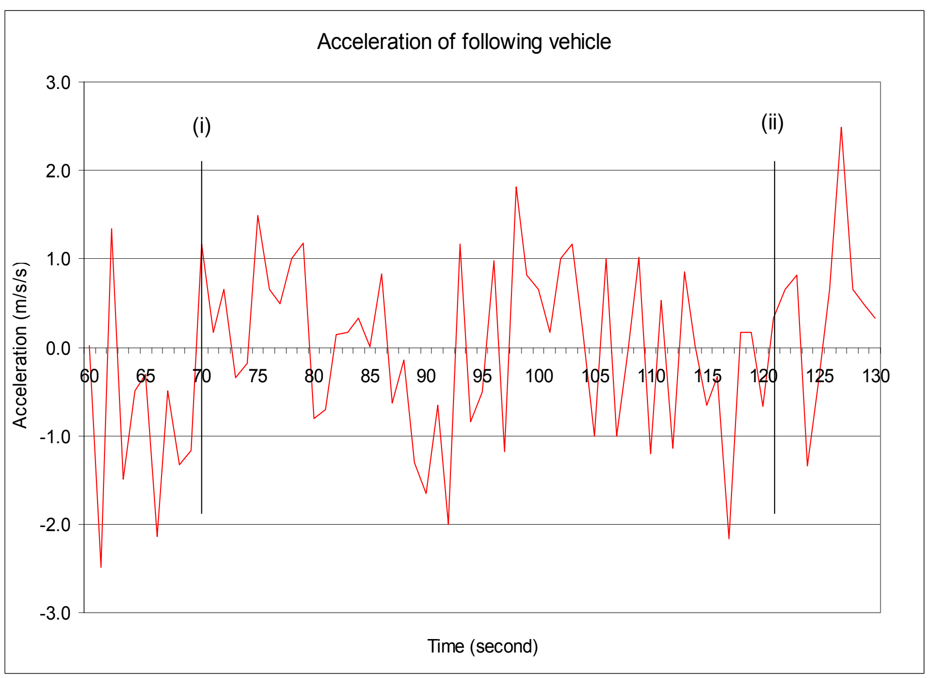
Figure 46. Different reactions caused by different driving maneuvers

2) Common following vehicle's reactions under the same driving maneuvers

In Section 5.1.3, we observed that an individual driver has his own driving rule and tends to maintain his driving attributes. Hence, we might assume that the following vehicle's reactions to the lead vehicle, such as acceleration and deceleration profiles, are expected to remain almost the same for each driver, and that car-following behavior for each driver may not be completely random in nature but rather demonstrate some temporal consistency. There should be some patterns in which the past car-following behavior repeats itself under the same driving maneuvers. Figure 47 shows examples where the common following vehicle's reactions under the same driving maneuvers exist in car-following behavior for a single time series (No. 59 on March 18, 2005 in the Appendix A). As shown in Figure 47 (a), both cases (i) and (ii) imply the time lines at which the same instantaneous states, i.e., the same leader speeds (19.4 kph), follower speeds (19.4 kph), and following distances (10 m), were produced under the same driving maneuver, which is an acceleration event. In this situation, the reactions of the following vehicle at the next time for both cases were exactly the same: the following vehicle accelerates nearly immediately because the current instantaneous states resulted from an acceleration event, as shown in Figure 47 (b), which displays only the acceleration profile of the following vehicle from 60 to 130 seconds. This result indicates that the reactions of the following vehicle caused by the same driving maneuvers in car-following situations can repeat itself over time and space and also confirms that car-following behavior for a driver is a series of common following vehicle's reactions under the various driving maneuvers.



(a) Same instantaneous states under same driving maneuvers



(b) Same reactions of the following vehicle

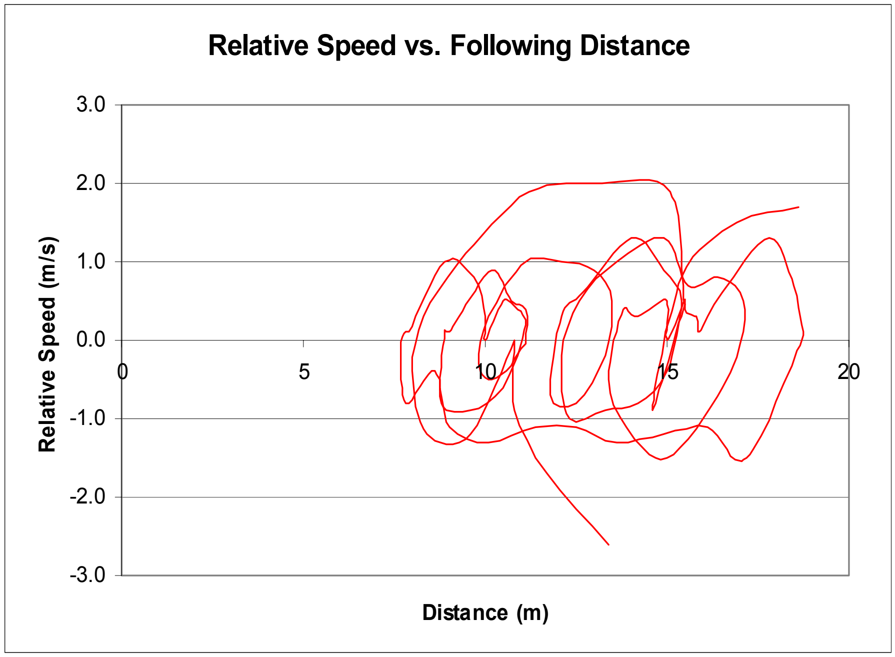
Figure 47. Existence of common following driving maneuvers

5.2 Effects of Various Causal Factors on Car-Following Behavior

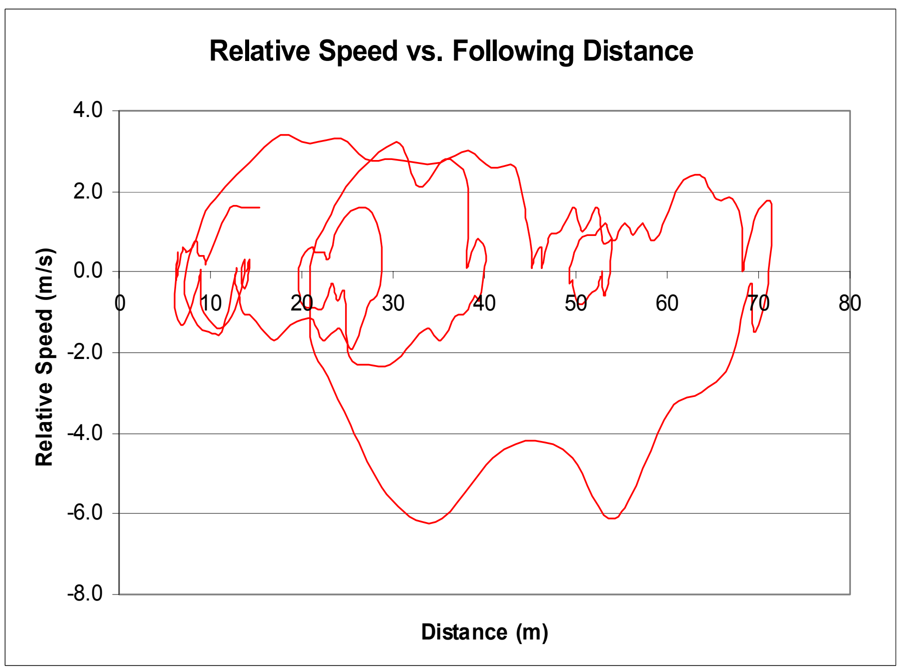
There are numerous factors that might influence car-following behavior, such as various human characteristics (e.g., gender, in-vehicle activities like telephoning and talking, vehicle occupancy (distraction level)), traffic and road characteristics (e.g., type of vehicle, congestion level, and number of lanes or location of driving lane), and environmental characteristics (weather condition, time of day or day of week). We have investigated and identified the relationships between those factors and the following vehicle's behavior and described some findings for each critical factor based on the differences of behavioral characteristics.

5.2.1 Vehicle types (auto vs. truck)

Different types of vehicles, such as auto and truck, might have different car-following behavior. Figure 48 shows two randomly chosen car-following time series for an auto and a truck, presenting the relationship between relative speed and following distance. It is very clear from the figure that the variations in following distance and in relative speed of the truck are much wider than those of the auto; i.e., the following distance and the relative speed for the truck vary from about 7 to 70 meters and –6 to +4 m/s, compared to 8 to 18 meters and –2 to +2 m/s for auto, respectively. This suggests that truck drivers are more careful when driving behind a lead vehicle, because the truck has a longer stopping distance than an auto. Also, the response of the truck to the action of the lead vehicle is slower than the auto, i.e., trucks accelerate or decelerate slowly because of the poorer operating capabilities than autos.



(a) Auto case



(b) Truck case

Figure 48. Relationship of relative speed vs. following speed by vehicle type

Figure 49 shows the distribution of following time gaps for a total of 301 car-following time series for both auto and truck. A number of 269 time series were auto, while 32 were truck, respectively. We notice that the distributions of the time gaps differ, depending on vehicle types. Autos have a more focused distribution around a smaller mean time gap, while truck gaps have a larger mean and longer tail. In order to observe the effect of vehicle types on car-following behavior, all the car-following time series were divided into 5 km/h speed intervals. After that, we classified the data points in each speed interval according to each individual driver and calculated a mean speed of each individual driver. Figure 50 shows the difference of following distance between auto and truck along the whole speed range in which each data point is an average value of drivers who belong to each speed interval. It seems visually that the average following distances of truck are longer than auto along most of the speed range, except for the highest and lowest speed ranges from 1 to 10 and 81 to 105 km/h in which the two are mostly indistinguishable. The lower speeds correspond to periods of greater congestion, so behavioral differences between the types of vehicles should manifest themselves more distinctly. At the very lowest speeds, of course, traffic is likely at jam density. Figure 51 shows the standard deviations of following distances for auto and truck in each speed range. The standard deviations of trucks are larger than autos along the whole speed range, with very few exceptions. For the middle speed range in which the two are distinct, this suggests that trucks have more variability in keeping their desired following distance within each speed range.

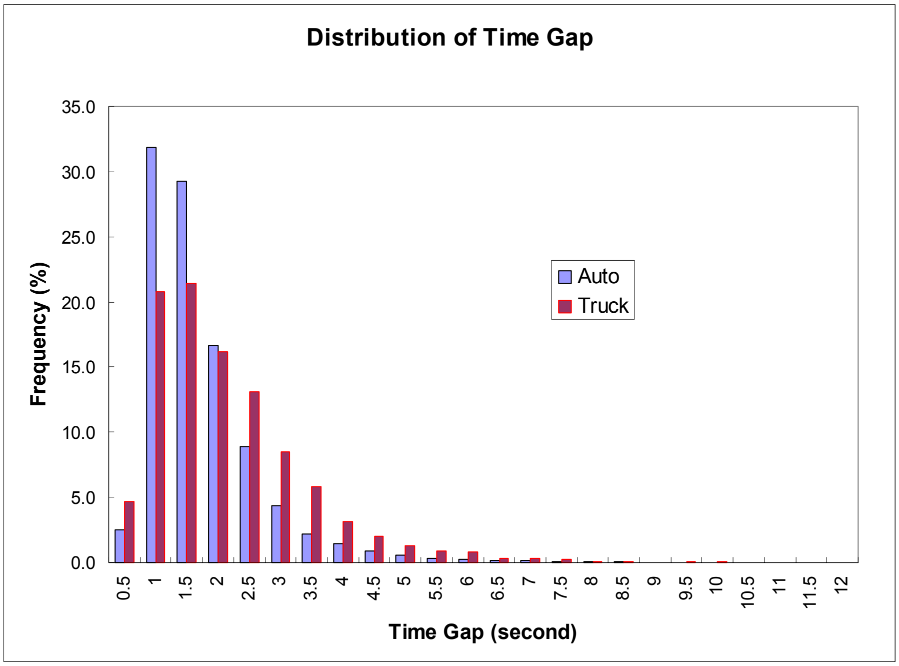


Figure 49. Distributions of following time gaps by vehicle types

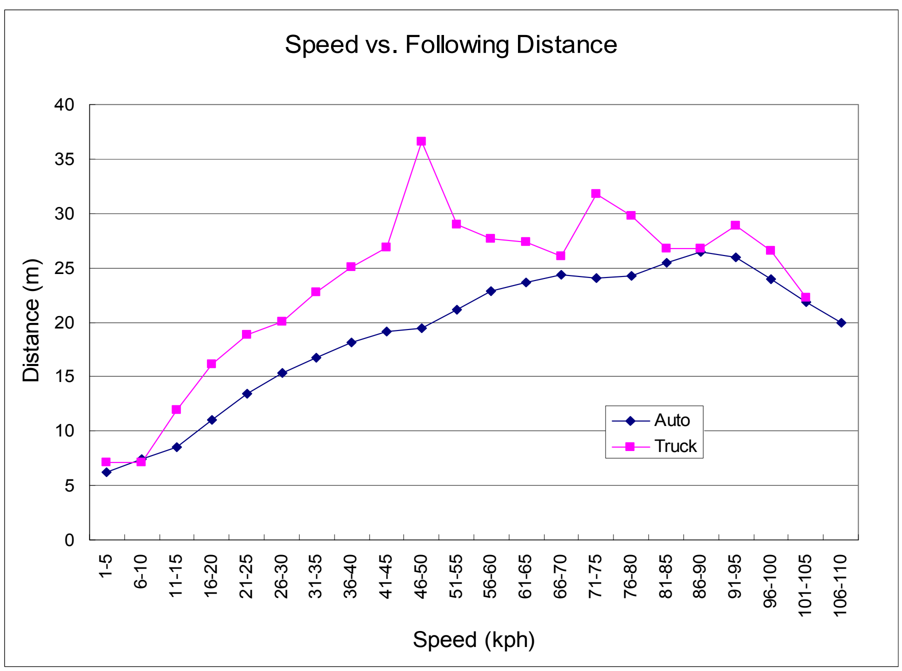


Figure 50. Speed vs. following distance by vehicle types

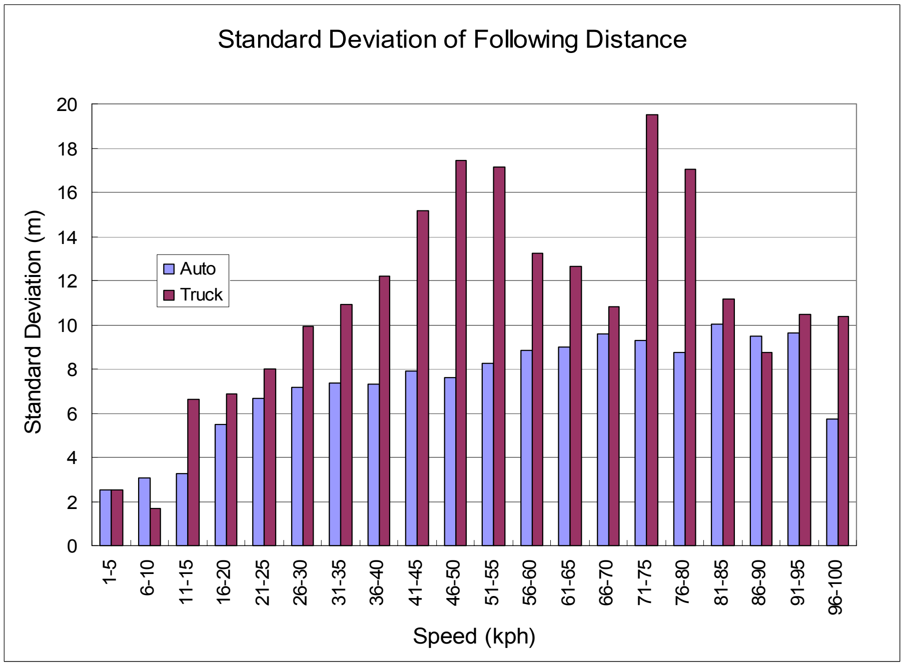


Figure 51. Standard deviations of following distances by vehicle types

Figure 52 shows how the accepted time gaps for each type of vehicle vary with speed. Generally, the time gaps decrease as speeds increase for both auto and truck and the average time gaps for trucks are longer than for autos along most of the speed range. This result suggests that truck drivers tend to have longer time gaps than auto. Furthermore, the standard deviations of time gaps for trucks are larger than for autos for most of the speed range, as shown in Figure 53. This tends to confirm both that truck drivers are more careful while following the lead vehicle and tend to adopt large time gaps in order to avoid rear end collisions and that their precise control of these gaps is not as good as autos, owing perhaps to performance differences between the two types of vehicles. To compare the different effects of vehicle types on car-following behavior, one-way ANOVA was used to identify the differences in following distances between auto and truck. The F-test results show that there are statistically significant differences in following distances (at significance level 0.05) for the speed ranges from 11 to 55 km/h and 71 to 80 km/h, as shown in Table 8. The significant rows are highlighted in gray.

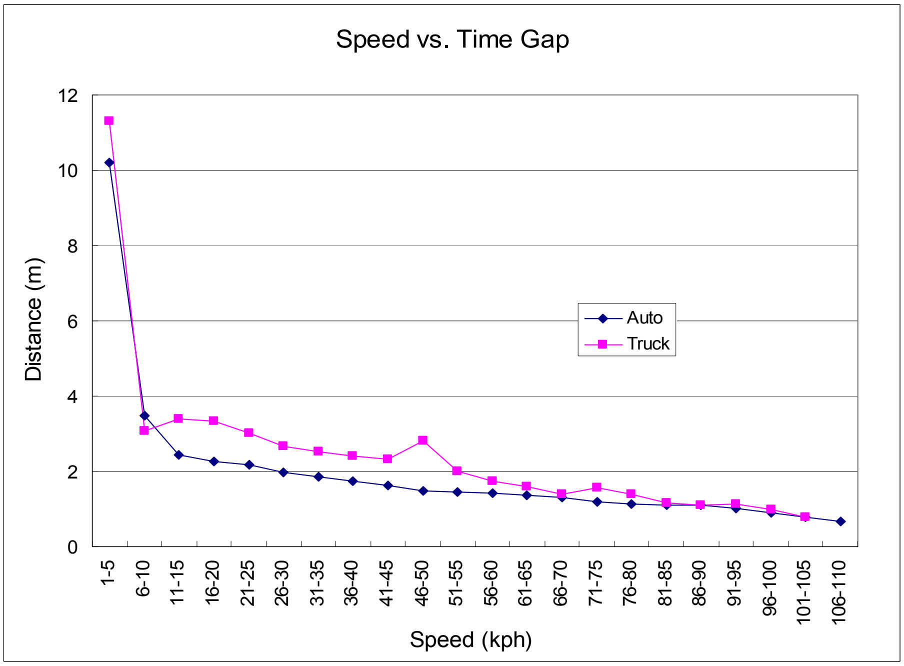


Figure 52. Speed vs. time gap by vehicle types

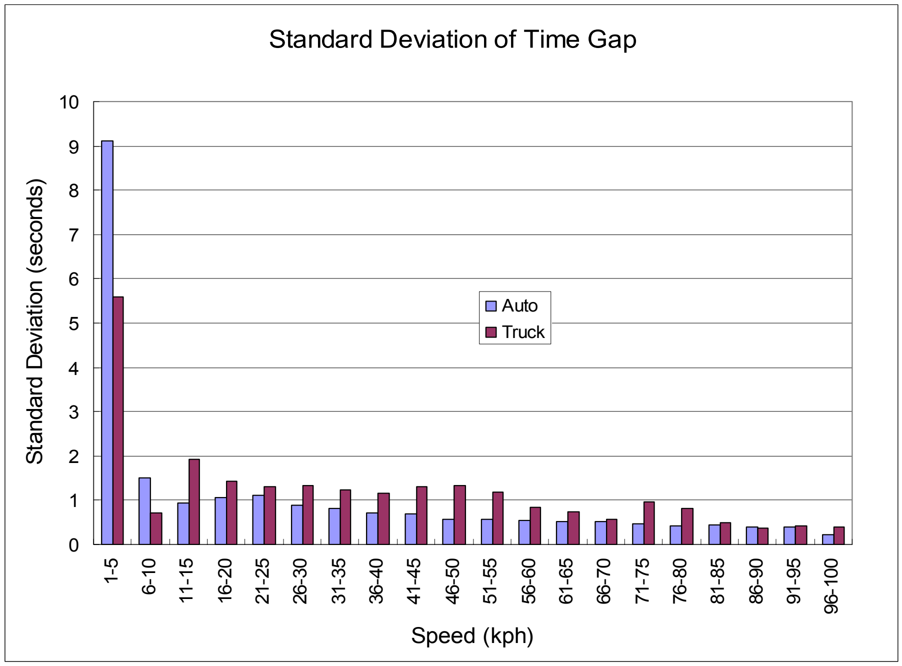


Figure 53. Standard deviations of time gaps by vehicle types

Table 8. ANOVA: effect of vehicle types on car-following behavior

Speed Range	d.f	Sample Size		F	P-value
		Auto	Truck		
1-5	1, 50	49	3	0.369	0.5464
6-10	1, 69	63	8	0.204	0.6528
11-15	1, 81	73	10	7.166	0.0090
16-20	1, 97	87	12	8.563	0.0043
21-25	1, 101	90	13	7.179	0.0086
26-30	1, 98	87	13	4.496	0.0365
31-35	1, 90	78	14	6.673	0.0114
36-40	1, 89	79	12	7.545	0.0073
41-45	1, 87	77	12	7.423	0.0078
46-50	1, 80	74	8	26.952	1.55E-06
51-55	1, 80	74	8	4.913	0.0295
56-60	1, 84	79	7	1.697	0.1963
61-65	1, 93	86	9	1.273	0.2622
66-70	1, 102	97	7	0.205	0.6518
71-75	1, 115	106	11	5.361	0.0224
76-80	1, 146	134	14	3.988	0.0477
81-85	1, 144	131	15	0.219	0.6407
86-90	1, 131	121	12	0.015	0.9020
91-95	1, 97	92	7	0.612	0.4359
96-100	1, 40	38	4	0.647	0.4260
101-105	1, 19	20	1	0.006	0.9397

5.2.2 Number of lanes (4 lanes vs. 2 lanes)

The effect of different roadways, which have different number of lanes, on the car-following behavior was investigated. The data were taken from 4-lane segments of I-495 and 2-lane segments of I-295. As autos and trucks have different car-following behavior, as shown in the previous section, and also because not much truck traffic was on I-295 compared to I-495, only car-following time series for autos were considered in this analysis. Therefore, 113 time series for I-295 and 148 time series for I-495 were extracted. Figure 54 shows the differences in following distances between two roadways along the whole speed range. Although there are small differences in following distances in each speed range, it seems visually that there are no significant differences in the following distances between the two roadways, except perhaps for the speed ranges from 51 to 75 km/h and 96 to 105 km/h. Hence, one-way ANOVA was used to identify statistically the differences in following distances. The F-test results in Table 9 show that there are statistically significant differences in following distances at significance level 0.05 for the speed ranges from 51 to 55 km/h and 61 to 65 km/h. The significant rows are shown in gray. The highways are different in ways other than the number of lanes, so some care should be taken drawing inferences here. For example, I-495 has much more curvature that the relatively straight I-295, so sight distance concerns might cause drivers to tend to adopt longer following distances.

