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Driving Performance Analysis of the ACAS FOT Data and Recommendations for a Driving Workload Manager

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13. ABSTRACT ***(Maximum 200 Words)***
This report contains analyses of driving performance data from the Advanced Collision Avoidance System (ACAS) Field Operational Test (FOT), with data from nearly 100 drivers and over 100,000 miles of driving. The analyses compared normal and distracted situations and determined thresholds that distinguish between maneuvering and non-maneuvering situations.

Four questions were addressed: 1. How are measures of driver input (steering wheel angle, etc.) and vehicle output (heading, speed, etc.) distributed as a function of 4 road types [(a) ramps, (b) interstates and freeways, (c) arterials and minor arterials, and (d) collectors and local roads]? 2. What is the effect of the number of tasks on measures of driver performance as a function of road type? (The distributions for 0 and 1 tasks were similar. For 2 tasks, the range was sometimes 50% less.) 3. How well do linear thresholds distinguish between maneuvering and non-maneuvering situations, and what should those values be? (It varies with the threshold; sometimes the odds were 10:1. Other times they were 1:1.) 4. How effectively do steering and throttle entropy predict distracted and normal driving? (Only steering entropy showed any differences.)

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1 Primary Questions

Q1. How are measures of driver input (steering wheel angle, throttle position) and vehicle output (heading, speed, lateral and longitudinal acceleration) distributed as a function of road type? That is, what is the variability of normal driving?

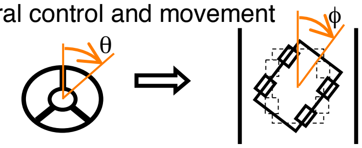
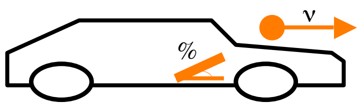
Q2. What is the effect of the number of secondary tasks (none, 1, or 2) on measures of driver performance (as listed in question 1) as a function of road type? Does performance differ as a function of the number of tasks?

Q3. What driving performance measures and thresholds are recommended for a workload manager as a function of road type to identify when the driver is maneuvering (and should not perform secondary tasks)?

Q4. How effectively do steering and throttle entropy predict distracted and normal driving? Do age, gender, and their interaction have a significant effect on steering and throttle entropy?