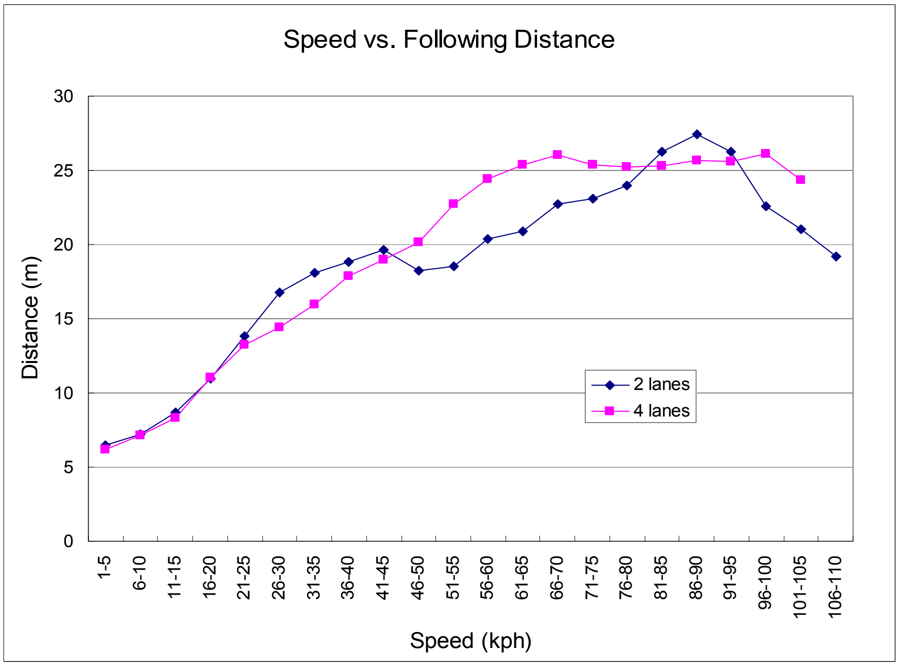


Figure 54. Speed vs. following distance by number of lanes

Table 9. ANOVA: effect of number of lanes on car-following behavior

Speed Range	d.f	Sample Size		F	P-value
		2 lanes	4 lanes		
1-5	1, 47	13	36	0.098	0.7553
6-10	1, 59	17	44	2.9E-05	0.9957
11-15	1, 69	21	50	0.231	0.6324
16-20	1, 82	27	57	0.001	0.9720
21-25	1, 85	29	58	0.149	0.7005
26-30	1, 82	33	51	2.102	0.1509
31-35	1, 73	28	47	1.440	0.2340
36-40	1, 75	28	49	0.288	0.5934
41-45	1, 73	26	49	0.104	0.7482
46-50	1, 71	23	50	0.989	0.3235
51-55	1, 71	24	49	4.331	0.0410
56-60	1, 76	28	50	3.893	0.0521
61-65	1, 82	28	56	4.872	0.0301
66-70	1, 93	43	52	2.864	0.0939
71-75	1, 102	50	54	1.584	0.2111
76-80	1, 128	68	62	0.653	0.4205
81-85	1, 125	71	56	0.270	0.6042
86-90	1, 114	71	45	0.965	0.3279
91-95	1, 85	54	33	0.088	0.7679
96-100	1, 33	25	10	3.017	0.0917
101-105	1, 16	17	1	0.435	0.5191

5.2.3 Location of driving lanes

We hypothesize that the location of the driving lane might have a different effect on car-following behavior, beyond any differences resulting from the number of total lanes on roadways. For example, driving behavior in the left-most lane (or fast lane) on a two-lane roadway should be different from that in the right-most lane (or slow lane) in which drivers have additional interference from on-ramps and off-ramps.

In order to investigate the effect of driving lane on car-following behavior, the car-following time series for autos only were grouped according to their driving lane, for different roadways (I-295 and I-495). Therefore, 269 time series for autos were extracted for this analysis. The numbering convention for driving lanes will be 1 for the right-most lane, and increasing for each lane to the left. Thus, the left-most lane on I-295 is lane 2, while the left-most lane on I-495 is lane 4. In particular, accidental distance gaps around exits (usually at the right-most lane) were excluded in this analysis. Figures 55 and 56 show the differences in following distances and time gaps between lane one (the right lane) and lane two (the left lane) on I-295 along the whole speed range. It is very clear that following distances and time gaps in lane one are longer than in lane two along the whole speed range except for the highest and lowest speed ranges. This seems reasonable, since vehicles in the right-most lane presumably are leaving gaps for merging vehicles, and since some of the longer spacings might result from vehicles departing the lane at off-ramps. The one-way ANOVA results show that there are statistically significant differences (significance level 0.05) in following distances between the two lanes for most of the speed range, as shown in Table 10. Figure 57 shows the standard deviations of following distances for lane one and lane two at each speed range.

Generally, the standard deviations of lane one are larger than those of lane two for most speed ranges, although there are few speed ranges at the extremes where this is not true. For the middle ranges, this confirms that lane one has more interference from things such as lane changing from on-ramps and off-ramps that might produce more variability in following distance within these speed ranges.

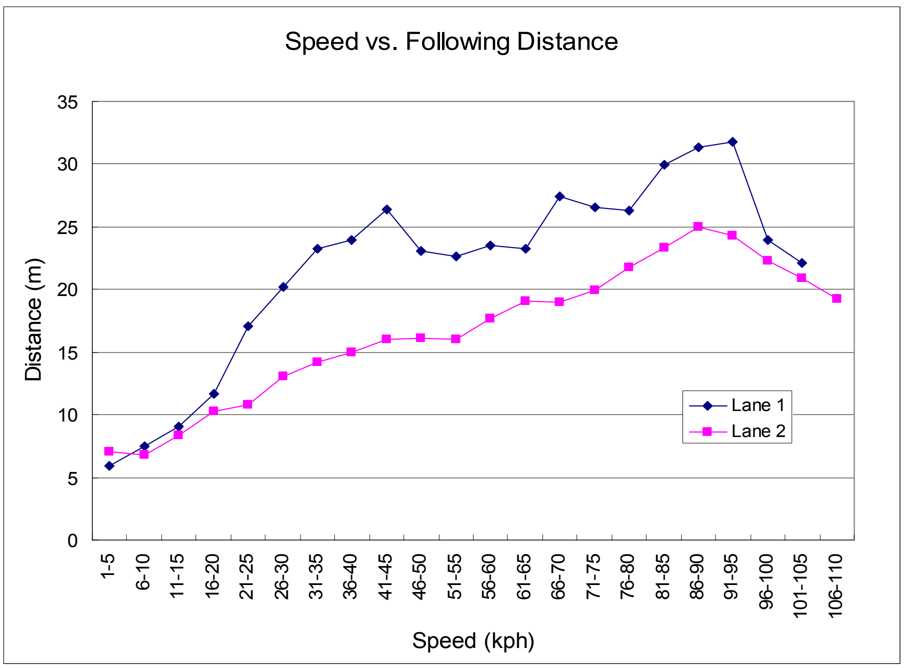


Figure 55. Speed vs. following distance by driving lanes on I-295

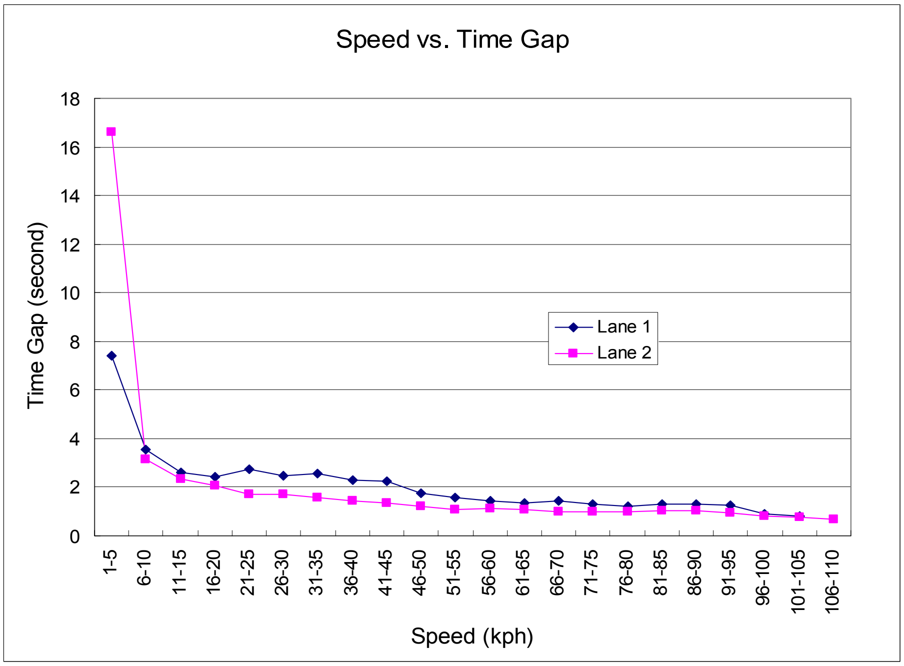


Figure 56. Speed vs. time gap by driving lanes on I-295

Table 10. ANOVA: effect of location of driving lane on car-following behavior on I-295

Speed Range	d.f	Sample Size		F	P-value
		Lane 1	Lane 2		
1-5	1, 11	7	6	0.552	0.4730
6-10	1, 15	9	8	0.690	0.4193
11-15	1, 19	11	10	0.560	0.4635
16-20	1, 25	14	13	1.529	0.2278
21-25	1, 27	14	15	4.643	0.0403
26-30	1, 30	16	16	7.136	0.0121
31-35	1, 26	12	16	9.878	0.0041
36-40	1, 26	12	16	12.780	0.0014
41-45	1, 24	9	17	10.308	0.0037
46-50	1, 21	7	16	4.645	0.0429
51-55	1, 22	9	15	5.110	0.0340
56-60	1, 26	13	15	3.999	0.0561
61-65	1, 26	12	16	2.147	0.1548
66-70	1, 41	19	24	8.920	0.0047
71-75	1, 48	24	26	6.714	0.0126
76-80	1, 66	33	35	4.259	0.0430
81-85	1, 69	31	40	6.023	0.0166
86-90	1, 69	27	44	5.811	0.0186
91-95	1, 52	14	40	5.069	0.0286
96-100	1, 16	4	14	1.462	0.2442
101-105	1, 15	2	15	0.103	0.7532

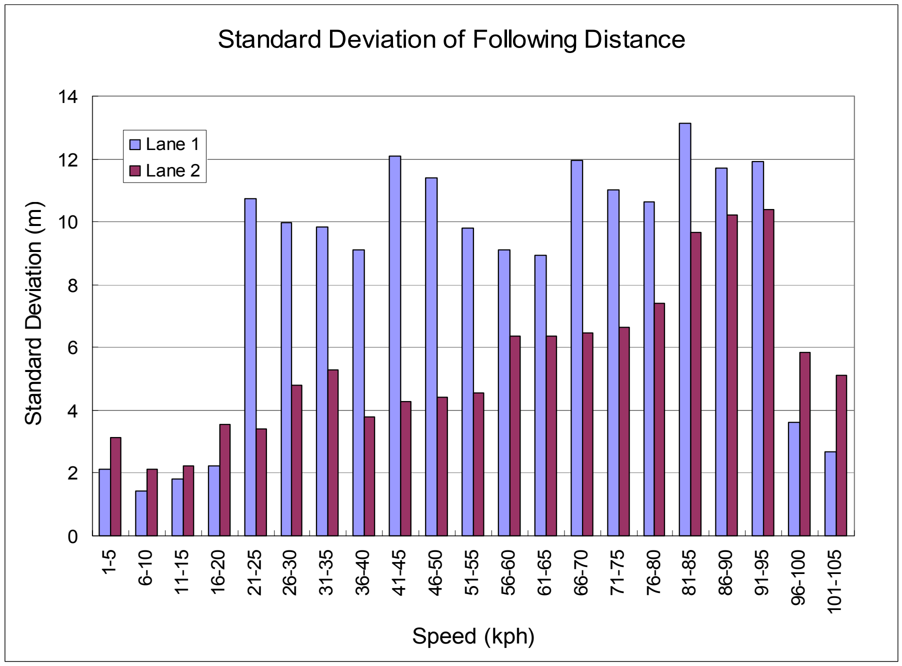


Figure 57. Standard deviations of following distances by driving lanes on I-295

The following deals with the same subject for the case of I-495. Again, car-following time series for autos were considered, to exclude the effects of trucks. Unexpectedly, no data points were available for the speed range from 56 to 60 km/h for lane four on I-495. As shown in Figures 58, it is difficult to find any general trend among lanes, but evident that there are significant variations in choosing following distances by each lane. What is interesting from the figure is that the following distances of lane four were relatively shorter than those of other lanes for the middle speed ranges from 31 to 55 km/h. The ANOVA results in Table 11 suggest that there are statistically significant differences in following distances among lanes for the lowest speed ranges from 1 to 20 km/h. Furthermore, the standard deviations in Figure 59 shows that the variability in choosing desired following distances exists by each lane, which suggests that drivers in each lane have different car-following behavior, rather than keeping a deterministic driving rule among lanes. Especially, there was a trend that the standard deviations of lane four were smaller than those of other lanes, for the lower speeds (below 50 km/h), which suggests that drivers in lane four have less variability in following distances within these speed ranges.

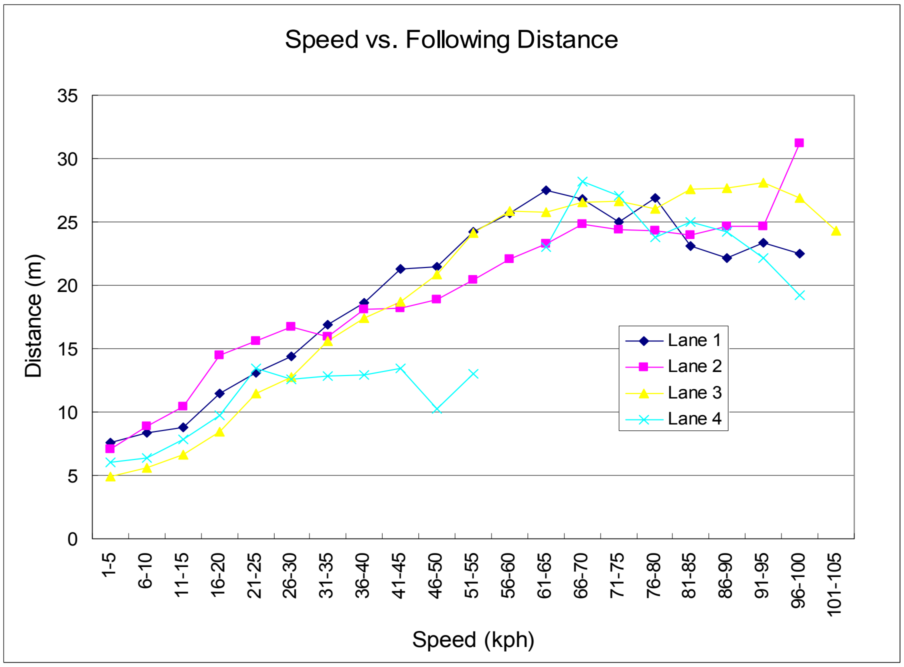


Figure 58. Speed vs. following distance by driving lanes on I-495

Table 11. ANOVA: effect of location of driving lane on car-following behavior on I-495

Speed Range	d.f	Sample Size				F	P-value
		Lane 1	Lane 2	Lane 3	Lane 4		
1-5	3, 32	11	6	16	3	3.408297	0.029206
6-10	3, 40	13	9	19	3	3.851083	0.016388
11-15	3, 46	14	13	20	3	3.399774	0.025445
16-20	3, 53	15	16	23	3	3.139297	0.032825
21-25	3, 54	19	16	20	3	1.513043	0.221553
26-30	3, 47	15	15	19	2	1.288558	0.289303
31-35	3, 43	13	17	15	2	0.240919	0.86731
36-40	3, 45	15	17	15	2	0.40562	0.749676
41-45	3, 45	13	18	16	2	0.88887	0.454173
46-50	3, 46	15	17	17	1	0.946382	0.426058
51-55	3, 45	14	17	17	1	1.216397	0.314698
56-60	2, 47	16	18	16	-	0.987018	0.380278
61-65	3, 52	17	20	18	1	0.658919	0.581053
66-70	3, 47	14	19	16	2	0.168481	0.917121
71-75	3, 50	10	24	16	4	0.257289	0.855781
76-80	3, 58	10	27	19	6	0.388235	0.761887
81-85	3, 52	7	22	20	7	1.030466	0.386794
86-90	3, 41	4	16	19	6	1.498115	0.229331
91-95	3, 29	4	10	14	5	1.357214	0.275387
96-100	3, 5	2	2	4	1	2.138912	0.213879

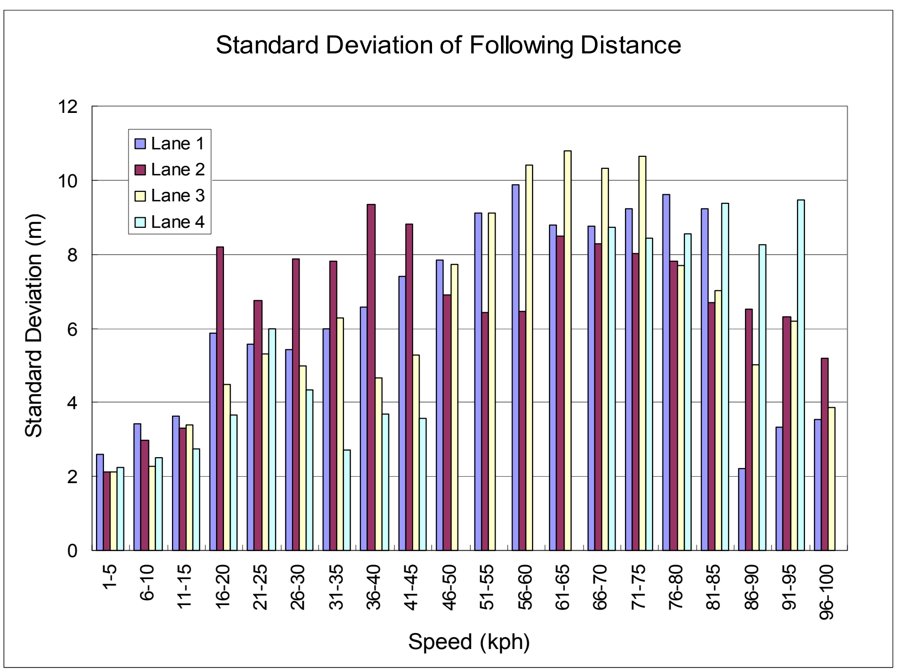


Figure 59. Standard deviations of following distances by driving lanes on I-495

5.2.4 Traffic conditions (rush vs. non-rush hour)

There might be some differences in car-following behavior between rush and non-rush hour periods. Rush hours usually mean that there is relatively heavy traffic, especially near metropolitan areas. Our study areas, such as I-495 and I-295, are in the vicinity of Washington D.C. and suffer from recurrent congestion during the rush hour periods, and sometimes even in non-rush hour periods. For this analysis, all the car-following time series, except data collected at night, were categorized into two groups: rush hours (7-9 am and 4-6 pm) and non-rush hours. Therefore, 263 time series collected at daytime were extracted and divided by rush hour data (179 time series) and non-rush hour data (84 time series). Figures 60 and 61 show the difference in following distances and time gaps between rush and non-rush hours along the whole speed range. Clear differences between different traffic conditions can be distinguished visually. It was observed that except perhaps for the speed ranges from 1 to 15 km/h and 96 to 100 km/h, following distances and time gaps in rush hour periods are longer than those in non-rush hour periods. The ANOVA results in Table 12 confirm that the differences were statistically significant between two traffic conditions for the speed ranges from 41 to 45 km/h and 61 to 95 km/h. This result suggests that drivers have a tendency to have relatively larger following distances and longer time gaps in rush hour periods within these speed ranges, compared to car-following in non-rush hours. Because these are situations in which there is relatively heavy traffic, there might be a greater possibility for the lead vehicle to accelerate or decelerate suddenly because of the unstable traffic conditions in rush hours. However, it is also frequently claimed that rush hour drivers are more familiar and proficient than non-rush drivers, which might suggest greater willingness to accept smaller time gaps and distances. This result, therefore, while clear from the data, was not fully expected. It is also confirmed from Figure 62 that the standard deviations of following distances in rush hour periods at each speed range are generally larger than those in non-rush hours, with very few exceptions. This indicates that drivers in rush hour periods have more variability in keeping their desired following distance than those in non-rush hour periods.

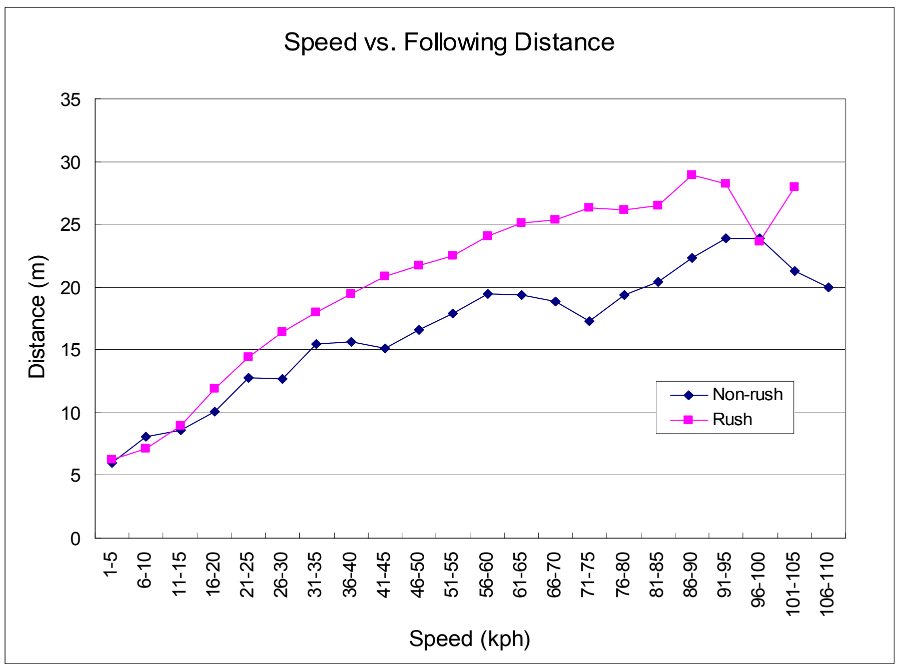


Figure 60. Speed vs. following distance by traffic conditions

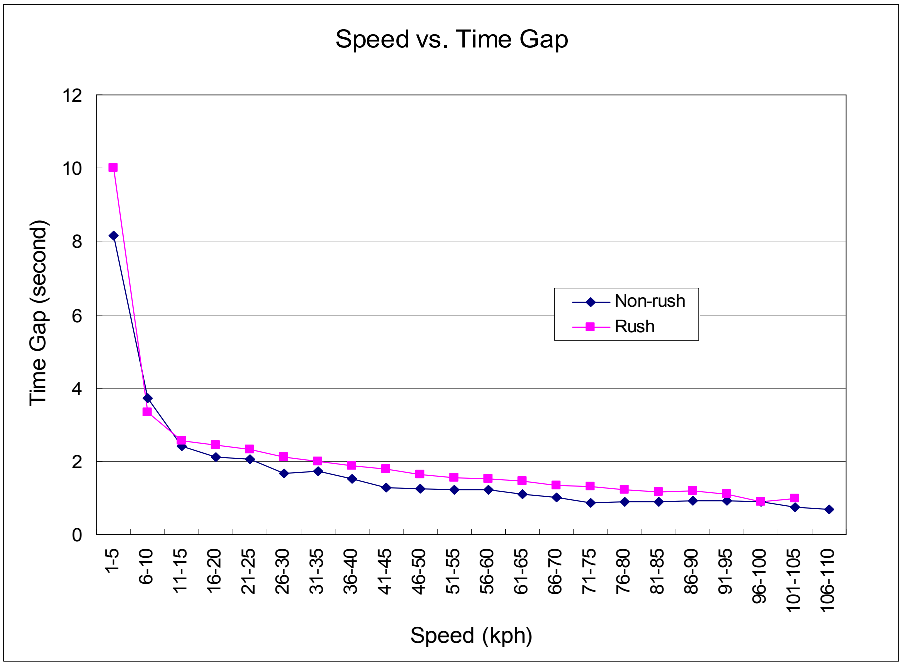


Figure 61. Speed vs. time gap by traffic conditions

Table 12. ANOVA: effect of different traffic conditions on car-following behavior

Speed Range	d.f	Sample Size		F	P-value
		Non-rush	Rush		
1-5	1, 47	8	41	0.083	0.7747
6-10	1, 66	12	56	0.922	0.3404
11-15	1, 78	14	66	0.109	0.7419
16-20	1, 95	15	82	1.291	0.2587
21-25	1, 98	16	84	0.766	0.3836
26-30	1, 96	15	83	3.017	0.0856
31-35	1, 89	14	77	1.107	0.2956
36-40	1, 87	12	77	2.174	0.1439
41-45	1, 85	14	73	4.528	0.0362
46-50	1, 76	14	64	2.905	0.0924
51-55	1, 75	13	64	2.077	0.1537
56-60	1, 76	15	63	2.985	0.0881
61-65	1, 82	20	64	5.627	0.0200
66-70	1, 79	21	60	7.525	0.0075
71-75	1, 89	25	66	13.551	0.0004
76-80	1, 116	46	72	15.490	0.0001
81-85	1, 115	55	62	15.937	0.0001
86-90	1, 111	60	53	18.439	3.77E-05
91-95	1, 86	56	32	5.784	0.0183
96-100	1, 37	32	7	0.005	0.9420
101-105	1, 19	19	2	3.863	0.0642

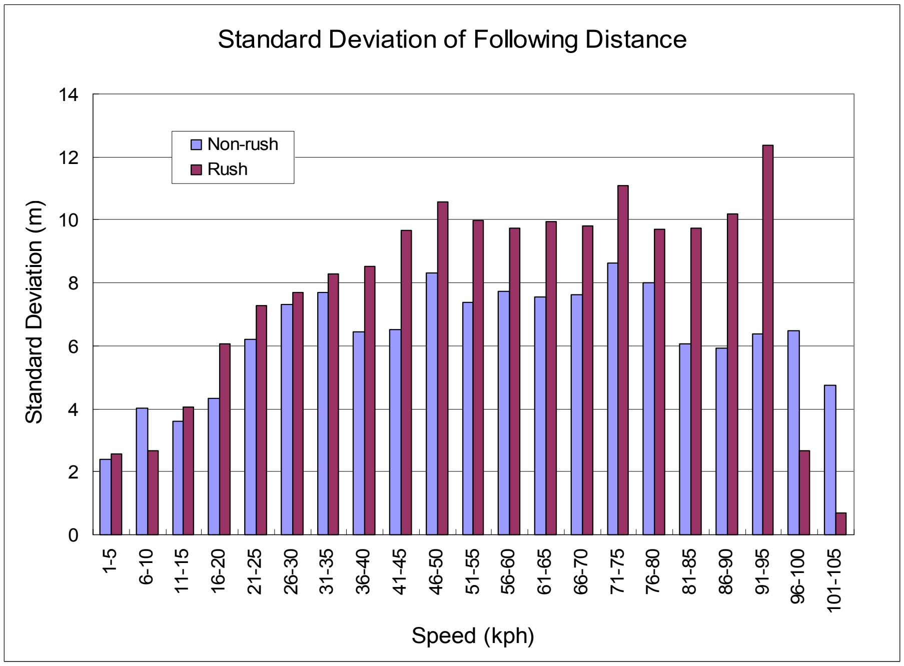
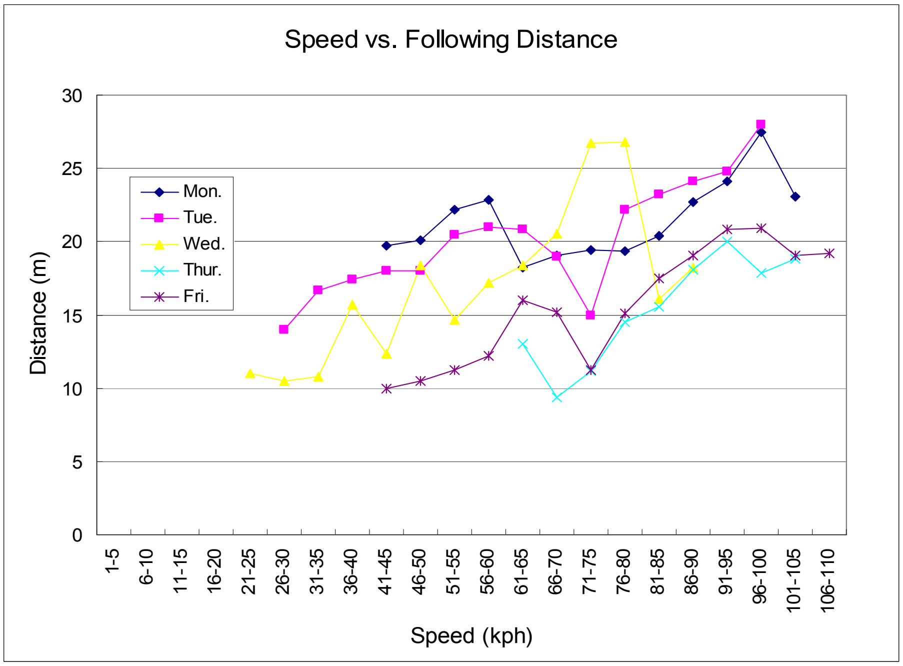


Figure 62. Standard deviations of following distances by traffic conditions

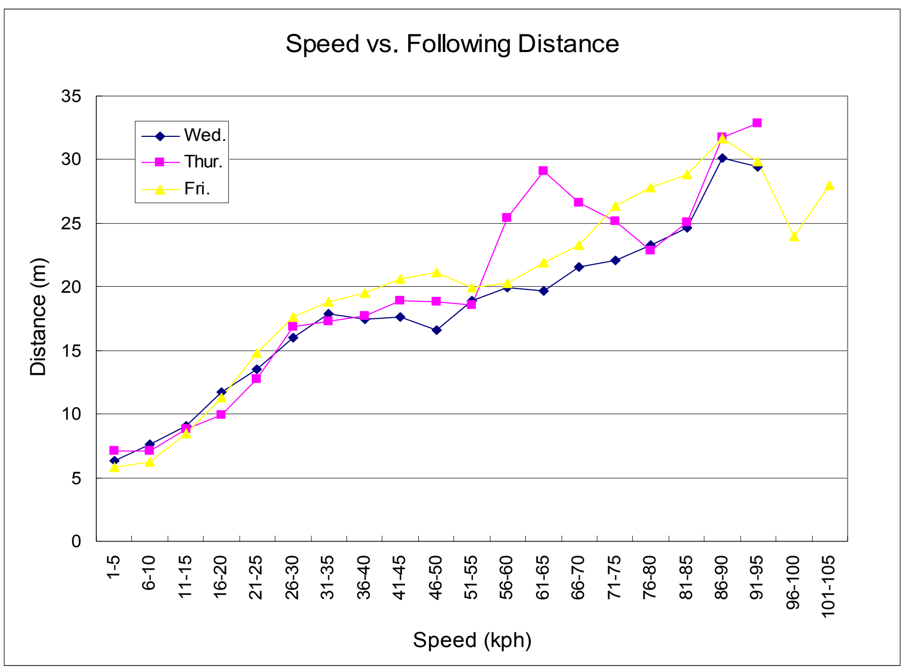
5.2.5 Day of the week distribution

The effect of day of the week distribution on car-following behavior was investigated. In order to identify any potential differences in following behavior, all the car-following time series, except data collected at night, were categorized into each day under the two different roadways. Rush hour data for Monday and Tuesday on I-295 were not available in the data collected, and no data were available for Monday on I-495.

As shown in Figures 63 and 64, the following distances increase as speed increases by each day for both roadways, which is expected. One can easily identify that there are significant variations in following distances across days and it is more evident in non-rush hour periods, compared to rush hour periods for both roadways. There could be various explanations for these differences. On Fridays, for example, tend to be more early weekend travelers than normal, which might offset some amount of commuter familiarity. In the Washington, D.C. area, it is common for federal government employees to work only 9 days every two weeks, with Friday the most common "compressed day." It is not possible to test any of these hypotheses using the data sources from this dissertation, and this would be extremely difficult in any event. It must suffice, therefore, to observe the results but without a clear causal relationship.

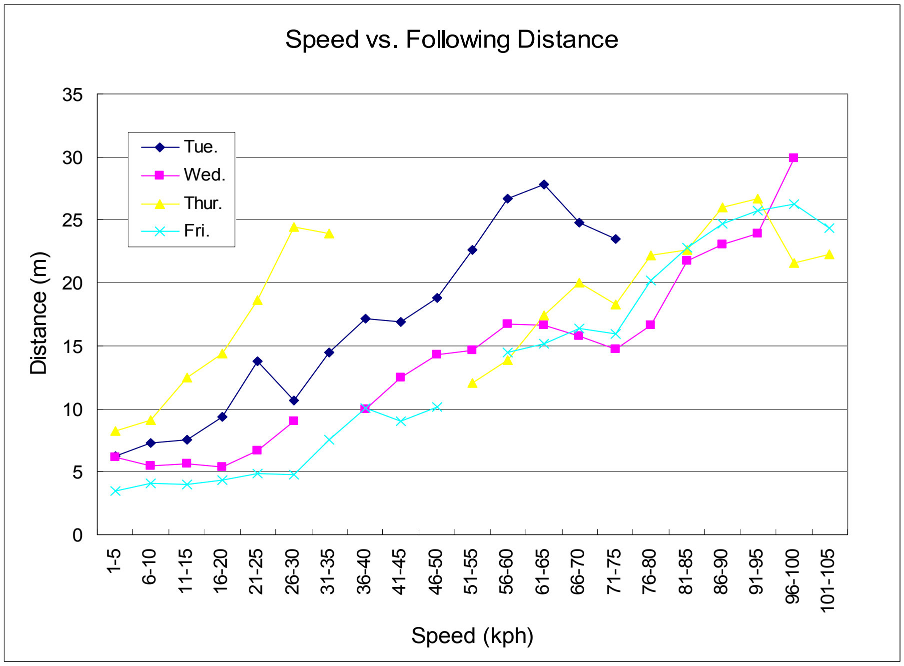


(a) Non-rush hour

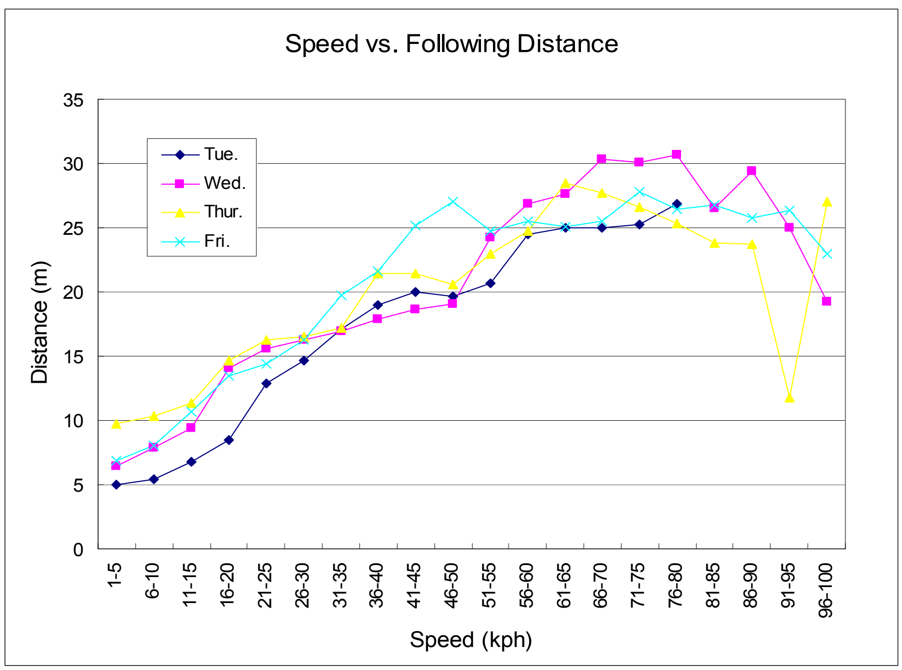


(b) Rush hour

Figure 63. Speed vs. following distance by days on I-295



(a) Non-rush hour



(b) Rush hour

Figure 64. Speed vs. following distance by days on I-495

5.2.6 Gender

There might be different driving behavior between male and female drivers. To identify these differences, we extracted car-following time series in which we could visually distinguish the gender of the drivers. Only autos were considered in this analysis since all the truck drivers were male, and differences between trucks and autos would confound the results. Furthermore, drivers doing some in-vehicle activities such as telephoning and talking were excluded to remove the effects of other distractions to the following drivers. These effects are studied in the next section. Therefore, 44 time series for male and 20 time series for female were considered in this analysis.

Figure 65 shows the difference in following distances between male and female drivers along the whole speed range. It seems visually that there are no differences at lower speed ranges, but perhaps clear differences exist for speeds greater than 40 km/h. However, the F-test results of one-way ANOVA in Table 13 show that there are no significant differences in following distance at significance level 0.05 for most of the speed range, except for the speed range from 81 to 85 km/h. It is interesting from Figure 66 that the standard deviations of following distance of male drivers at each speed range are generally larger than those of female drivers, with very few exceptions, which indicates that male drivers have more variability in keeping desired following distance than female drivers. Of course, the data contain no additional factors that might suggest causal relations, and it is unwise to speculate.

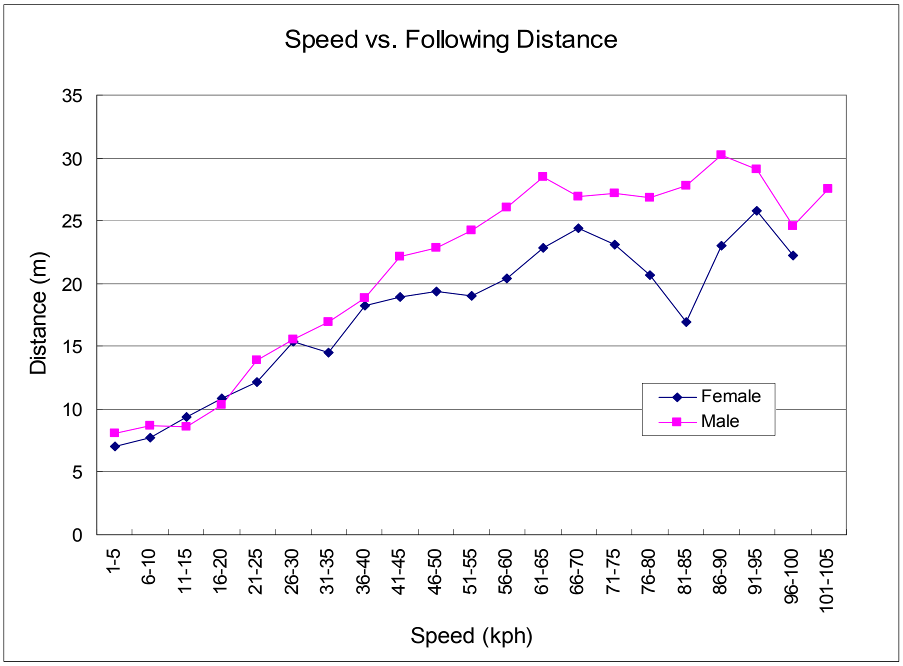


Figure 65. Speed vs. following distance by gender

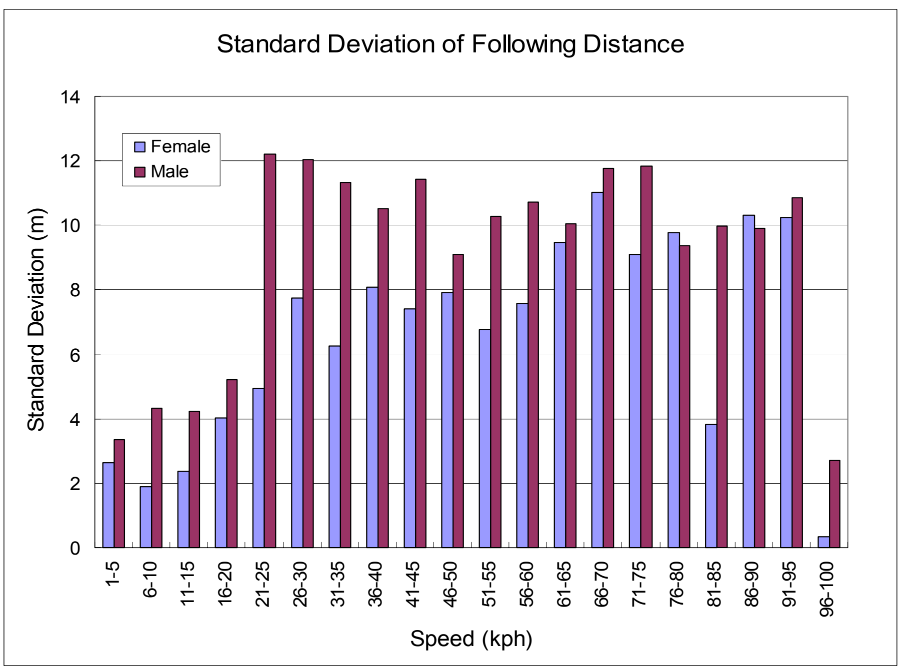


Figure 66. Standard deviations of following distances by gender

Table 13. ANOVA: effect of gender on car-following behavior

Speed Range	d.f	Sample Size		F	P-value
		Female	Male		
1-5	1, 10	7	5	0.352	0.5662
6-10	1, 12	8	6	0.324	0.5797
11-15	1, 15	8	9	0.176	0.6811
16-20	1, 19	9	12	0.064	0.8026
21-25	1, 22	10	14	0.170	0.6841
26-30	1, 23	11	14	0.003	0.9574
31-35	1, 21	10	13	0.355	0.5575
36-40	1, 23	11	14	0.030	0.8632
41-45	1, 21	9	14	0.569	0.4590
46-50	1, 22	10	14	0.949	0.3406
51-55	1, 24	12	14	2.249	0.1468
56-60	1, 25	10	17	2.138	0.1561
61-65	1, 25	12	15	2.177	0.1526
66-70	1, 26	10	18	0.313	0.5807
71-75	1, 27	7	22	0.711	0.4066
76-80	1, 31	7	26	2.347	0.1357
81-85	1, 30	5	27	5.588	0.0248
86-90	1, 26	4	24	1.800	0.1913
91-95	1, 16	4	14	0.285	0.6010
96-100	1, 2	2	2	13.235	0.0679

5.2.7 Distraction factors

While following a lead vehicle, various environmental conditions (or distraction factors) exhibited in the following vehicle such as occupancy and telephoning. Vehicle occupancy could be a potential distraction to the driver of the following vehicle, which may influence car-following behavior and driving safety. One could hypothesize that drivers with passengers allow greater distances in passive recognition of their own distraction, they feel more responsible for safe driving with passengers on board, etc. Of course, none of these can be readily tested. In order to investigate the effect of vehicle occupancy on the car-following behavior, we considered only auto car-following time series in which we can clearly see the inside of vehicle and distinguish the number of people. Also, drivers who have other distraction factors such as telephoning were not considered in this analysis. To keep things simple, we have only distinguished between drivers driving alone and those with passengers in the car. Therefore, 64 time series with driving alone and 9 time series with passengers in the car were extracted for this analysis.