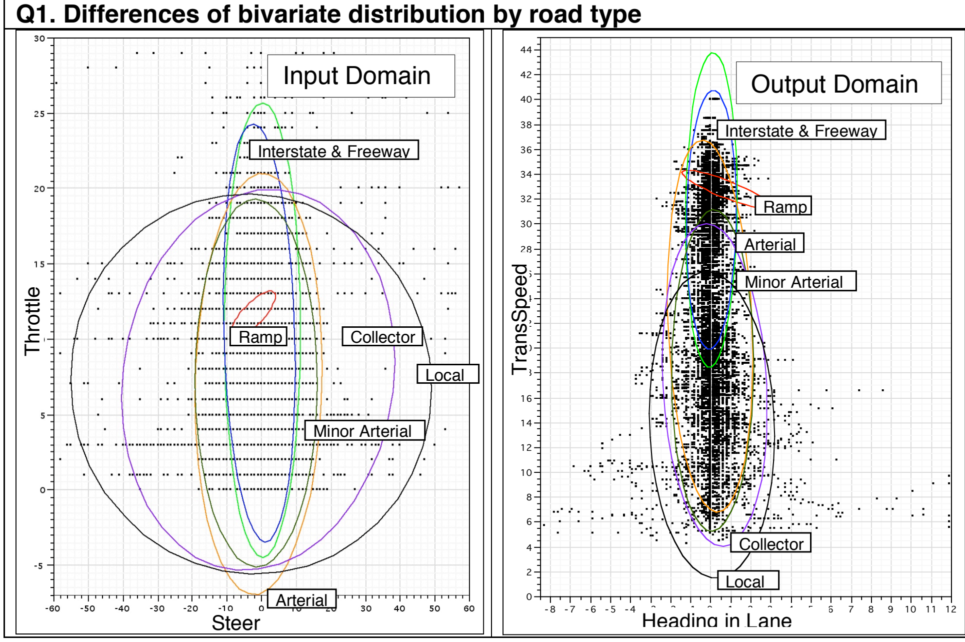
2 Methods

Data acquisition and manipulation	
* ACAS FOT data naturalistic driving 100,000 miles total * 96 drivers Equal numbers of men & women, in their 20s, 40s, and 60s	Phase 1: * 2,914 randomly selected clips of 3.8 - 4.0 s * coded for secondary task (use phone, smoke, etc.) Phase 2: * Roughly equal number of attentive and distracted driving clips (831 total clips, 15,962 frames) * Coded on a frame-by-frame basis to indicate subtask (dial a hand-held phone, groom using a tool, etc.), also direction of gaze, head orientation, etc.

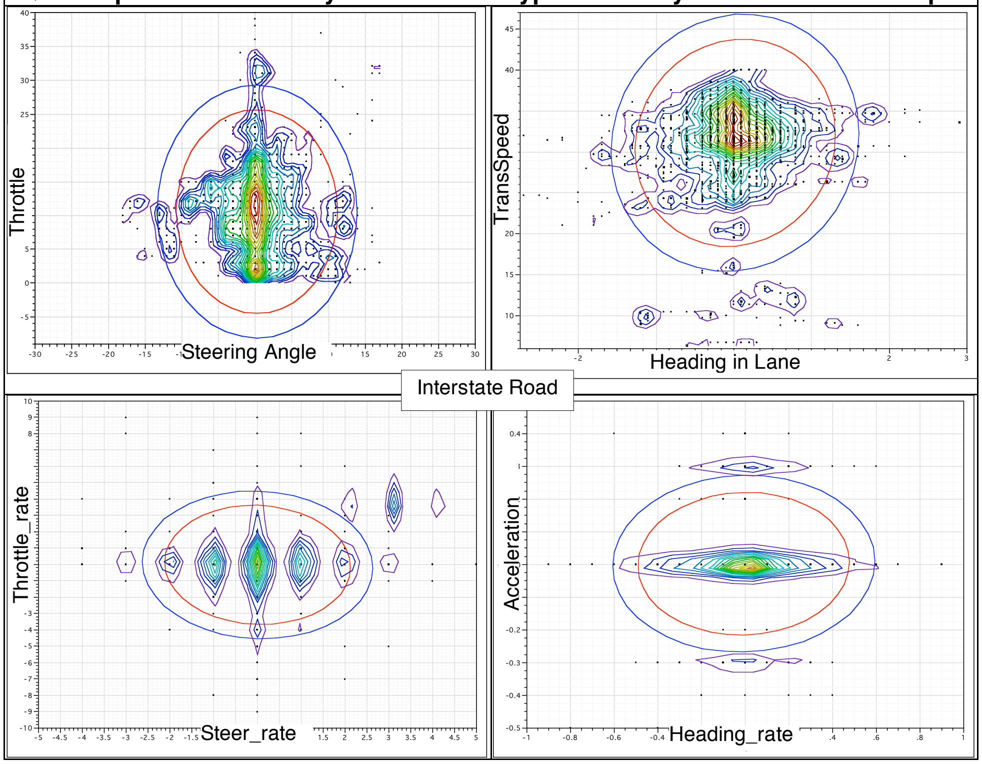
Input domain and output domain		
Lateral control and movement 	Input variable: Steering wheel angle (θ) Output variable: Heading angle (ϕ)	Both original variables and derivative variables were included.
Longitudinal control and movement 	Input variable: Throttle percentage (%) Output variable: Speed (ν)	