Figures 67 shows the differences in following distances according to the number of people in the car. It seems visually that there are not much differences in the following distances between the two groups, except for several speed ranges. Hence, one-way ANOVA was used to identify statistically the differences in following distances. Table 14 shows the F-test results, in which there are no significant differences in following distances at significance level 0.05 along the whole speed range. Figure 68 shows the standard deviation of following distances partitioned by occupancy. In general, the standard deviations of following distances increase with speed for both situations. However, it is interesting that the standard deviations with greater occupancy are nearly uniformly smaller than those with less occupancy for most speed ranges. This finding suggests that although there are no significant differences in choosing desired following distances between two groups, they are more careful and cautious to the change of the lead vehicle. Hence, they react very promptly to the action of the lead vehicle, which may result in decreasing variability in choosing following distances.

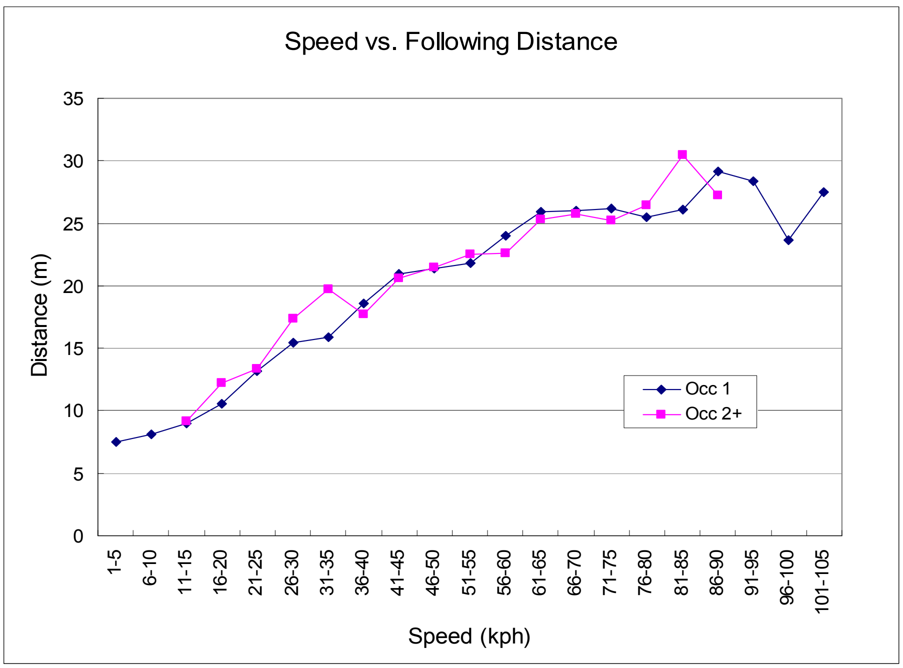


Figure 67. Speed vs. following distance by occupancy

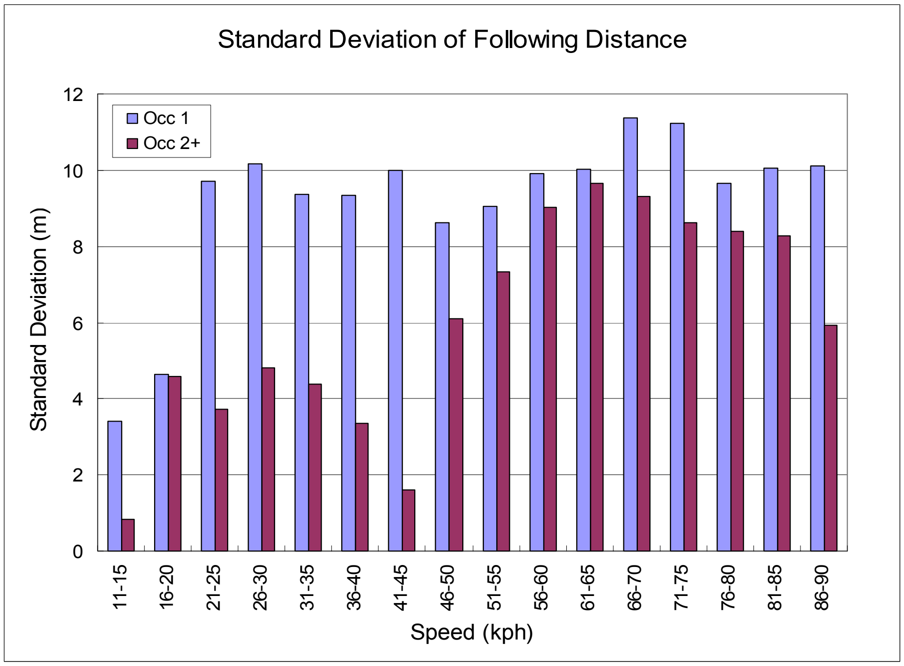


Figure 68. Standard deviations of following distances by occupancy

Table 14. ANOVA: effect of different occupancy on car-following behavior

Speed Range	d.f	Sample Size		F	P-value
		Occ 1	Occ 2+		
11-15	1, 18	17	3	0.012	0.9137
16-20	1, 24	21	5	0.523	0.4766
21-25	1, 27	24	5	0.001	0.9695
26-30	1, 28	25	5	0.169	0.6845
31-35	1, 26	23	5	0.790	0.3821
36-40	1, 27	25	4	0.032	0.8589
41-45	1, 25	23	4	0.004	0.9474
46-50	1, 27	24	5	0.0002	0.9887
51-55	1, 29	26	5	0.028	0.8688
56-60	1, 30	27	5	0.084	0.7737
61-65	1, 32	27	7	0.025	0.8764
66-70	1, 33	28	7	0.003	0.9546
71-75	1, 33	29	6	0.037	0.8477
76-80	1, 37	33	6	0.054	0.8173
81-85	1, 34	32	4	0.701	0.4083
86-90	1, 28	28	2	0.071	0.7914

The following deals with a similar subject, but with different distraction factor, i.e., telephoning activity while following the lead vehicle. The car-following time series in which we can identify the in-vehicle activities and distinguish telephoning activity were extracted and drivers who have other distraction factors except telephoning were excluded. Therefore, 9 time series for driving with telephoning activity and 64 time series for driving without telephoning were considered in this analysis. As shown in Figures 69, while there are small differences in following distances between driving with telephoning and without telephoning along the whole speed range, there is no general trend between the two situations. The drivers who are telephoning perhaps take relatively larger following distances for some speed ranges, especially lower speed ranges, but take smaller following distances for some speed ranges. The F-test results of the one-way ANOVA in Table 15 suggest that there are no significant differences in following distances at significance level 0.05 along the whole speed range. Figure 70 compares the standard deviations of following distances between the two situations. Interestingly, the same result as with occupancy occurs here. The standard deviations with telephoning activity are smaller than without telephoning for most speed ranges. This finding again suggests that drivers with more distractions like telephoning are more careful and attentive to the situations of the lead vehicle, react very quickly to the change of the lead vehicle, and furthermore try to stay in relatively stable following distances. Of course, this defies the conventional wisdom concerning the distractive influence of telephoning, and other data suggest that accidents are more likely with such activity than without (Alm and Nilsson, 1995).

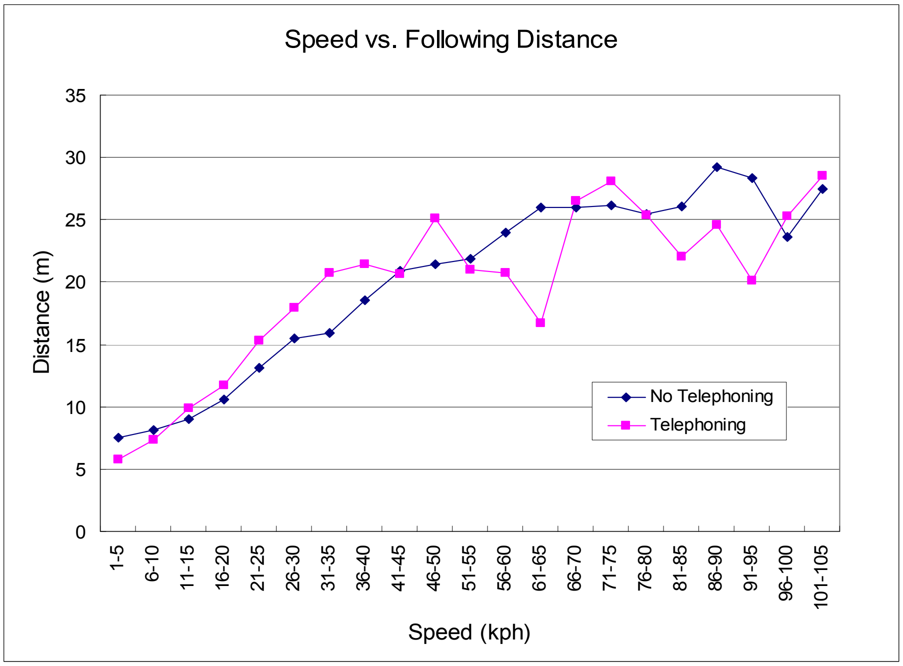


Figure 69. Speed vs. following distance by telephoning activity

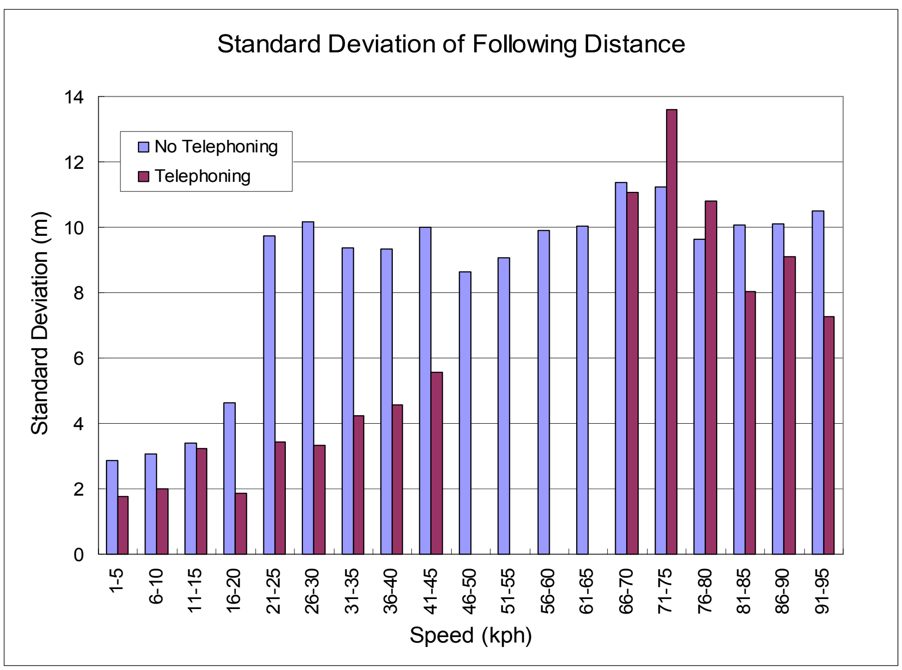


Figure 70. Standard deviations of following distances by telephoning activity

Table 15. ANOVA: effect of telephoning activity on car-following behavior

Speed Range	d.f	Sample Size		F	P-value
		No Telephoning	Telephoning		
1-5	1, 12	12	2	0.676	0.4269
6-10	1, 15	14	3	0.205	0.6568
11-15	1, 19	17	4	0.218	0.6462
16-20	1, 24	21	5	0.288	0.5966
21-25	1, 27	24	5	0.236	0.6310
26-30	1, 28	25	5	0.277	0.6029
31-35	1, 26	23	5	1.244	0.2749
36-40	1, 28	25	5	0.434	0.5153
41-45	1, 25	23	4	0.003	0.9592
46-50	1, 23	24	1	0.174	0.6802
51-55	1, 25	26	1	0.008	0.9279
56-60	1, 26	27	1	0.103	0.7510
61-65	1, 26	27	1	0.824	0.3724
66-70	1, 28	28	2	0.004	0.9528
71-75	1, 29	29	2	0.054	0.8172
76-80	1, 34	33	3	0.0003	0.9855
81-85	1, 34	32	4	0.592	0.4471
86-90	1, 30	28	4	0.743	0.3956
91-95	1, 19	18	3	1.680	0.2104
96-100	1, 4	5	1	0.447	0.5403

5.2.8 Time of day (day vs. night)

There might be different driver behavior and traffic characteristics between day and night. One would normally expect that low visibility at night would greatly increase the following distance, compared to daytime. The effect of time of day on car-following behavior was investigated. Car-following time series under non-rush hours were considered and categorized into the two groups as day and night. Especially, night time data collection worked poorly because the headlights interfaced with the infrared sensor. Therefore, some of the data in various time series collected at night were missing or had unreasonable values. Hence, relatively small numbers of time series were available, compared to those at daytime. Therefore, 38 time series for night and 84 time series for day were considered in this analysis. Figures 71 and 72 show the differences in following distances and time gaps between day and night. We can easily identify the differences in the following distances between day and night along the whole speed range, except for the lowest speed ranges from 1 to 25 km/h. Table 16 shows the one-way ANOVA results in which the differences in the following distances between day and night are statistically significant at significance level 0.05 for the higher speed ranges, particularly over 40 km/h. Figure 73 shows the standard deviation of following distances between day and night in each speed range. In general, the standard deviations of following distances increase as speed increases for both day and night. The standard deviations during the night are smaller than those during the day at lower speed regions below 75 km/h, while a different trend exists at higher speed regions over 75 km/h. We hypothesize from this result that drivers are more careful while following the lead vehicle and more sensitive to the action of the lead vehicle at night. Hence, they will react promptly to the acceleration or deceleration of the lead vehicle, especially at lower speed ranges since it is easier for drivers to estimate the distance to the lead vehicle and keep their desired following distance because of the shorter inter-vehicle distance. However, at higher speeds, it becomes more difficult to accurately estimate the distance and keep the desired following distance at night, which may increase variability in choosing desired following distances.

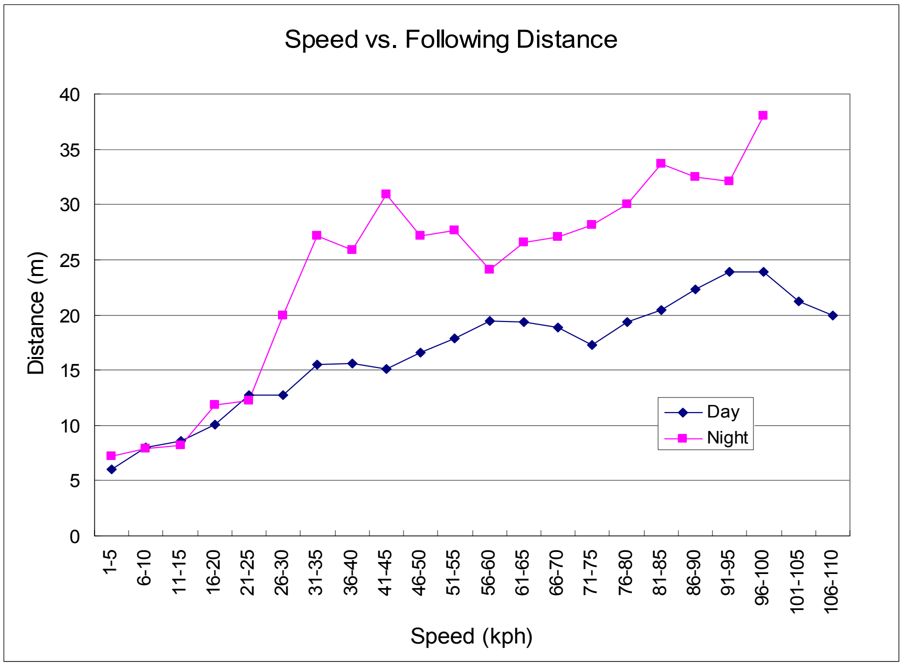


Figure 71. Speed vs. following distance by time of day

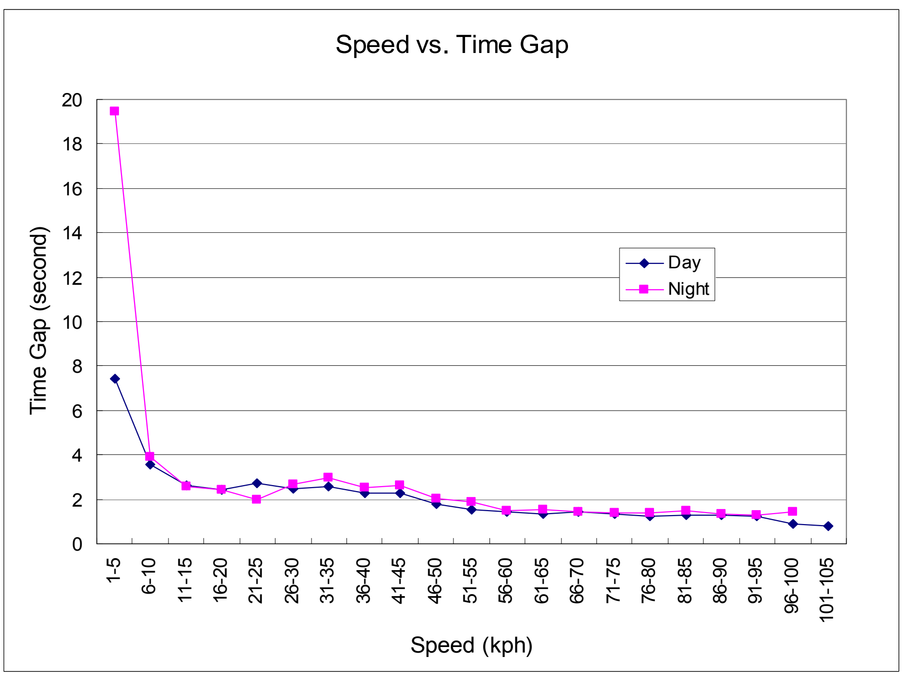


Figure 72. Speed vs. time gaps by time of day

Table 16. ANOVA: effect of time of day on car-following behavior

Speed Range	d.f	Sample Size		F	P-value
		Day	Night		
1-5	1, 9	8	3	0.492	0.5006
6-10	1, 13	12	3	0.002	0.9663
11-15	1, 15	14	3	0.036	0.8525
16-20	1, 15	15	2	0.262	0.6164
21-25	1, 17	16	3	0.014	0.9057
26-30	1, 15	15	2	1.870	0.1916
31-35	1, 13	14	1	2.169	0.1646
36-40	1, 12	12	2	4.098	0.0658
41-45	1, 14	14	2	10.952	0.0052
46-50	1, 16	14	4	5.871	0.0276
51-55	1, 16	14	4	5.897	0.0273
56-60	1, 21	15	8	2.029	0.1691
61-65	1, 29	20	11	7.551	0.0102
66-70	1, 42	21	23	10.247	0.0026
71-75	1, 49	25	26	20.241	4.21E-05
76-80	1, 74	46	30	28.303	1.06E-06
81-85	1, 82	55	29	47.967	8.93E-10
86-90	1, 78	60	20	29.518	6.11E-07
91-95	1, 64	56	10	10.620	0.0018
96-100	1, 31	32	1	4.567	0.0406

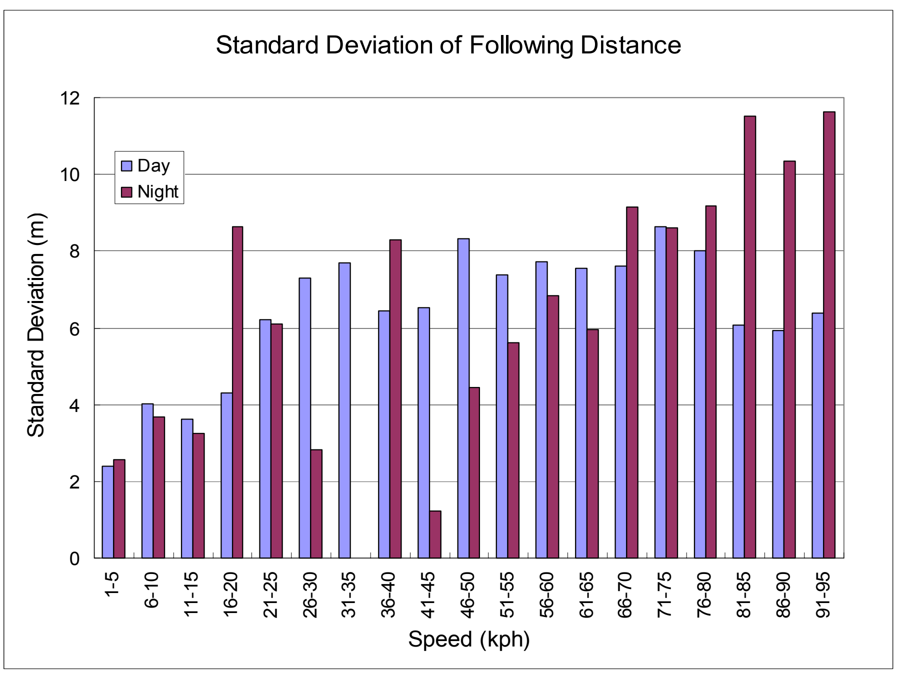


Figure 73. Standard deviations of following distances by time of day

5.2.9 Weather conditions (dry vs. wet)

It is common that drivers take more caution while driving under adverse weather conditions than under normal conditions. Hence, there might be some differences in following behavior between dry and wet conditions. Since we did not collect any other data under weather conditions such as ice or snow, only data in rainy condition were considered in this analysis. During the data collection under rainy weather, there was a limitation that the infrared range sensor performance reduced drastically when obstacles such as mud or water drops stuck on the windows of the range sensor, especially under heavy rain. Therefore, some of the data in various time series were missing or had unreasonable values. Hence, only small numbers of time series in rainy condition were available for data analysis. As the data in rainy condition were collected only on I-495 during non-rush hour periods, only car-following time series on I-495 under non-rush periods were considered. As a result, 3 time series in rainy condition and 37 time series in dry condition were extracted. Figures 74 and 75 show the differences in following distances and time gaps between dry and wet conditions. It is visually very clear that there are significant differences in the following distances and time gaps between dry and wet conditions along the whole speed range, except for the speed ranges from 1 to 5 km/h in the figure 75. This result seems to suggest that drivers in rainy conditions tend to have larger following distances (or longer time gaps) than under dry conditions. However, no solid inferences can be drawn from this result, since very fewer data points were available in rainy condition.

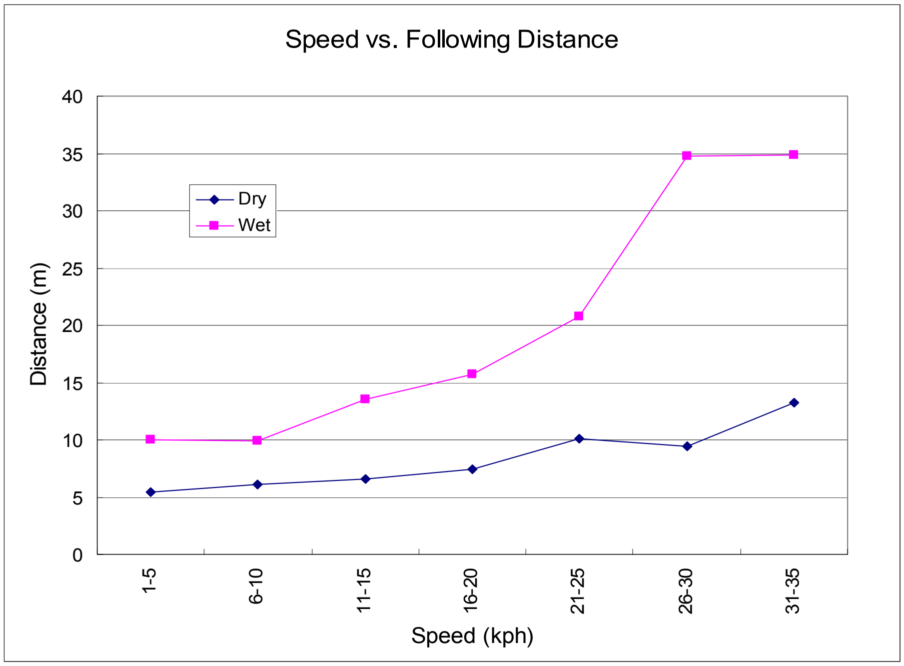


Figure 74. Speed vs. following distance by weather conditions

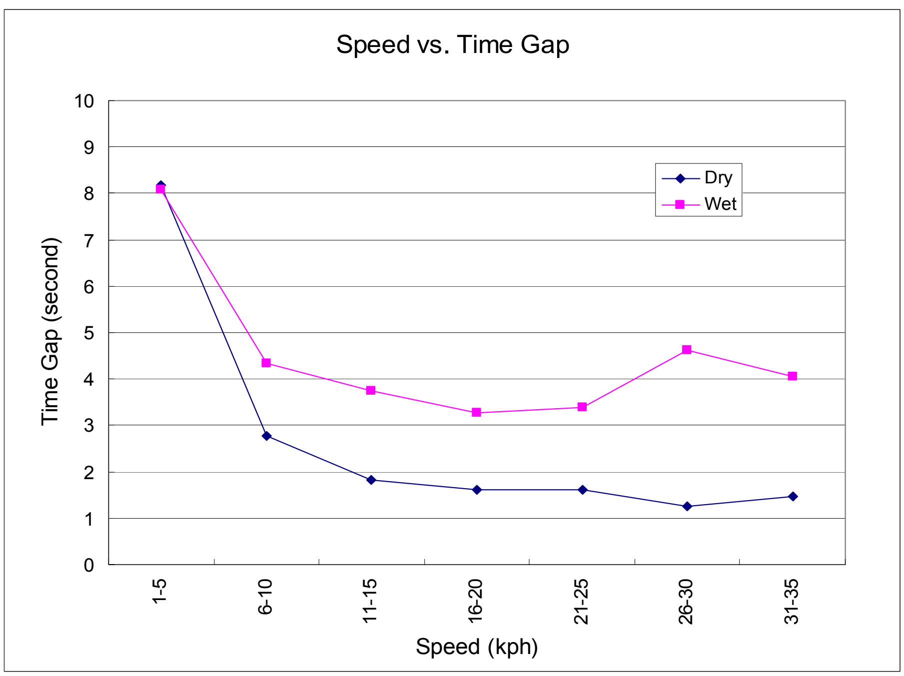


Figure 75. Speed vs. time gaps by weather conditions

Chapter 6: Conclusions

The main goal of this dissertation has been to contribute to the better understanding of car-following behavior, and more specifically, on the variability in car-following behavior that is commonly observed in naturalistic driving situations. Efforts have been made to disclose the problems and the limitations in previous experimental studies and models on car-following behavior, to build a new data collection system, including hardware and software architectures, and to investigate and discover the characteristics of real driving behavior while following a lead vehicle.

6.1 Summary of Research Findings

This dissertation includes a thorough review of the literature in this area. Chapter 2 describes some important limitations of current car-following experimental studies and models, which make them inconsistent with naturalistic driving behavior under car-following situations. Due to the absence of modern technologies at the time the previous car-following models were developed, the research approach adopted in most previous car-following models was to propose an extremely simple and uniform model of driver response (such as collision avoidance or maintaining safe following distances), and then to use the necessarily crude experimental methods of the time to calibrate the small number of parameters involved in the model. Furthermore, only certain elements, such as relative speed and spacings, have been considered as causal mechanisms, although there are numerous other factors besides basic kinematics that influence car-following behavior. Therefore, it is in question whether the car-following behavior adopted by the above research approach, is in any way "natural." In particular, there are not enough modern data sets collected under appropriate experimental conditions to make this determination. As a result, limitations in the kinds and amounts of data that could be collected made it more reasonable to conjecture a simple model form, and then to use limited data to calibrate that model. However, it was possible in this dissertation to collect better data and to let these data speak for themselves, without the temptation necessarily to hasten to simple models.

The design of experimental studies in existing car-following models had the obvious weakness that it could not capture what normal drivers do under normal conditions. The knowledge gained from those limitations in the design of experimental studies made it possible to propose a new data collection system that can overcome shortcomings of previous data collection methods. Section 2.4 shows that it is essential to investigate sequences of car motions for determining following behavior rather than instantaneous states because the most natural following response differ, depending on how that state was reached. This is in contrast to current car-following models, treat the dynamic evolution of cars at a given state as a "memoryless" process.

Chapter 3 describes a new data collection system using an instrumented test vehicle, equipped with four sets of measurement instrumentation (e.g., infrared radar sensor (the type normally used for ACC), DGPS/inertial Distance Measuring Instrument, vehicle computer, and video camera). Furthermore, a synchronized user interface program incorporated with two separate CAN networks has been developed to check the status of each device and concurrently store the information transferred from each device to the laptop computer. This chapter also offers several issues concerning the feasibility of the data collection apparatus. In particular, some issues were highlighted concerning the rear-facing infrared radar sensor, because the sensor originally was developed for looking forward. The preliminary test, regarding the proper height and working offset (or angle) of the sensor was conducted to investigate reliable radar returns from following vehicles and to determine which distance away from the lead vehicle will generate reliable radar returns from following vehicles, i.e., a limitation on traffic density conditions for properly designing the experimental studies that need to take place in real traffic conditions. Section 3.3 describes some geometric analysis of the specific circumstances under which the range sensor used in this study can be obfuscated at curve transitions. These results are valid for data collection purposes similar to those described in this study, as well as when the sensor is used in its intended application as a forward-facing rage sensor for adaptive cruise control (ACC).

While developing and testing the new data collection system for the purpose of our research, a preliminary survey was conducted to observe real car-following behavior on roadways and furthermore to identify driving maneuvers that would be observed in car-following situations. Some findings from the preliminary survey were described in Section 4.1 of Chapter 4. From the preliminary survey, we had better understanding for real car-following behavior under naturalistic driving situations. In addition, it gave us some insights on how to design the data collection plan, such as the data list to be observed, including some important causal factors, which can affect car-following behavior, and strategies to better capture driver human characteristics using digital video camera. This chapter also presents the field data collection with the new data collection system. The field data collection was conducted over ten days during rush and non-rush hour periods on freeways, including I-495 and I-295 near the Washington D.C. area. A total of 301 car-following time series with an average length of 99 seconds were collected. Section 4.2 shows a summary of baseline statistics that characterize in various ways the data collected through the field measurements. The detailed information such as duration of time, human, traffic and roadway characteristics, and environmental conditions for each car-following time series were summarized in Appendix A.

Chapter 5 describes the research findings through the data analysis for the collected car-following time series data. Basically, time series data collected by the DMI and infrared radar sensor were regenerated to calculate the speed, acceleration or deceleration, and spacing between the lead and following vehicles. These data were used, in conjunction with video records and additional information such as type of roadway, geometric condition, congestion level, and weather condition, etc., to investigate driving behavior of the following vehicles, to distinguish the relationships between various causal factors and the following vehicles' behavior, and to categorize the range of each critical factor based on the differences of behavioral characteristics. Section 5.1 presents some findings related to behavioral characteristics in car-following behavior under naturalistic driving conditions. There was an oscillatory (or "drift") process in car-following behavior, which appears as a sequence of parabolic shapes in keeping desired following distance. This pattern was typical of the majority of leader-follower interactions captured in these experiments. It was also shown that traffic hysteresis exists in car-following behavior, which is the phenomenon that drivers' acceleration and deceleration have different speed-density curves and in which the phase trajectories form a hysteresis loop.

There were significant variations in following distances across different drivers. This result suggests that the desired following distance is an individual driver characteristic and that what drivers believe to be safe following distances vary. It confirms that each individual driver has his or her own driving rule, rather than keeping a deterministic and strict driving law. It was also found that although an individual driver has his own driving behavior or attribute, the following distance for the individual driver differs over time and space under different driving maneuvers and conditions, such as traffic, geometric, or environmental conditions.

Drivers behave differently under different driving maneuvers, although they have exactly the same (current) instantaneous states, such as speeds of the lead and following vehicles and following distances. It was also found that the reactions of the following vehicle caused by the same driving maneuvers in car-following situations repeat themselves over time and space, which indicates that car-following behavior for a driver is a series of common following vehicle's reactions under the various driving maneuvers. Those results gave us insights that it is more important to investigate sequences of car motions for determining following behavior than instantaneous states. This type of information should help guide the construction of more realistic car-following models.

Section 5.2 describes the effects of various causal factors, such as human characteristics, traffic and road characteristics, and environmental characteristics, on the car-following behavior and the statistical differences in following behavior. It was evident from the analysis that different traffic and road characteristics, such as vehicle type (e.g., auto vs. truck), number of lanes (e.g., 4 lanes vs. 2 lanes), the location of the driving lane (e.g., lane 1 vs. lane 2 on I-295), and traffic condition (rush vs. non-rush) have different effects on car-following behavior. Clear differences in following distances and time gaps between different traffic and road characteristics were found visually. Moreover, ANOVA confirmed that a large number of there were statistically the differences in following behavior. For example, truck drivers were more careful when driving behind a lead vehicle because trucks commonly have longer stopping distance than auto, and the response of truck to the action of the lead vehicle was slower than the auto, i.e., trucks accelerated or decelerated slowly because of the poorer operating capabilities than autos. Drivers had a tendency to have relatively larger following distances or longer time gaps in rush hour periods, compared to car-following in non-rush hours, under the situations in which there are relatively heavy traffic and more possibility for the lead vehicle to accelerate or decelerate suddenly because of the unstable traffic conditions in rush hours.

Obviously, different human characteristics, such as gender (e.g., male vs. female) and distraction factors (e.g., occupancy or in-vehicle activities like telephoning), had different effects on car-following behavior. From the data analysis, it was found that the standard deviations of following distance of male drivers at each speed range were generally larger than those of female drivers along most speed ranges, which suggests that male drivers have more variability in keeping desired following distance than female drivers. For the effects of distraction factors, it was found that although there are no significant differences in choosing desired following distances between drivers with more occupancy or telephoning activity and those with less occupancy or no telephoning activity, drivers with more distractions are more careful and attentive to the situations of the lead vehicle, react very quickly to the change of the lead vehicle, and furthermore try to stay in relatively stable following distances, which may result in decreasing variability in choosing following distances.

Different environmental characteristics, such as time of day (e.g., day vs. night) and weather (dry vs. wet), had different effects on car-following behavior. It should be noted that the performance of infrared sensor was drastically reduced when data collection was conducted under bad weather conditions like rain because water drops stuck on the window of infrared sensor. Therefore, some of data points in time series were missing or had unreasonable values. Moreover, night time data collection worked poorly because the headlights of the following vehicle interfered with the infrared sensor. The results of the data analysis demonstrated that there were statistically clear differences in following distances between day and night for the higher speed ranges, particularly over 40 km/h, which is expected. It was also shown that drivers under rainy condition tend to have larger following distances (or longer time gaps) than under dry condition, because drivers take more caution while driving under adverse weather conditions than under normal conditions.

6.2 Future Research

This research has sought a greater understanding of driving behavior while following a lead vehicle in car-following situations. This study has also examined the effects of various causal factors on car-following behavior. We hope that the findings of this dissertation will provide clues to guide the construction of more realistic car-following models. This should help improve the realism of microscopic traffic simulators, for which car-following logic is the core, with new high-fidelity data, and it might also be used to develop more appropriate ACC algorithms and control strategies.

Further research needs to be followed to examine whether the research findings from this dissertation are transferable to car-following behavior in other areas. More data collection and analysis with different locations or roadways is required to address the above issue. It is possible to evaluate and validate numerous previous car-following models, making use of the new high-fidelity field data, since most previous models were developed with the necessarily crude experimental methods of the time to calibrate the small number of parameters involved in the model. It is necessary to investigate special cases of car-following, which were not dealt with in this dissertation, such as the process of cut-in of a new lead vehicle between a stable following pair, and its effects on the following driver. An adequate description of this process may have instant application in the design of devices such as ACC or control algorithms.

Finally, one of the important contributions of this dissertation is the development of a method to collect high-resolution driving behavior data using contemporary technology. We believe that this approach is realistic, accurate, and relatively inexpensive and may be the only method that can produce a sufficient quality and quantity of data on real driving behavior. The instrumented test vehicle designed in this dissertation should be deployed in a wide range of experiments for a better understanding of the dynamic characteristics of traffic flow, including lane changing and stop/go traffic.

Appendix A.

Summary of car-following data sets

Summary of car-following data set (12/09/04)

No.	Time period	Duration (sec.)	Human characteristics			Traffic and road characteristics					Environmental characteristics			Note
			Gender	Occup-ancy	In-vehicle Activity	Vehicle type	Driving lane #	# of lanes	Traffic condition	Road type	Weather condition	Time of day	Day of week	
1	13:33:35 – 13:34:45	71	N/A	N/A	N/A	Truck	2	4	Low	I-495	Dry	Day	Thur.	①
2	13:38:07 – 13:39:11	65	N/A	N/A	N/A	Auto	3	4	Heavy	I-495	Wet (Rain)	Day	Thur.	⑤
3	13:42:12 – 13:42:50	39	N/A	N/A	N/A	Truck	2	4	Heavy	I-495	Wet (Rain)	Day	Thur.	②
4	13:44:39 – 13:45:52	74	N/A	N/A	N/A	Bus	1	4	Heavy	I-495	Wet (Rain)	Day	Thur.	②

Note: Causes of terminating car-following situation

① Case 1: lane changing of following vehicle

② Case 2: cut-in of new lead vehicle

③ Case 3: too far following distance

④ Case 4: lane changing (or exit) of lead vehicle

⑤ Case 5: infrared sensor capability degradation caused by sunlight, headlight at night and adverse weather such as rain

⑥ Case 6: dropout of infrared sensor in curve sections

⑦ Case 7: complete stop of following vehicle under heavy congested condition

Summary of car-following data set (12/13/04)

No.	Time Period	Duration (sec.)	Human characteristics			Traffic and road characteristics					Environmental characteristics			Note
			Gender	Occup-ancy	In-vehicle Activity	Vehicle type	Driving lane #	# of lanes	Traffic condition	Road type	Weather condition	Time of day	Day of week	
1	15:30:24 – 15:33:12	169	N/A	N/A	N/A	Auto	1	2	Low	I-295	Dry	Day	Mon.	①
2	15:33:52 – 15:34:41	50	N/A	N/A	N/A	Auto	1	2	Low	I-295	Dry	Day	Mon.	③
3	15:34:59 – 15:36:24	86	N/A	N/A	N/A	Auto	1	2	Low	I-295	Dry	Day	Mon.	③
4	15:37:00 – 15:40:08	189	N/A	N/A	N/A	Van	2	2	Low	I-295	Dry	Day	Mon.	③
5	15:40:37 – 15:43:56	200	N/A	N/A	N/A	Van	2	2	Low	I-295	Dry	Day	Mon.	③
6	15:46:13 – 15:49:24	192	N/A	N/A	N/A	Truck	1	2	Low	I-295	Dry	Day	Mon.	⑤
7	16:04:52 – 16:08:03	192	N/A	N/A	N/A	Auto	2	2	Low	I-295	Dry	Day	Mon.	③
8	16:09:02 – 16:15:38	398	N/A	N/A	N/A	Auto	2	2	Low	I-295	Dry	Day	Mon.	①
9	16:16:02 – 16:17:30	89	N/A	N/A	N/A	Auto	2	2	Low	I-295	Dry	Day	Mon.	③

Summary of car-following data set (12/14/04)

No.	Time period	Duration (sec.)	Human characteristics			Traffic and road characteristics					Environmental characteristics			Note
			Gender	Occup-ancy	In-vehicle Activity	Vehicle type	Driving lane #	# of lanes	Traffic condition	Road type	Weather condition	Time of day	Day of week	
1	15:04:32 – 15:05:15	44	N/A	N/A	N/A	Van	2	2	Low	I-295	Dry	Day	Tue.	⑤
2	15:09:32 – 15:10:40	69	N/A	N/A	N/A	Auto	1	2	Low	I-295	Dry	Day	Tue.	③
3	15:25:56 – 15:26:56	61	N/A	N/A	N/A	Van	1	2	Low	I-295	Dry	Day	Tue.	③
4	15:27:34 – 15:29:55	142	N/A	N/A	N/A	Van	1	2	Low	I-295	Dry	Day	Tue.	③
5	15:46:43 – 15:47:55	73	N/A	N/A	N/A	Auto	1	4	Heavy	I-495	Dry	Day	Tue.	①
6	15:48:16 – 15:49:50	95	N/A	N/A	N/A	Auto	1	4	Heavy → Low	I-495	Dry	Day	Tue.	④
7	15:50:02 – 15:50:50	49	N/A	N/A	N/A	Truck	2	4	Heavy → Low	I-495	Dry	Day	Tue.	①
8	15:51:07 – 15:54:02	176	N/A	N/A	N/A	Auto	2	4	Heavy	I-495	Dry	Day	Tue.	①
9	15:54:32 – 15:55:30	59	N/A	N/A	N/A	Auto	2	4	Low	I-495	Dry	Day	Tue.	①
10	15:56:44 – 15:57:33	50	N/A	N/A	N/A	Van	3	4	Heavy	I-495	Dry	Day	Tue.	①

Summary of car-following data set (12/15/04)

No.	Time period	Duration (sec.)	Human characteristics			Traffic and road characteristics					Environmental characteristics			Note
			Gender	Occup-ancy	In-vehicle Activity	Vehicle type	Driving lane #	# of lanes	Traffic condition	Road type	Weather condition	Time of day	Day of week	
1	15:06:48 – 15:09:52	185	N/A	N/A	N/A	Van	2	4	Low	I-495	Dry	Day	Wed.	⑥
2	5:12:28 – 15:13:31	64	N/A	N/A	N/A	Auto	1	4	Heavy	I-495	Dry	Day	Wed.	⑦
3	15:14:10 – 15:15:24	75	N/A	N/A	N/A	Auto	1	4	Heavy	I-495	Dry	Day	Wed.	⑤
4	15:19:13 – 15:20:18	66	N/A	N/A	N/A	Auto	2	4	Low	I-495	Dry	Day	Wed.	①
5	15:25:52 – 15:26:42	51	N/A	N/A	N/A	Auto	2	4	Low	I-495	Dry	Day	Wed.	②
6	15:26:47 – 15:27:12	26	N/A	N/A	N/A	Bus	2	4	Low	I-495	Dry	Day	Wed.	④
7	15:31:02 – 15:31:33	32	N/A	N/A	N/A	Auto	1	2	Low	I-295	Dry	Day	Wed.	①
8	15:36:06 – 15:37:45	100	N/A	N/A	N/A	Auto	2	2	Low	I-295	Dry	Day	Wed.	①
9	15:42:22 – 15:45:15	174	N/A	N/A	N/A	Truck	2	2	Heavy	I-295	Dry	Day	Wed.	①
10	15:45:25 – 15:46:58	94	N/A	1	N/A	Auto	2	2	Heavy	I-295	Dry	Day	Wed.	④
11	15:51:28 – 15:52:53	86	N/A	N/A	N/A	Auto	1	4	Low	I-495	Dry	Day	Wed.	①

Summary of car-following data set (12/16/04)