3 Results and Conclusions

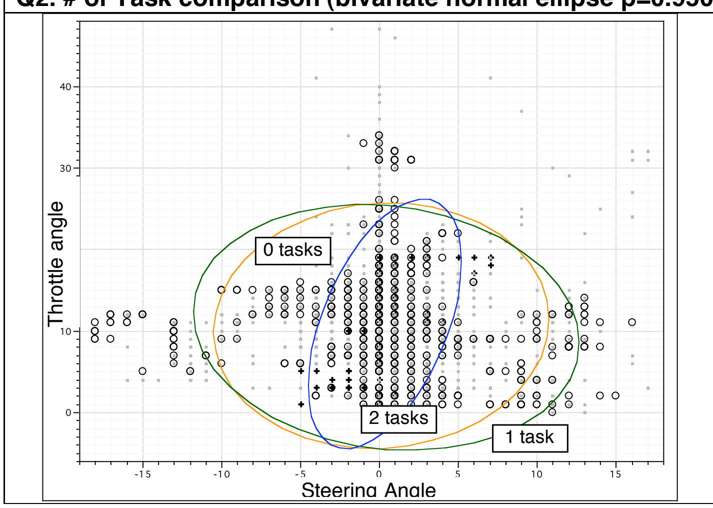
Q1. Differences of bivariate distribution by road type



Q1. Nonparametric density for each road type: Not fit by bivariate normal ellipse



Q2. # of Task comparison (bivariate normal ellipse p=0.950)



0 task (•) or 1 task (o)
: No significant difference

2 tasks (+)
: Significantly restricted steering movement
=> 2 tasks are usually performed when driver is in non-maneuvering status.

(Steer vs. throttle relationship for interstates)

Q3. Types of maneuvers detected

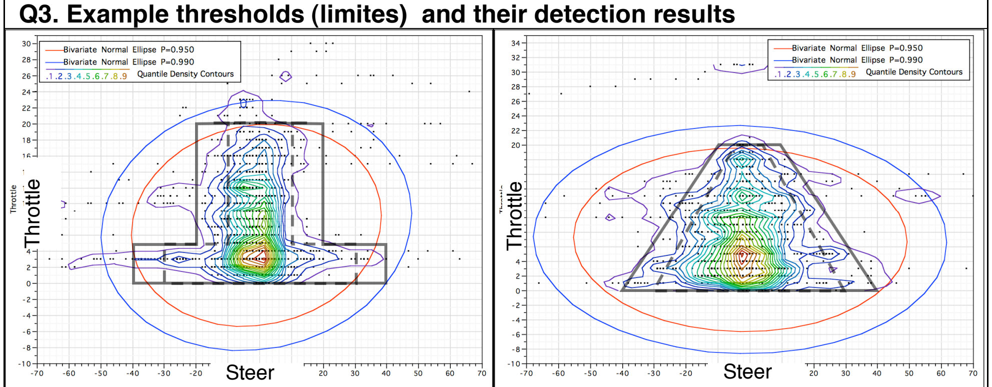
Demand	Type	Description	Value	Used for classification
High	Lane	Changing lane	Left, right, both	All variables
	Merge/exit	Merge, exit, or change roads	Merge, exit, change	All variables
	Stop	Stopping	Stop	Derivative variables
	High G	Rapid change of longitudinal acceleration	Accel, decel	Derivative variables
	Turn	Turning at the intersection	Left, right, U, Z	All variables
Low	Curve	Driving on a curved road	Left, right, S	All variables

Q3. Threshold design rules

Rule 1: Draw a simple diagram such as box, triangle, or their combination based on nonparametric density distribution.

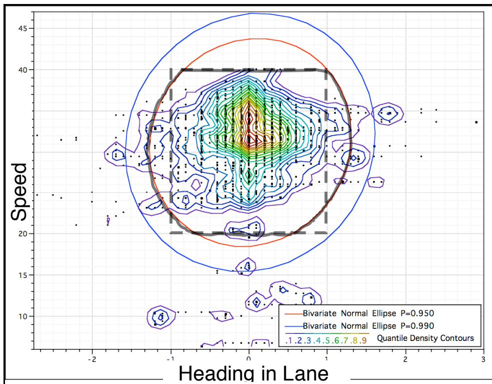
Rule 2: Maintain the same or similar shape of the diagram for different road types as much as possible.