No.	Time period	Duration (sec.)	Human characteristics			Traffic and road characteristics					Environmental characteristics			Note
			Gender	Occup-ancy	In-vehicle Activity	Vehicle type	Driving lane #	# of lanes	Traffic condition	Road type	Weather condition	Time of day	Day of week	
1	13:41:55 – 13:42:39	45	N/A	1	N/A	Auto	1	4	Low	I-495	Dry	Day	Thur.	⑤
2	13:44:22 – 13:44:58	37	N/A	1	N/A	Auto	1	4	Low	I-495	Dry	Day	Thur.	②
3	13:59:37 – 14:03:40	244	N/A	1	N/A	Truck	3	4	Low	I-495	Dry	Day	Thur.	①
4	14:04:12 – 14:07:00	169	N/A	N/A	N/A	Auto	1	4	Low	I-495	Dry	Day	Thur.	①
5	14:10:22 – 14:11:05	44	N/A	N/A	N/A	Auto	2	2	Low	I-295	Dry	Day	Thur.	①
6	14:11:22 – 14:12:27	66	N/A	N/A	N/A	Van	2	2	Low	I-295	Dry	Day	Thur.	①
7	14:15:57 – 14:17:20	84	N/A	1	N/A	Van	2	3	Low	I-295	Dry	Day	Thur.	①
8	14:22:01 – 14:23:38	98	N/A	2	N/A	Auto	2	2	Low	I-295	Dry	Day	Thur.	①
9	14:24:02 – 14:24:59	58	N/A	N/A	N/A	Auto	2	2	Low	I-295	Dry	Day	Thur.	⑥
10	14:41:42 – 14:43:37	116	N/A	2	N/A	Auto	3	4	Heavy	I-495	Dry	Day	Thur.	⑤
11	14:45:27 – 14:46:37	71	N/A	N/A	N/A	Van	3	3	Heavy	I-495	Dry	Day	Thur.	⑤
12	14:48:17 – 14:49:00	44	N/A	N/A	N/A	Auto	3	4	Low	I-495	Dry	Day	Thur.	①
13	14:49:52 – 14:52:10	139	N/A	N/A	N/A	Auto	3	4	Low	I-495	Dry	Day	Thur.	①
14	14:53:01 – 14:53:37	37	N/A	N/A	N/A	Auto	2	4	Low	I-495	Dry	Day	Thur.	①

Summary of car-following data set (12/17/04)

No.	Time period	Duration (sec.)	Human characteristics			Traffic and road characteristics					Environmental characteristics			Note
			Gender	Occup-ancy	In-vehicle Activity	Vehicle type	Driving lane #	# of lanes	Traffic condition	Road type	Weather condition	Time of day	Day of week	
1	9:51:25 – 9:53:47	143	N/A	N/A	N/A	Auto	1	2	Low	I-295	Dry	Day	Fri.	④
2	9:53:53 – 9:58:33	281	N/A	N/A	N/A	Auto	2	2	Low	I-295	Dry	Day	Fri.	①
3	9:58:36 – 9:59:31	56	N/A	N/A	N/A	Auto	2	2	Low	I-295	Dry	Day	Fri.	①
4	10:00:23 – 10:00:59	37	N/A	N/A	N/A	Auto	2	2	Low	I-295	Dry	Day	Fri.	④
5	10:01:34 – 10:02:47	74	N/A	N/A	N/A	Auto	1	2	Low	I-295	Dry	Day	Fri.	①
6	10:06:34 – 10:08:40	127	N/A	N/A	N/A	Van	1	2	Low	I-295	Dry	Day	Fri.	②
7	10:08:43 – 10:09:40	58	N/A	N/A	N/A	Van	1	2	Low	I-295	Dry	Day	Fri.	①
8	10:09:51 – 10:10:34	44	N/A	N/A	N/A	Auto	1	3	Low	I-295	Dry	Day	Fri.	①
9	10:19:58 – 10:20:47	50	N/A	N/A	N/A	Auto	3	3	Low	I-295	Dry	Day	Fri.	①
10	10:21:13 – 10:22:00	48	N/A	N/A	N/A	Auto	3	3	Low	I-295	Dry	Day	Fri.	①
11	10:26:22 – 10:27:43	82	N/A	N/A	N/A	Auto	1	2	Low	I-295	Dry	Day	Fri.	④
12	10:27:48 – 10:28:28	41	N/A	N/A	N/A	Auto	2	2	Low	I-295	Dry	Day	Fri.	⑤

No.	Time period	Duration (sec.)	Human characteristics			Traffic and road characteristics					Environmental characteristics			Note
			Gender	Occup-ancy	In-vehicle Activity	Vehicle type	Driving lane #	# of lanes	Traffic condition	Road type	Weather condition	Time of day	Day of week	
13	10:51:49 – 10:53:17	89	N/A	N/A	N/A	Auto	2	2	Low	I-295	Dry	Day	Fri.	④
14	10:54:24 – 10:58:30	247	N/A	N/A	N/A	Auto	2	2	Low	I-295	Dry	Day	Fri.	①
15	10:59:24 – 11:00:28	65	N/A	1	N/A	Auto	2	2	Low	I-295	Dry	Day	Fri.	④
16	11:02:07 – 11:03:02	56	N/A	N/A	N/A	Auto	2	3	Low	I-295	Dry	Day	Fri.	①
17	11:06:22 – 11:07:30	69	N/A	N/A	N/A	Auto	2	2	Low	I-295	Dry	Day	Fri.	④
18	11:08:23 – 11:12:02	220	N/A	N/A	N/A	Auto	2	2	Low	I-295	Dry	Day	Fri.	①
19	11:12:52 – 11:14:47	116	N/A	1	N/A	Auto	2	2	Low	I-295	Dry	Day	Fri.	④
20	11:16:57 – 11:17:56	60	N/A	N/A	N/A	Truck	2	4	Low	I-495	Dry	Day	Fri.	④
21	13:27:47 – 13:28:50	64	N/A	N/A	N/A	Van	2	4	Low	I-495	Dry	Day	Fri.	①
22	13:29:57 – 13:31:45	109	N/A	N/A	N/A	Auto	3	4	Low	I-495	Dry	Day	Fri.	⑥
23	13:40:52 – 13:41:35	44	N/A	1	N/A	Auto	3	4	Low	I-495	Dry	Day	Fri.	①
24	13:45:17 – 13:46:00	44	N/A	N/A	N/A	Auto	3	4	Low	I-495	Dry	Day	Fri.	①
25	13:46:47 – 13:48:10	84	N/A	1	N/A	Auto	3	4	Low	I-495	Dry	Day	Fri.	④

No.	Time period	Duration (sec.)	Human characteristics			Traffic and road characteristics					Environmental characteristics			Note
			Gender	Occup-ancy	In-vehicle Activity	Vehicle type	Driving lane #	# of lanes	Traffic condition	Road type	Weather condition	Time of day	Day of week	
26	13:49:02 – 13:50:32	91	N/A	N/A	N/A	Auto	2	4	Low	I-495	Dry	Day	Fri.	④
27	13:53:12 – 13:54:02	51	N/A	1	N/A	Auto	3	4	Low	I-495	Dry	Day	Fri.	①
28	13:57:20 – 13:58:18	59	N/A	N/A	N/A	Van	3	4	Low	I-495	Dry	Day	Fri.	①
29	14:01:33 – 14:02:15	43	N/A	1	N/A	Auto	2	4	Low	I-495	Dry	Day	Fri.	①
30	14:09:37 – 14:10:16	40	N/A	N/A	N/A	Truck	2	4	Low	I-495	Dry	Day	Fri.	①
31	14:10:37 – 14:11:23	47	N/A	N/A	N/A	Van	2	4	Low	I-495	Dry	Day	Fri.	④
32	14:17:47 – 14:20:27	161	N/A	1	N/A	Auto	3	4	Heavy	I-495	Dry	Day	Fri.	⑦
33	14:20:45 – 14:22:10	86	N/A	1	N/A	Auto	3	4	Heavy	I-495	Dry	Day	Fri.	⑦
34	14:24:02 – 14:25:28	87	N/A	N/A	N/A	Auto	3	3	Heavy	I-495	Dry	Day	Fri.	②
35	14:25:33 – 14:28:03	151	N/A	1	N/A	Auto	3	3	Heavy	I-495	Dry	Day	Fri.	①
36	14:30:02 – 14:31:02	61	N/A	1	N/A	Auto	3	4	Low	I-495	Dry	Day	Fri.	④

Summary of car-following data set (3/15/05)

No.	Time period	Duration (sec.)	Human characteristics			Traffic and road characteristics					Environmental characteristics			Note
			Gender	Occup-ancy	In-vehicle Activity	Vehicle type	Driving lane #	# of lanes	Traffic condition	Road type	Weather condition	Time of day	Day of week	
1	17:06:10 – 17:06:51	42	N/A	1	N/A	Auto	3	4	Low	I-495	Dry	Day	Tue.	⑥
2	17:07:18 – 17:09:08	111	Female	1	Normal	Auto	3	4	Heavy	I-495	Dry	Day	Tue.	⑦
3	17:10:30 – 17:16:29	360	N/A	1	N/A	Auto	3	4	Heavy	I-495	Dry	Day	Tue.	⑥
4	17:16:44 – 17:18:08	85	N/A	1	N/A	Auto	3	4	Heavy	I-495	Dry	Day	Tue.	⑦
5	17:37:42 – 17:39:40	119	N/A	1	N/A	Auto	3	4	Heavy	I-495	Dry	Day	Tue.	②
6	17:39:47 – 17:41:20	94	N/A	N/A	N/A	Auto	3	4	Heavy	I-495	Dry	Day	Tue.	①
7	17:41:27 – 17:42:30	64	N/A	N/A	N/A	Auto	3	4	Heavy	I-495	Dry	Day	Tue.	①
8	17:42:37 – 17:48:55	379	N/A	1	N/A	Auto	3	4	Heavy	I-495	Dry	Day	Tue.	①
9	17:49:02 – 17:51:59	178	N/A	1	N/A	Auto	3	4	Heavy	I-495	Dry	Day	Tue.	⑦
10	17:52:15 – 17:54:16	122	N/A	1	N/A	Auto	3	4	Heavy	I-495	Dry	Day	Tue.	⑦
11	17:54:29 – 17:57:17	169	N/A	1	N/A	Auto	3	4	Heavy	I-495	Dry	Day	Tue.	⑦
12	17:57:42 – 18:00:51	190	N/A	N/A	N/A	Auto	4	4	Heavy	I-495	Dry	Day	Tue.	⑥
13	18:01:29 – 18:03:20	112	N/A	N/A	N/A	Auto	4	4	Heavy	I-495	Dry	Day	Tue.	①
14	18:04:52 – 18:07:07	136	N/A	1	N/A	Auto	4	4	Heavy	I-495	Dry	Day	Tue.	④
15	18:07:15 – 18:10:20	186	N/A	N/A	N/A	Auto	3	4	Heavy	I-495	Dry	Day	Tue.	④

No.	Time period	Duration (sec.)	Human characteristics			Traffic and road characteristics					Environmental characteristics			Note
			Gender	Occup-ancy	In-vehicle Activity	Vehicle type	Driving lane #	# of lanes	Traffic condition	Road type	Weather condition	Time of day	Day of week	
16	18:14:37 – 18:16:00	84	N/A	N/A	N/A	Auto	1	4	Heavy	I-495	Dry	Day	Tue.	⑤
17	18:17:57 – 18:19:25	89	N/A	N/A	N/A	Auto	1	4	Heavy	I-495	Dry	Day	Tue.	④
18	19:07:12 – 19:08:12	61	N/A	N/A	N/A	Auto	1	4	Heavy	I-495	Dry	Night	Tue.	⑤
19	19:10:17 – 19:10:50	34	N/A	N/A	N/A	Auto	2	4	Low	I-495	Dry	Night	Tue.	①
20	19:13:44 – 19:14:46	63	N/A	N/A	N/A	Auto	1	4	Heavy	I-495	Dry	Night	Tue.	⑤
21	19:18:07 – 19:18:40	34	N/A	N/A	N/A	Auto	1	4	Low	I-495	Dry	Night	Tue.	①
22	19:21:39 – 19:22:02	24	N/A	N/A	N/A	Auto	2	4	Low	I-495	Dry	Night	Tue.	②
23	19:28:32 – 19:29:12	41	N/A	N/A	N/A	Auto	2	4	Low	I-495	Dry	Night	Tue.	④
24	19:32:07 – 19:36:17	251	N/A	1	N/A	Auto	2	2	Low	I-295	Dry	Night	Tue.	①
25	19:37:07 – 19:42:15	309	N/A	N/A	N/A	Auto	2	2	Low	I-295	Dry	Night	Tue.	④
26	19:42:23 – 19:43:24	62	N/A	N/A	N/A	Auto	1	2	Low	I-295	Dry	Night	Tue.	⑥
27	19:43:45 – 19:45:08	84	N/A	N/A	N/A	Auto	1	2	Low	I-295	Dry	Night	Tue.	①
28	19:51:48 – 19:55:34	227	N/A	N/A	N/A	Auto	1	2	Low	I-295	Dry	Night	Tue.	①
29	20:05:51 – 20:07:10	80	N/A	N/A	N/A	Auto	2	4	Low	I-495	Dry	Night	Tue.	⑤
30	20:07:22 – 20:08:50	89	N/A	N/A	N/A	Auto	2	4	Low	I-495	Dry	Night	Tue.	⑥

No.	Time period	Duration (sec.)	Human characteristics			Traffic and road characteristics					Environmental characteristics			Note
			Gender	Occup-ancy	In-vehicle Activity	Vehicle type	Driving lane #	# of lanes	Traffic condition	Road type	Weather condition	Time of day	Day of week	
31	20:10:39 – 20:12:24	106	N/A	N/A	N/A	Truck	2	4	Low	I-495	Dry	Night	Tue.	①
32	20:17:47 – 20:18:32	46	N/A	N/A	N/A	Auto	2	4	Low	I-495	Dry	Night	Tue.	⑥
33	20:18:46 – 20:21:47	182	N/A	1	N/A	Auto	2	4	Low	I-495	Dry	Night	Tue.	④

Summary of car-following data set (3/16/05)

No.	Time period	Duration (sec.)	Human characteristics			Traffic and road characteristics					Environmental characteristics			Note
			Gender	Occup-ancy	In-vehicle Activity	Vehicle type	Driving lane #	# of lanes	Traffic condition	Road type	Weather condition	Time of day	Day of week	
1	7:21:09 – 7:22:08	60	N/A	N/A	N/A	Auto	2	2	Low	I-295	Dry	Day	Wed.	④
2	7:22:57 – 7:25:20	144	N/A	N/A	N/A	Auto	1	2	Low	I-295	Dry	Day	Wed.	④
3	7:25:30 – 7:28:40	191	N/A	N/A	N/A	Bus	2	2	Low	I-295	Dry	Day	Wed.	①
4	7:28:57 – 7:30:47	111	N/A	N/A	N/A	Auto	2	2	Low	I-295	Dry	Day	Wed.	①
5	7:30:57 – 7:33:14	138	N/A	N/A	N/A	Auto	2	2	Low	I-295	Dry	Day	Wed.	④
6	7:37:38 – 7:38:11	34	N/A	N/A	N/A	Auto	1	2	Low	I-295	Dry	Day	Wed.	④
7	7:40:47 – 7:48:58	492	N/A	1	N/A	Auto	2	2	Heavy	I-295	Dry	Day	Wed.	②
8	7:49:04 – 7:52:23	200	N/A	N/A	N/A	Auto	2	2	Heavy	I-295	Dry	Day	Wed.	①
9	7:55:02 – 7:56:15	74	N/A	1	N/A	Auto	1	4	Low	I-495	Dry	Day	Wed.	①
10	7:58:22 – 8:00:26	125	N/A	N/A	N/A	Auto	3	4	Heavy	I-495	Dry	Day	Wed.	⑦
11	8:01:47 – 8:02:56	70	N/A	1	N/A	Auto	3	4	Heavy	I-495	Dry	Day	Wed.	⑦
12	8:03:02 – 8:05:40	159	N/A	1	N/A	Auto	3	4	Heavy	I-495	Dry	Day	Wed.	⑦
13	8:06:31 – 8:07:51	81	N/A	1	N/A	Auto	3	4	Heavy	I-495	Dry	Day	Wed.	⑦
14	8:12:52 – 8:13:22	31	N/A	1	N/A	Auto	2	4	Heavy	I-495	Dry	Day	Wed.	⑤
15	8:14:32 – 8:15:35	64	N/A	1	N/A	Auto	2	4	Heavy	I-495	Dry	Day	Wed.	⑦

No.	Time period	Duration (sec.)	Human characteristics			Traffic and road characteristics					Environmental characteristics			Note
			Gender	Occup-ancy	In-vehicle Activity	Vehicle type	Driving lane #	# of lanes	Traffic condition	Road type	Weather condition	Time of day	Day of week	
16	8:16:02 – 8:19:25	204	N/A	1	N/A	Auto	2	4	Heavy	I-495	Dry	Day	Wed.	①
17	8:19:47 – 8:20:46	60	N/A	N/A	N/A	Van	2	4	Heavy	I-495	Dry	Day	Wed.	②
18	8:24:00 – 8:25:35	96	N/A	N/A	N/A	Auto	2	4	Heavy	I-495	Dry	Day	Wed.	①
19	8:25:52 – 8:26:53	62	N/A	N/A	N/A	Auto	2	4	Heavy	I-495	Dry	Day	Wed.	④
20	8:41:28 – 8:42:13	46	N/A	N/A	N/A	Auto	2	4	Low	I-495	Dry	Day	Wed.	②
21	8:45:52 – 8:46:55	64	N/A	N/A	N/A	Auto	1	4	Low	I-495	Dry	Day	Wed.	②
22	16:22:30 – 16:23:29	60	N/A	N/A	N/A	Auto	1	2	Heavy	I-295	Dry	Day	Wed.	⑦
23	16:23:35 – 16:24:45	72	N/A	N/A	N/A	Auto	1	2	Heavy	I-295	Dry	Day	Wed.	②
24	16:24:52 – 16:25:53	62	N/A	1	N/A	Auto	1	2	Heavy	I-295	Dry	Day	Wed.	②
25	16:26:01 – 16:27:36	96	N/A	N/A	N/A	Auto	1	2	Heavy	I-295	Dry	Day	Wed.	⑦
26	16:27:51 – 16:32:23	263	N/A	N/A	N/A	Auto	1	2	Heavy	I-295	Dry	Day	Wed.	⑦
27	16:32:25 – 16:35:35	190	N/A	N/A	N/A	Auto	1	2	Heavy	I-295	Dry	Day	Wed.	②
28	16:36:53 – 16:37:39	47	N/A	N/A	N/A	Auto	1	2	Heavy	I-295	Dry	Day	Wed.	④
29	16:37:47 – 16:40:39	173	N/A	N/A	N/A	Auto	2	2	Heavy	I-295	Dry	Day	Wed.	⑤
30	16:41:05 – 16:41:46	42	N/A	N/A	N/A	Auto	2	2	Low	I-295	Dry	Day	Wed.	①

No.	Time period	Duration (sec.)	Human characteristics			Traffic and road characteristics					Environmental characteristics			Note
			Gender	Occup-ancy	In-vehicle Activity	Vehicle type	Driving lane #	# of lanes	Traffic condition	Road type	Weather condition	Time of day	Day of week	
31	16:43:34 – 16:49:40	367	N/A	N/A	N/A	Auto	1	2	Heavy	I-295	Dry	Day	Wed.	④
32	16:51:46 – 16:53:30	105	N/A	N/A	N/A	Auto	1	2	Low	I-295	Dry	Day	Wed.	①
33	16:53:47 – 16:56:43	177	N/A	N/A	N/A	Auto	1	2	Low	I-295	Dry	Day	Wed.	②
34	17:04:04 – 17:05:23	80	N/A	N/A	N/A	Auto	1	2	Low	I-295	Dry	Day	Wed.	⑤
35	17:08:17 – 17:08:56	40	N/A	1	N/A	Auto	2	4	Heavy	I-495	Dry	Day	Wed.	②
36	17:09:17 – 17:09:43	27	N/A	1	N/A	Auto	3	4	Heavy	I-495	Dry	Day	Wed.	②
37	17:09:47 – 17:10:40	54	N/A	1	N/A	Auto	3	4	Heavy	I-495	Dry	Day	Wed.	①
38	17:10:57 – 17:11:42	46	N/A	1	N/A	Auto	3	4	Low	I-495	Dry	Day	Wed.	⑥
39	17:12:26 – 17:13:38	73	N/A	1	N/A	Auto	3	4	Low	I-495	Dry	Day	Wed.	④
40	17:13:45 – 17:14:15	31	N/A	N/A	N/A	Auto	4	4	Low	I-495	Dry	Day	Wed.	①
41	17:15:02 – 17:17:30	149	N/A	1	N/A	Auto	4	4	Low	I-495	Dry	Day	Wed.	④
42	17:17:56 – 17:19:31	96	N/A	N/A	N/A	Truck	3	4	Heavy	I-495	Dry	Day	Wed.	⑦
43	17:20:12 – 17:21:58	107	N/A	1	N/A	Auto	3	4	Heavy	I-495	Dry	Day	Wed.	⑥
44	17:22:11 – 17:23:03	53	N/A	1	N/A	Auto	3	4	Heavy	I-495	Dry	Day	Wed.	④
45	17:26:20 – 17:27:17	58	N/A	N/A	N/A	Auto	1	4	Heavy	I-495	Dry	Day	Wed.	②

No.	Time period	Duration (sec.)	Human characteristics			Traffic and road characteristics					Environmental characteristics			Note
			Gender	Occup-ancy	In-vehicle Activity	Vehicle type	Driving lane #	# of lanes	Traffic condition	Road type	Weather condition	Time of day	Day of week	
46	17:27:32 – 17:28:52	81	N/A	1	N/A	Auto	1	4	Heavy	I-495	Dry	Day	Wed.	⑥
47	17:29:59 – 17:30:40	42	N/A	1	N/A	Auto	1	4	Low	I-495	Dry	Day	Wed.	②
48	17:31:07 – 17:33:05	119	N/A	1	N/A	Auto	1	4	Heavy	I-495	Dry	Day	Wed.	①
49	17:33:27 – 17:34:53	27	N/A	1	N/A	Auto	2	4	Heavy	I-495	Dry	Day	Wed.	⑤
50	17:35:41 – 17:36:47	67	N/A	N/A	N/A	Auto	3	4	Heavy	I-495	Dry	Day	Wed.	⑤
51	17:38:12 – 17:39:01	50	N/A	1	N/A	Auto	4	4	Low	I-495	Dry	Day	Wed.	⑤
52	17:39:42 – 17:43:12	211	N/A	1	N/A	Auto	2	4	Heavy	I-495	Dry	Day	Wed.	④
53	17:43:19 – 17:45:28	130	N/A	N/A	N/A	Auto	3	4	Heavy	I-495	Dry	Day	Wed.	①
54	17:47:24 – 17:48:19	56	N/A	N/A	N/A	Auto	1	4	Heavy	I-495	Dry	Day	Wed.	②
55	17:55:28 – 17:56:14	47	N/A	N/A	N/A	Auto	2	4	Low	I-495	Dry	Day	Wed.	②
56	17:59:37 – 18:01:02	86	N/A	1	N/A	Auto	1	4	Heavy	I-495	Dry	Day	Wed.	②
57	18:01:12 – 18:01:47	36	N/A	1	N/A	Van	1	4	Low	I-495	Dry	Day	Wed.	④

Summary of car-following data set (3/17/05)

No.	Time period	Duration (sec.)	Human characteristics			Traffic and road characteristics					Environmental characteristics			Note
			Gender	Occupancy	In-vehicle Activity	Vehicle type	Driving lane #	# of lanes	Traffic condition	Road type	Weather condition	Time of day	Day of week	
1	16:18:52 – 16:20:39	108	N/A	N/A	N/A	Auto	1	4	Heavy	I-495	Dry	Day	Thur.	②
2	16:22:12 – 16:23:31	80	Male	1	Normal	Auto	1	4	Heavy	I-495	Dry	Day	Thur.	①
3	16:24:15 – 16:25:55	101	Male	1	Telephoning	Auto	2	4	Heavy	I-495	Dry	Day	Thur.	②
4	16:26:55 – 16:28:15	81	Male	1	Normal	Truck	3	4	Heavy	I-495	Dry	Day	Thur.	②
5	16:29:40 – 16:30:54	75	Male	1	Telephoning	Auto	4	4	Low	I-495	Dry	Day	Thur.	④
6	16:32:34 – 16:33:37	64	Male	1	Normal	Truck	1	4	Heavy	I-495	Dry	Day	Thur.	②
7	16:34:38 – 16:36:40	123	Male	1	Normal	Auto	2	4	Heavy	I-495	Dry	Day	Thur.	①
8	16:37:39 – 16:38:33	55	Male	1	Telephoning	Auto	4	4	Low	I-495	Dry	Day	Thur.	④
9	16:38:39 – 16:39:55	77	Male	1	Normal	Auto	3	4	Low	I-495	Dry	Day	Thur.	④
10	16:42:27 – 16:43:18	52	Female	1	Normal	Auto	2	2	Heavy	I-295	Dry	Day	Thur.	⑦
11	16:43:31 – 16:47:07	217	Female	1	Normal	Auto	2	2	Heavy	I-295	Dry	Day	Thur.	⑦
12	16:47:59 – 16:48:58	60	Female	1	Telephoning	Van	1	2	Heavy	I-295	Dry	Day	Thur.	⑦
13	16:49:06 – 16:50:23	78	Female	1	Telephoning	Van	1	2	Heavy	I-295	Dry	Day	Thur.	④
14	16:50:29 – 16:52:37	129	Female	1	Normal	Van	2	2	Heavy	I-295	Dry	Day	Thur.	②
15	16:52:42 – 16:53:38	57	Female	2	Talking	Auto	2	2	Heavy	I-295	Dry	Day	Thur.	①

No.	Time period	Duration (sec.)	Human characteristics			Traffic and road characteristics					Environmental characteristics			Note
			Gender	Occup-ancy	In-vehicle Activity	Vehicle type	Driving lane #	# of lanes	Traffic condition	Road type	Weather condition	Time of day	Day of week	
16	16:54:14 – 16:54:53	40	Female	1	Normal	Auto	2	2	Low	I-295	Dry	Day	Thur.	①
17	16:59:00 – 17:03:00	241	Male	1	Normal	Van	2	2	Heavy	I-295	Dry	Day	Thur.	①
18	17:03:27 – 17:04:20	54	Male	1	Normal	Auto	1	2	Low	I-295	Dry	Day	Thur.	④
19	17:04:29 – 17:05:07	39	Male	1	Normal	Auto	2	2	Low	I-295	Dry	Day	Thur.	①
20	17:09:12 – 17:10:34	83	Male	1	Normal	Auto	2	2	Low	I-295	Dry	Day	Thur.	②
21	17:10:39 – 17:12:27	109	Male	1	Normal	Auto	1	2	Low	I-295	Dry	Day	Thur.	①
22	17:13:05 – 17:16:14	190	Male	1	Normal	Auto	2	2	Low	I-295	Dry	Day	Thur.	①
23	17:16:22 – 17:16:54	33	Male	1	Normal	Auto	2	2	Low	I-295	Dry	Day	Thur.	②
24	17:17:59 – 17:20:37	159	Male	3	Talking	Van	2	2	Low	I-295	Dry	Day	Thur.	④
25	17:20:42 – 17:23:49	188	Female	1	Normal	Auto	1	2	Heavy	I-295	Dry	Day	Thur.	③
26	17:25:00 – 17:26:10	71	Male	1	Normal	Truck	2	4	Heavy	I-495	Dry	Day	Thur.	②
27	17:26:57 – 17:29:05	129	Male	1	Normal	Auto	2	4	Low	I-495	Dry	Day	Thur.	④
28	17:32:18 – 17:32:50	33	Male	1	Normal	Auto	3	4	Low	I-495	Dry	Day	Thur.	①
29	17:35:12 – 17:36:08	57	Male	2	Talking	Auto	1	4	Low	I-495	Dry	Day	Thur.	⑥
30	17:41:55 – 17:43:53	119	Male	1	Normal	Auto	2	4	Low	I-495	Dry	Day	Thur.	④

No.	Time period	Duration (sec.)	Human characteristics			Traffic and road characteristics					Environmental characteristics			Note
			Gender	Occup-ancy	In-vehicle Activity	Vehicle type	Driving lane #	# of lanes	Traffic condition	Road type	Weather condition	Time of day	Day of week	
31	17:44:05 – 17:45:07	63	Male	1	Normal	Truck	1	4	Heavy	I-495	Dry	Day	Thur.	③
32	17:47:09 – 17:47:49	41	Male	1	Normal	Auto	1	4	Heavy	I-495	Dry	Day	Thur.	③
33	17:50:26 – 17:50:58	33	Female	1	Normal	Auto	3	4	Heavy	I-495	Dry	Day	Thur.	①
34	17:53:02 – 17:55:53	172	Female	1	Normal	Auto	1	4	Heavy	I-495	Dry	Day	Thur.	⑦
35	17:58:32 – 17:59:35	64	Female	1	Normal	Auto	2	4	Heavy	I-495	Dry	Day	Thur.	③
36	19:00:08 – 19:00:43	36	N/A	N/A	N/A	Auto	1	4	Low	I-495	Dry	Night	Thur.	①
37	19:03:17 – 19:04:26	70	N/A	1	N/A	Auto	2	4	Low	I-495	Dry	Night	Thur.	⑤
38	19:08:46 – 19:09:14	29	N/A	N/A	N/A	Auto	1	4	Heavy	I-495	Dry	Night	Thur.	⑤
39	19:11:32 – 19:12:45	74	N/A	2	N/A	Auto	2	4	Low	I-495	Dry	Night	Thur.	⑥
40	19:20:17 – 19:21:05	48	N/A	N/A	N/A	Bus	3	4	Low	I-495	Dry	Night	Thur.	②
41	19:21:09 – 19:23:30	142	N/A	N/A	N/A	Truck	2	4	Heavy	I-495	Dry	Night	Thur.	①
42	19:24:45 – 19:26:22	98	N/A	N/A	N/A	Auto	3	4	Heavy	I-495	Dry	Night	Thur.	⑤
43	19:27:16 – 19:29:01	106	N/A	N/A	N/A	Auto	2	4	Low	I-495	Dry	Night	Thur.	④
44	19:37:37 – 19:39:41	125	N/A	N/A	N/A	Auto	3	4	Low	I-495	Dry	Night	Thur.	⑤
45	19:43:29 – 19:45:43	135	N/A	N/A	N/A	Auto	2	2	Low	I-295	Dry	Night	Thur.	①

No.	Time period	Duration (sec.)	Human characteristics			Traffic and road characteristics					Environmental characteristics			Note
			Gender	Occup-ancy	In-vehicle Activity	Vehicle type	Driving lane #	# of lanes	Traffic condition	Road type	Weather condition	Time of day	Day of week	
46	19:45:52 – 19:47:33	102	N/A	1	N/A	Auto	1	2	Low	I-295	Dry	Night	Thur.	②
47	19:49:44 – 19:50:57	74	N/A	N/A	N/A	Auto	2	2	Low	I-295	Dry	Night	Thur.	④
48	19:51:52 – 19:52:59	68	N/A	N/A	N/A	Auto	2	2	Low	I-295	Dry	Night	Thur.	④
49	19:55:20 – 19:55:55	36	N/A	N/A	N/A	Auto	2	2	Low	I-295	Dry	Night	Thur.	①
50	19:56:52 – 19:58:15	84	N/A	N/A	N/A	Auto	1	2	Low	I-295	Dry	Night	Thur.	④
51	20:02:51 – 20:05:38	167	N/A	N/A	N/A	Auto	1	2	Low	I-295	Dry	Night	Thur.	①
52	20:06:16 – 20:07:31	76	N/A	N/A	N/A	Auto	1	2	Low	I-295	Dry	Night	Thur.	⑤
53	20:07:42 – 20:08:25	44	N/A	N/A	N/A	Auto	1	2	Low	I-295	Dry	Night	Thur.	①
54	20:09:30 – 20:10:47	78	N/A	N/A	N/A	Auto	1	2	Low	I-295	Dry	Night	Thur.	④
55	20:10:53 – 20:12:31	99	N/A	1	N/A	Auto	2	2	Low	I-295	Dry	Night	Thur.	⑤
56	20:17:22 – 20:18:35	74	N/A	1	N/A	Auto	3	4	Low	I-495	Dry	Night	Thur.	⑤
57	20:19:45 – 20:20:53	69	N/A	1	N/A	Auto	3	4	Low	I-495	Dry	Night	Thur.	⑤

Summary of car-following data set (3/18/05)

No.	Time Period	Duration (sec.)	Human characteristics			Traffic and road characteristics					Environmental characteristics			Note
			Gender	Occup-ancy	In-vehicle Activity	Vehicle type	Driving lane #	# of lanes	Traffic condition	Road type	Weather condition	Time of day	Day of week	
1	7:51:44 – 7:53:15	92	Male	2	Talking	Auto	1	4	Low	I-495	Dry	Day	Fri.	①
2	7:55:14 – 7:56:22	69	Male	1	Normal	Auto	3	4	Low	I-495	Dry	Day	Fri.	④
3	7:56:29 – 7:56:55	27	Male	1	Normal	Truck	2	4	Low	I-495	Dry	Day	Fri.	①
4	7:57:54 – 7:58:42	49	Male	1	Normal	Truck	1	4	Low	I-495	Dry	Day	Fri.	②
5	8:01:04 – 8:02:20	77	Female	1	Normal	Auto	2	4	Heavy	I-495	Dry	Day	Fri.	②
6	8:02:42 – 8:04:37	116	Female	2	Talking	Auto	3	4	Low	I-495	Dry	Day	Fri.	④
7	8:04:42 – 8:05:33	52	Male	1	Normal	Auto	2	4	Low	I-495	Dry	Day	Fri.	①
8	8:06:54 – 8:07:27	34	Male	1	Normal	Auto	1	2	Low	I-295	Dry	Day	Fri.	⑥
9	8:08:24 – 8:11:26	183	Male	1	Telepho-ning	Auto	2	2	Low	I-295	Dry	Day	Fri.	④
10	8:11:32 – 8:13:53	142	Male	1	Normal	Auto	1	2	Low	I-295	Dry	Day	Fri.	④
11	8:13:59 – 8:14:47	49	Male	1	Taking Coffee	Auto	2	2	Low	I-295	Dry	Day	Fri.	②
12	8:14:52 – 8:18:20	209	Male	1	Smoking	Auto	2	2	Low	I-295	Dry	Day	Fri.	④
13	8:19:27 – 8:20:15	49	Male	1	Normal	Auto	1	2	Low	I-295	Dry	Day	Fri.	④
14	8:24:17 – 8:26:36	140	Female	1	Normal	Auto	2	2	Low	I-295	Dry	Day	Fri.	④
15	8:28:07 – 8:29:47	101	Male	1	Normal	Auto	1	2	Low	I-295	Dry	Day	Fri.	④

No.	Time period	Duration (sec.)	Human characteristics			Traffic and road characteristics					Environmental characteristics			Note
			Gender	Occup-ancy	In-vehicle Activity	Vehicle type	Driving lane #	# of lanes	Traffic condition	Road type	Weather condition	Time of day	Day of week	
16	8:29:53 – 8:32:24	152	Male	1	Normal	Auto	2	2	Low	I-295	Dry	Day	Fri.	④
17	8:32:30 – 8:34:07	98	Male	1	Normal	Auto	1	2	Low	I-295	Dry	Day	Fri.	⑥
18	8:37:04 – 8:37:42	39	Male	1	Normal	Auto	2	4	Low	I-495	Dry	Day	Fri.	①
19	8:39:29 – 8:40:24	56	Male	1	Normal	Auto	4	4	Low	I-495	Dry	Day	Fri.	⑥
20	8:42:33 – 8:43:24	52	Male	1	Normal	Van	3	4	Heavy	I-495	Dry	Day	Fri.	②
21	8:44:35 – 8:45:11	37	Male	1	Normal	Truck	2	4	Heavy	I-495	Dry	Day	Fri.	⑥
22	8:45:59 – 8:47:08	70	Male	1	Normal	Truck	2	4	Heavy	I-495	Dry	Day	Fri.	③
23	8:48:10 – 8:49:49	100	Female	1	Normal	Auto	2	4	Heavy	I-495	Dry	Day	Fri.	②
24	8:50:25 – 8:50:59	35	Male	1	Normal	Auto	3	4	Heavy	I-495	Dry	Day	Fri.	②
25	8:59:04 – 8:59:46	43	Male	1	Normal	Auto	2	4	Low	I-495	Dry	Day	Fri.	①
26	9:03:22 – 9:03:50	29	Male	1	Normal	Truck	2	4	Low	I-495	Dry	Day	Fri.	⑥
27	9:04:18 – 9:05:07	50	Male	1	Normal	Auto	2	4	Low	I-495	Dry	Day	Fri.	①
28	9:06:02 – 9:07:22	81	Male	1	Normal	Van	3	4	Heavy	I-495	Dry	Day	Fri.	④
29	9:07:30 – 9:08:40	71	Female	1	Make-up	Auto	2	4	Heavy	I-495	Dry	Day	Fri.	④
30	9:13:22 – 9:14:07	46	N/A	N/A	N/A	Truck	3	4	Low	I-495	Dry	Day	Fri.	①

No.	Time period	Duration (sec.)	Human characteristics			Traffic and road characteristics					Environmental characteristics			Note
			Gender	Occup-ancy	In-vehicle Activity	Vehicle Type	Driving lane #	# of lanes	Traffic condition	Road type	Weather condition	Time of day	Day of week	
31	15:49:32 – 15:50:05	34	Male	1	Normal	Van	1	4	Heavy	I-495	Dry	Day	Fri.	①
32	15:50:42 – 15:53:40	179	Male	1	Normal	Auto	1	4	Heavy	I-495	Dry	Day	Fri.	②
33	15:54:27 – 15:57:32	186	Male	2	Talking	Auto	2	4	Heavy	I-495	Dry	Day	Fri.	①
34	15:58:50 – 15:59:25	36	Female	1	Normal	Auto	2	4	Low	I-495	Dry	Day	Fri.	④
35	15:59:33 – 16:00:34	62	Male	1	Normal	Auto	3	4	Heavy	I-495	Dry	Day	Fri.	①
36	16:01:04 – 16:04:30	207	Male	2	Talking	Auto	3	4	Heavy	I-495	Dry	Day	Fri.	④
37	16:04:54 – 16:05:38	45	Female	1	Normal	Auto	1	4	Low	I-495	Dry	Day	Fri.	②
38	16:07:27 – 16:10:50	204	Female	1	Normal	Van	2	4	Low	I-495	Dry	Day	Fri.	④
39	16:10:57 – 16:11:55	59	Male	1	Normal	Truck	3	4	Low	I-495	Dry	Day	Fri.	④
40	16:13:44 – 16:14:30	47	N/A	N/A	N/A	Auto	1	2	Heavy	I-295	Dry	Day	Fri.	⑤
41	16:16:35 – 16:18:17	103	Female	1	Telepho-ning	Auto	1	2	Heavy	I-295	Dry	Day	Fri.	⑦
42	16:18:59 – 16:19:30	32	Female	1	Telepho-ning	Auto	1	2	Heavy	I-295	Dry	Day	Fri.	④
43	16:19:47 – 16:20:26	40	Male	1	Normal	Bus	2	2	Heavy	I-295	Dry	Day	Fri.	⑤
44	16:20:35 – 16:21:20	36	Male	1	Normal	Bus	2	2	Heavy	I-295	Dry	Day	Fri.	②
45	16:21:25 – 16:22:12	48	Male	1	Smoking	Van	2	2	Heavy	I-295	Dry	Day	Fri.	⑦

No.	Time period	Duration (sec.)	Human characteristics			Traffic and road characteristics					Environmental characteristics			Note
			Gender	Occup-ancy	In-vehicle Activity	Vehicle type	Driving lane #	# of lanes	Traffic condition	Road type	Weather condition	Time of day	Day of week	
46	16:23:42 – 16:27:10	209	Male	1	Normal	Bus	2	2	Heavy	I-295	Dry	Day	Fri.	②
47	16:27:19 – 16:27:52	34	Female	1	Normal	Auto	2	2	Heavy	I-295	Dry	Day	Fri.	①
48	16:30:31 – 16:31:14	44	Male	1	Normal	Auto	2	2	Heavy	I-295	Dry	Day	Fri.	②
49	16:31:22 – 16:37:40	380	Female	1	Normal	Auto	2	2	Heavy	I-295	Dry	Day	Fri.	④
50	16:38:42 – 16:41:14	153	Male	1	Normal	Auto	1	2	Heavy	I-295	Dry	Day	Fri.	④
51	16:41:22 – 16:43:30	129	Male	1	Normal	Auto	2	2	Low	I-295	Dry	Day	Fri.	④
52	16:43:42 – 16:44:28	47	Male	1	Normal	Auto	1	2	Heavy	I-295	Dry	Day	Fri.	④
53	16:45:59 – 16:50:58	300	Male	1	Normal	Auto	2	2	Heavy	I-295	Dry	Day	Fri.	④
54	16:51:07 – 16:53:10	124	Male	1	Normal	Auto	1	2	Heavy	I-295	Dry	Day	Fri.	⑦
55	16:54:11 – 16:54:53	43	Female	2	Talking	Auto	2	2	Heavy	I-295	Dry	Day	Fri.	②
56	16:54:58 – 16:58:08	191	Female	1	Normal	Auto	2	2	Heavy	I-295	Dry	Day	Fri.	①
57	16:58:25 – 17:00:12	108	Female	1	Telepho-ning	Auto	2	2	Low	I-295	Dry	Day	Fri.	①
58	17:00:37 – 17:03:20	164	Male	1	Normal	Auto	1	2	Heavy	I-295	Dry	Day	Fri.	④
59	17:03:29 – 17:05:45	137	Female	2	Talking	Auto	2	2	Heavy	I-295	Dry	Day	Fri.	④
60	17:08:26 – 17:09:07	42	Male	1	Normal	Bus	1	4	Heavy	I-495	Dry	Day	Fri.	②

No.	Time period	Duration (sec.)	Human characteristics			Traffic and road characteristics					Environmental characteristics			Note
			Gender	Occup-ancy	In-vehicle Activity	Vehicle type	Driving lane #	# of lanes	Traffic condition	Road type	Weather condition	Time of day	Day of week	
61	17:10:22 – 17:10:54	32	Male	1	Normal	Bus	2	4	Heavy	I-495	Dry	Day	Fri.	②
62	17:11:07 – 17:12:58	112	Male	1	Normal	Auto	2	4	Heavy	I-495	Dry	Day	Fri.	①
63	17:13:07 – 17:13:31	25	Female	1	Normal	Auto	3	4	Low	I-495	Dry	Day	Fri.	①
64	17:17:01 – 17:19:08	128	Male	1	Normal	Auto	4	4	Low	I-495	Dry	Day	Fri.	④
65	17:19:15 – 17:19:43	29	Female	1	Normal	Auto	3	4	Low	I-495	Dry	Day	Fri.	①
66	17:24:07 – 17:25:02	56	Male	1	Normal	Auto	1	4	Heavy	I-495	Dry	Day	Fri.	④
67	17:28:00 – 17:30:21	142	Female	1	Normal	Auto	2	4	Heavy	I-495	Dry	Day	Fri.	④
68	17:31:07 – 17:34:20	194	Male	1	Normal	Truck	3	4	Heavy	I-495	Dry	Day	Fri.	②
69	17:34:25 – 17:35:30	66	Male	1	Normal	Auto	3	4	Heavy	I-495	Dry	Day	Fri.	④
70	17:35:38 – 17:37:07	90	Male	1	Normal	Van	2	4	Heavy	I-495	Dry	Day	Fri.	④

References

AASHTO (2001). A policy on geometric design of highways and streets. American Association of State Highway and Transportation Officials, Washington, D.C.

Ahmed, K. I. (1999). Modeling divers' acceleration and lane changing behavior. Sc.D. Dissertation, Massachusetts Institute of Technology, Department of Civil and Environmental Engineering, Cambridge, Massachusetts.

Ahn, S., M. J. Cassidy and J. Laval (2004). Verification of a simplified car-following theory, *Transportation Research B*, Vol. 38, 431-440.

Allen, R. W., R. E. Magdeleno, C. Serafin, S. Eckert and T. Sieja (1997). Driver car following behavior under test track and open road driving conditions. *Intelligent Transportation Systems*, Society of Automotive Engineers, 7-17.

Alm H. and L. Nilsson (1995). The effects of a mobile telephone task on driver behavior in a car following situation. *Accident Analysis and Prevention*, Vol. 27, No. 5, 707-715.

Aron, M. (1988). Car following in an urban network: simulation and experiments. Proceedings of Seminar D, 16th PTRC Meeting, 27-39.

Aycin, M. F. and R. F. Benekohal (1998). A linear acceleration car-following model development and validation. *Transportation Research Record 1644*, 10-19.

Aycin, M. F. and R. F. Benekohal (1999). Comparison of car-following models for simulation. *Transportation Research Record 1678*, 116-127.

Aycin, M. F. and R. F. Benekohal (2000). Stability and performance of car-following models in congested traffic. *Journal of Transportation Engineering*, Vol. 127, No. 1, 2-12.

Aycin, M. F. and R. F. Benekohal (2000). Longitudinal control algorithms for simulation of driver and intelligent cruise controlled vehicles. Paper presented at the 79th TRB Annual Meeting, Washington, D.C.

Bando, M., K. Hasabe, A. Nakayama, A. Shibata and Y. Sugiyama (1995). Dynamical model of traffic congestion and numerical simulation. *Physical Review E*, Vol. 51, No. 2, 1035-1042.

Bekey, G. A., G. O. Burnham and J. Seo (1977). Control theoretic models of human drivers in car following. *Human Factors*, Vol. 19, No. 4, 399-413.

Bender, J. G. and R. E. Fenton (1969). A study of automatic car following. *IEEE Transactions on Vehicular Technology*, Vol. 40, No. 1, 134-140.

Benekohal, R. F. and J. Treiterer (1988). CARSIM: car-following model for simulation of traffic in normal and stop-and-go conditions. *Transportation Research Record 1194*, 99-111.

Bexelius, S. (1968). An extended model for car following. *Transportation Research*, Vol. 2, No. 1, 13-21.

Bjornberg, A. (1994). Control design for autonomous intelligent cruise control. *IFAC Transportation Systems: Theory and Application of Advanced Technology*, Vol. 2, 835-840.

Boer, E. R. (1999). Car following from the driver's perspective. *Transportation Research F*, Vol. 2, 201-206.

Brackstone, M., B. Sultan and M. McDonald (2002). Motorway driver behaviour: studies on car-following. *Transportation Research F*, Vol. 5, 329-344.

Brackstone, M. and M. McDonald (1999). Car-following: a historical review. *Transportation Research F*, Vol. 2, 181-196.

Brackstone, M. and M. McDonald (1999). What is the answer? And come to that, what are the questions?. *Transportation Research F*, Vol. 2, 221-224.

Brackstone, M., M. McDonald and B. Sultan (1999). Dynamic behavioral data collection using an instrumental vehicle. *Transportation Research Record 1689*, 9-17.

Brill, E. A. (1972). A car-following model relating reaction times and temporal headways to accident frequency. *Transportation Science*, Vol. 6, No. 4, 343-353.

Burnham, G. O., J. Seo and G. A. Bekey (1974). Identification of human driver models in car following. *IEEE Transactions on Automatic Control*, Vol. AC-19, No. 6, 911-915.

Cassidy, M. and J. Windover (1998). Driver memory: motorist selection and retention of individualized headways in highway traffic. *Transportation Research A*, Vol. 32, 129-137.

Caudill, R. J. and W. L. Garrard (1977). Vehicle-follower longitudinal control for automated transit vehicles. *Transactions of the ASME Journal of Dynamic Systems, Measurement, and Control*, Vol. 99, 241-248.

Ceder, A. (1979). Stable phase-plane and car following behavior as applied to a macroscopic phenomenon. *Transportation Science*, Vol. 13, No. 1, 64-79.

Chakroborty, P. and S. Kikuchi (1999). Evaluation of the General Motors based car-following models and a proposed fuzzy inference model. *Transportation Research C*, Vol. 7, 209-235.

Chandler, R. E., R. Herman and E. W. Montroll (1958). Traffic dynamics: studies in car following. *Operations Research,* Vol. *6*, 165-184.

Chen, S., T. Sheridan, S. Ahn, M. Mathew, M. Kambourides, H. Kusunoki and N. Komoda (1995). Car-following behavior: effect of environment. Proceedings of the 1995 Annual Meeting of ITS America, 993-999.

Chien, C. and P. A. Ioannou (1992). Automatic vehicle following. Proceedings of the 1992 American Control Conference, Vol. 2, 1748-1752.

Chishaki, T. and Y. Tamura (1984). Headway distribution model based on the distinction between leaders and followers. Proceedings of the 9th International Symposium on Transportation and Traffic Theory, Delft University of Technology, The Netherlands, 43-63.

Cho, Minyoung, A. J. Lichtenberg and M. A. Lieberman (1996). Minimum stopping distance for linear control of an automatic car-following system. *IEEE Transactions on Vehicular Technology*, Vol. 45, No. 2, 383-390.

Chow, T. S. (1958). Operational analysis of a traffic-dynamics problem. *Operations Research,* Vol. 6, 827-834.

Chundury, S. and B. Wolshon (2000). Evaluation of the CORSIM car-following model using GPS field data. *Transportation Research Record 1710*, 114-121.

Cosgriff, R. L., J. J. English and W. B. Roeca (1966). An automatic system for longitudinal control of individual vehicles. *Highway Research Record 122*, 7-18.

Darbha, S. and K. Rajagopal (1999). Intelligent cruise control systems and traffic flow stability. *Transportation Research C*, Vol. 7, 329-352.

Darroch, J. N. and R. W. Rothery (1972). Car following and spectral analysis. Proceedings of the 5th International Symposium on Transportation and Traffic Theory, University of California, Berkeley, U.S.A., 47-56.

Del Castillo, J. M. (1996). A car following model based on the Lighthill-Whitham theory. Proceedings of the 13th International Symposium on Transportation and Traffic Theory, Lyon, France, 517-538.

Del Castillo, J. M. and F. G. Benitez (1995). On the functional form of the speed-density relationship, part I: general theory. *Transportation Research B*, Vol. 29, 373-389.

Del Castillo, J. M. and F. G. Benitez (1995). On the functional form of the speed-density relationship, part II: empirical investigation. *Transportation Research B*, Vol. 29, 391-406.

Del Castillo, J. M. and P. Pintado (1994). The reaction time of drivers and the stability of traffic flow. *Transportation Research B*, Vol. 28, 35-60.

Dijker, T., P. H. L. Bovy and R. G. M. M. Vermijs (1998). Car-following under congested conditions: empirical findings. *Transportation Research Record 1644*, 20-28.

Dijker, T., P. H. L. Bovy and R. G. M. M. Vermijs (1998). Car following behavior in different traffic flow regimes, Motorway traffic flow analysis: new methodologies and recent empirical findings. Delft University of Technology.

Disbro, J. and M. Frame (1989). Traffic flow theory and chaotic behavior. *Transportation Research Record 1225*, 109-115.

Domsch, C. and D. Sandkuhler (2000). Test procedures for ACC-sensors. Proceedings of the 7th World Congress on Intelligent Transport Systems, 1-8.

Drake, J. S., J. L. Schofer and A. D. May, Jr. (1967). A statistical analysis of speed-density hypotheses. *Highway Research Record 154*, 53-87.

Edie, L. C. (1961). Car-following and steady-state theory for non-congested traffic. *Operations Research, Vol. 9*, 66-76.

Eliasson. A. (1992). A controller for autonomous intelligent cruise control – a preliminary design. Vehicle Navigation and Information Systems, 170-175.

Evans, L. and R. W. Rothery (1973). Experimental measurements of perceptual thresholds in car-following. *Highway Research Record 464*, 13-29.

Evans, L. and R. W. Rothery (1977). Perceptual thresholds in car-following – a recent comparison. *Transportation Science*, Vol. 11, No. 1, 60-72.

Evans, L. and P. Wasielewski (1983). Risky driving related to driver and vehicle characteristics. *Accident Analysis and Prevention*, Vol. 15, 121-136.

Fancher, P. S., R. D. Ervin, J. Sayer, M. Hagan, S. Bogard, Z. Bareket, M. Mefford, and J. Haugen (1998). Intelligent cruise control field operational test (final report). University of Michigan Transportation Research Institute (UMTRI), Ann Arbor, MI.

Fancher, P. S., R. D. Ervin, Z. Bareket, G. E. Johnson, M. Trefalt, J. Tiedecke and W. Hagleitner (1994). Intelligent cruise control: performance studies based upon an operating prototype. 1993 Annual Meeting of ITS America, 391-399.

Fancher, P. S. and Z. Bareket, G. Johnson and J. Sayer (1995). Evaluation of human factors and safety performance in the longitudinal control of headway. Proceedings of the Second World Congress on Intelligent Transport Systems, Yokohama, Japan, 1732-1738.

Fenton, R. E. (1979). A headway safety policy for automated highway operations. *IEEE Transactions on Vehicular Technology*, Vol. 28, No. 1, 22-28.

Fenton, R. E. and R. J. Mayhan (1991). Automated highway studies at the Ohio State university – an overview. *IEEE Transactions on Vehicular Technology*, Vol. 40, No. 1, 100-113.

Ferrari, P. (1994). The instability of motorway traffic. *Transportation Research B,* Vol. 28, 175-186.

Forbes, T. W. and M. E. Simpson (1968). Driver and vehicle response in freeway deceleration waves. *Transportation Science*, Vol. 2, No. 1, 77-104.

Forchhammer, N. (1965). Single lane saturated flow – starting performance. Proceedings of the 2nd International Symposium on Transportation and Traffic Theory, London, England, 27-43.

Fox, P. and F. G. Lehman (1967). A digital simulation of car following and overtaking. *Highway Research Record 199*, 33-41.

Gantzer, D. and T. Rockwell (1967). Effects of discrete headway and relative velocity information on car-following performance. *Highway Research Record 159*, 36-46.

Gazis, D. C., R. Herman and R. B. Pott (1959). Car-following theory of steady-state traffic flow. *Operations Research,* Vol. 7, 499-505.

Gazis, D. C., R. Herman and W. R. Richard (1961). Nonlinear follow-the-leader models of traffic flow. *Operations Research*, Vol. 9, 545-567.

Gipps, P. G. (1981). A behavioral car following model for computer simulation. *Transportation Research B*, Vol. 15, 105-111.

Gordon, D. (1971). The driver in single lane traffic. *Highway Research Record 349*, 31-40.

Hancock, P. A. (1999). Is car following the real question – are equations the answer?. *Transportation Research F*, Vol. 2, 197-199.

Hanken, A. and T. H. Rockwell (1967). A model of car following derived empirically by piece-wise regression analysis. Proceedings of the 3rd International Symposium on Transportation and Traffic Theory, New York, U.S.A., 40-41.

Hatipkarasulu, Y., B. Wolshon and C. Quiroga (2000). Results of car-following analyses using global positioning system. *Journal of Transportation Engineering*, Vol. 126, No. 4, 324-331.

Hattori, Y., K. Asano, N. Iwama and T. Shigematsu (1995). Analysis of driver's decelerating strategy in a car-following situation. *Vehicle System Dynamics*, Vol. 24, 299-311.

Heidemann, D. (1998). On the integration of car-following equations. Third IMA International Conference on Mathematics in Transport Planning and Control, 331-339.

Helly, W. (1961). Simulation of bottleneck in single-lane traffic flow. Proceedings of the 1st International Symposium on Transportation and Traffic Theory, Warren, Michigan, U.S.A., 207-238.

Herman, R., E. W. Montroll and R. B. Potts (1959). Traffic dynamics: analysis of stability in car following. *Operations Research*, Vol. 7, 86-106.

Herman, R. and R. B. Potts (1961). Single-lane traffic theory and experiment. Proceedings of the 1st International Symposium on Transportation and Traffic Theory, Warren, Michigan, U.S.A., 120-146.

Herman, R. and R. W. Rothery (1965). Car-following and steady state flow. Proceedings of the 2nd International Symposium on Transportation and Traffic Theory, London, England, 1-11.

Herman, R. and R. W. Rothery (1967). Propagation of disturbances in vehicular platoons. Proceedings of the 3rd International Symposium on Transportation and Traffic Theory, New York, U.S.A., 14-25.

Herman, R., R. W. Rothery and R. G. Rule (1977). Analysis of car-following experiments employing spectral analysis. Proceedings of the 7th International Symposium on Transportation and Traffic Theory, Kyoto, Japan, 37-67.

Heyes, M. P. and R. Ashworth (1972). Further research on car-following models. *Transportation Research*, Vol. 6, No. 3, 287-291

Hogema, J. H. and B. V. Arem (1997). Modeling changes in driving behavior: on the effects of autonomous intelligent cruise control. Traffic and Transport Psychology: Theory and Application, 237-246.

Hogema, J. H. (1998). Modeling motorway driving behavior. *Transportation Research Record 1689*, 25-32.

Holland, E. (1998). A generalized stability criterion for motorway traffic. *Transportation Research B*, Vol. 32, 141-154.

Ioannou, P. and C. C. Chien (1993). Autonomous intelligent cruise control. *IEEE Transactions on Vehicular Technology*, Vol. 42, No. 4, 657-672.

ITS America (1997). Modeling ITS collision avoidance benefits, Expert Panel Proceedings, ITS America, Washington D.C., U.S.A.

Jagtman, H.M. and E. Wiersma (2003). Driving with adaptive cruise control in the real world. 16th ICTCT Workshop, 1-8.

Kapur, K. C. (1971). Vehicle following behavior by calculus of variations. *Transportation Research*, Vol. 5, No. 2, 69-73.

Khan, S., P. Maini and K. Thanasupsin (2000). Car-following and collision constraint models for uninterrupted traffic: reexamination using high-precision global positioning system data. *Transportation Research Record 1710*, 37-46.

Kikuchi, S. and P. Chakroborty (1992). Car following model based on fuzzy inference system. *Transportation Research Record 1365*, 82-91.

Kohler R. (1974). Stability of vehicle platoons. Proceedings of the 6th International Symposium on Transportation and Traffic Theory, Sydney, Australia, 39-55.

Kometani, E. and T. Sasaki (1959). A safety index for traffic with linear spacing. *Operations Research,* Vo1. 7, 704-720.

Kometani, E. and T. Sasaki (1961). Dynamic behavior of traffic with a non-Linear spacing-speed relationship. Proceedings of the 1st International Symposium on Transportation and Traffic Theory, Warren, Michigan, U.S.A., 105-119.

Lee, G. (1966). A generalization of linear car-following theory. *Operations Research*, Vol. 14, 595-606.

Leipnik, R. B. (1968). A solution of Pipes' vehicle following equation without lag. *Transportation Research*, Vol. 2, No. 3, 279-281.

Lovell, D. J. (1999). Automated calculation of sight distance from horizontal geometry. *ASCE Journal of Transportation Engineering*, Vol. 125, No. 4, 297-304.

Lovell, D. J., J.-C. Jong, and P. C. Chang (2001). Improvements to sight distance algorithm. *ASCE Journal of Transportation Engineering*, Vol. 127, No. 4, 283-288.

Low, D. and P. Addison (1998). The complex dynamical behavior of congested road traffic. Third IMA International Conference on Mathematics in Transport Planning and Control, 341-350.

Mahut, M. (1999). Speed maximizing car following models and macroscopic curves based on safe stopping rules. Paper presented at the 78th TRB Annual Meeting, Washington, D.C.

McMahon, D. H., V. K. Narendran, D. Swaroop and J. K Hedrick (1992). Longitudinal vehicle controllers for IVHS: theory and experiment. Proceedings of the 1992 American Control Conference Vol. 2, 1753-1757.

McDonald, M., M. A. Brackstone, B. Sultan and C. Roach (1997). Close following on the motorway: initial findings of an instrumented vehicle study. Paper presented at the 7th Vision in Vehicles Conference, Marseille, France.

May, A. D. and H. E. M. Keller (1967). Non-integer car-following models. *Highway Research Record 199*, 19-32.

Mehmood A., F. Saccomanno and B. Hellinga (2003). Application of system dynamics in car-following models. *ASCE Journal of Transportation Engineering*, Vol. 129, No. 6, 625-634.

Michaels, R. M. (1965). Perceptual factors in car following. Proceedings of the 2nd International Symposium on Transportation and Traffic Theory, London, England, 44-59.

Misener, J. A., H. S. J. Tsao, B. Song and A. Steinfeld (2000). The emergence of a cognitive car following driver model: application to rear-end crashes with a stopped lead vehicle. *Transportation Research Record 1724*, 29-38.

Newell, G. F. (1961). A theory of traffic flow in tunnels. Proceedings of the 1st International Symposium on Transportation and Traffic Theory, Warren, Michigan, U.S.A., 193-206.

Newell, G. F. (1961). Nonlinear effects in the dynamics of car following. *Operations Research*, Vol. 9, 209-229.

Newell, G. F. (1965). Instability in dense highway traffic, a review. Proceedings of the 2nd International Symposium on Transportation and Traffic Theory, London, England, 73-83.

Newell, G. F. (2002). A simplified car-following theory: a lower order model. *Transportation Research B*, Vol. 36, 195-205.

Oliver, R. M. and B. Catoire and R. S. Skeates (1965). On a mathematical function of traffic flow theory. Proceedings of the 2nd International Symposium on Transportation and Traffic Theory, London, England, 12-26.

Olson, D. E. and W. L. Garrard (1979). Model-follower longitudinal control for automated guideway transit vehicles. *IEEE Transactions on Vehicular Technology*, Vol. 28, No. 1, 36-45.

Ozaki, H. (1993). Reaction and anticipation in the car following behavior. Proceedings of the 12th International Symposium on Transportation and Traffic Theory, University of California, Berkeley, U.S.A., 349-366.

Parent, M., P. Daviet, J. C. Denis and M. Tarek (1993). Automatic stop-and-go driving in heavy traffic. 1993 Annual Meeting of ITS America, 139-143.

Peppard, L. E. and V. Gourishankar (1972). An optimal automatic car-following system. *IEEE Transactions on Vehicular Technology*, Vol. 21, No. 2, 67-73.

Piao J. and M. McDonald (2003). Low speed car following behaviour from floating vehicle data. Proceedings of the IEEE Intelligent Vehicles Symposium 2003, Columbus, Ohio, U.S.A.

Pipes, L. A. (1953). An operational analysis of traffic dynamics. *Journal of Applied Physics*, Vol. 24, No. 3, 274-281.

Pipes, L. A. (1967). Car following models and the fundamental diagram of road traffic. *Transportation Research*, Vol. 1, No. 1, 21-29.

Rajamani, R. and C. Zhu (2002). Semi-autonomous adaptive cruise control systems. *IEEE Transactions on Vehicular Technology*, Vol. 51, No. 5, 1186-1192.

Ranney, T. A. (1999). Psychological factors that influence car-following and car-following model development. *Transportation Research F*, Vol. 2, 213-219.

Reuschel, A. (1950). Vehicle movements in a platoon. *Oesterreichisches Ingenieeur-Archir*, Vol. 4, 193-215.

Rockwell, T. R. (1972). Skills, judgment, and information acquisition in driving. Human Factors in Highway Traffic Safety Research, New York, Wiley.

Rockwell, T. R., R. L. Ernst and A. Hanken (1968). A sensitivity analysis of empirically derived car following models. *Transportation Research*, Vol. 2, No. 4, 363-373.

Roess, R. P., W. R. McShane, and E. S. Prassas (1998). Traffic engineering, 2nd edition. Pearson, New York, NY.

Rothery, R. W., R. Silver, R. Herman and C. Torner (1964). Analysis of experiments on single-lane bus flow. *Operations Research*, Vol. 12, 913-933.

Ruspini, E. (1996). The semantics of approximate reasoning. C.A. Chen, ed., Fuzzy logic and neural network handbook, McGraw-Hill, New York, 5.1-5.27.

Shladover, S. E., C. A. Desoer, J. K. Hedrick, M. Tomizuka, J. Walrand, W. B. Zhang, D. H. McMahon, H. Peng, S. Shwikholeslam and N. McKeown (1991). Automatic vehicle control developments in the PATH program. *IEEE Transactions on Vehicular Technology*, Vol. 40, No. 1, 114-130.

Subramanian, H. (1996). Estimation of car-following models. Master's thesis, Massachusetts Institute of Technology, Department of Civil and Environmental Engineering, Cambridge, Massachusetts.

Tijerina L. (1995). Key human factors research needs in intelligent vehicle-highway system crash avoidance. *Transportation Research Record 1485*, 1-9.

Todosiev, E. P. and R. E. Fenton (1966). Velocity thresholds in car-following at night. *Highway Research Record 122*, 94-104.

Tolle, J. E. (1974). Composite car-following models. *Transportation Research*, Vol. 8, 91-96.

Treiterer, J. (1967). Improvement of traffic flow and safety by longitudinal control. *Transportation Research*, Vol. 1, No. 3, 231-251.

Treiterer, J. and J. A. Myers (1974). The hysteresis phenomenon in traffic flow. Proceedings of the 6th International Symposium on Transportation and Traffic Theory, Sydney, Australia, 13-38.

Tuck, E. (1961). Stability of following in two dimensions. *Operations Research*, Vol. 9, 479-495.

Unwin, E. A. and L. Duckstein (1967). Stability of reciprocal-spacing type car following models. *Transportation Science*, Vol. 1, No. 2, 95-108.

van der Horst, R. and H. Godthelp (1989). Measuring road user behavior with an instrumented car and an outside-the-vehicle video observation technique. *Transportation Research Record 1213*, 72-81.

Wang J. and R. Rajamani (2004). Should adaptive cruise-control systems be designed to maintain a constant time gap between vehicles?. *IEEE Transactions on Vehicular Technology*, Vol. 53, No. 5, 1480-1490.

Wasielewski, P. (1979). Car-following headways on freeways interpreted by the semi-poisson headway distribution model. *Transportation Science*, Vol. 13, No. 1, 36-55.

Weiss G. (1969). On the statistics of the linear car following model. *Transportation Science*, Vol. 3, No. 1, 88-89.

Wilhelm, W. and J. Schmidt (1973). Review of car-following theory. *Journal of Transportation Engineering*, Vol. 99, No. 4, 923-933.

Winsum, W. V. (1999). The human element in car following models. *Transportation Research F*, Vol. 2, 207-211.

Wolshon, B. and Y. Hatipkarasulu (2000). Results of car following analyses using global positioning system. *Journal of Transportation Engineering*, Vol. 126, No. 4, 324-331.

Xing, J. (1995). A parameter identification of a car-following model. Proceedings of the Second World Congress on Intelligent Transport Systems, Yokohama, Japan, 1739-1745.

Zhang, H. M. (1999). A mathematical theory of traffic hysteresis. *Transportation Research B*, Vol. 33, 1-23.

Zhang, H. M. and T. Kim (2005). A car-following theory for multiphase vehicular traffic flow. *Transportation Research B*, Vol. 39, 385-399.

Zhang, Y., L. E. Owen and J. E. Clark. (1998). Multiregime approach for microscopic traffic simulation. *Transportation Research Record 1644*, 103-115.

Zhang, X. and D. Jarrett (1997). Stability analysis of the classical car-following model. *Transportation Research B*, Vol. 31, 441-462.