Q3. Example thresholds (limites) and their detection results

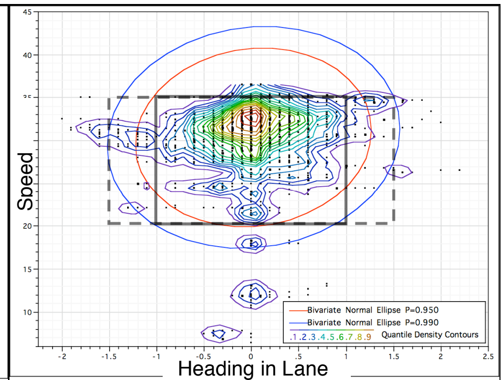


Limit	Loc.	Maneuver: Curve	Lane	Merge /exit	Turn	Tot
1st	In	9	2	0	0	11
	Out	6	0	0	24	30
2nd	In	5	1	0	0	6
	Out	12	0	0	15	27

Limit	Loc.	Maneuver: Curve	Lane	Merge /exit	Turn	Tot
1st	In	5	1	0	0	6
	Out	10	0	0	20	30
2nd	In	5	0	0	0	5
	Out	11	1	0	16	28

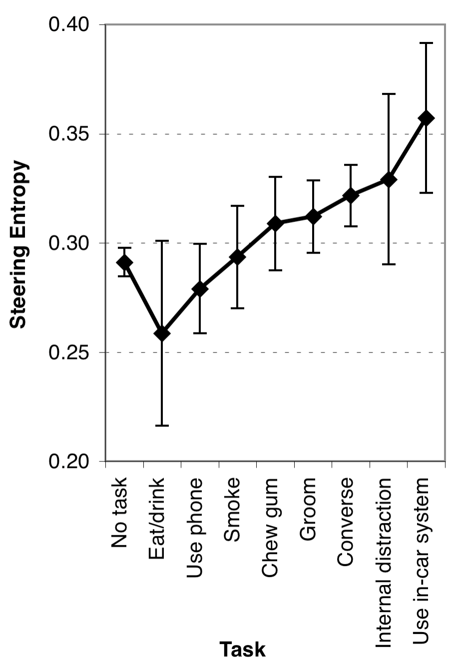


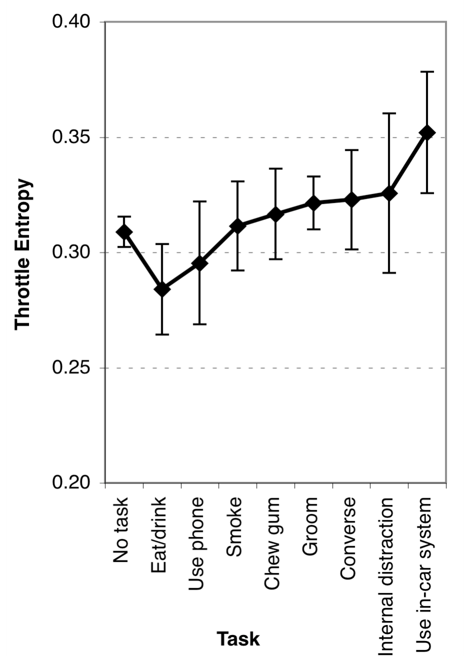
		Maneuver				
	Loc.	Curve	Lane	Merge /exit	Turn	Tot
1st	In	10	3	2	0	15
	Out	3	18	6	0	27
2nd	In	9	1	2	0	12
	Out	12	14	1	0	27



		Maneuver				
Limit	Loc.	Curve	Lane	Merge /exit	Turn	Tot
1st	In	12	1	2	0	15
	Out	10	14	4	0	28
2nd	In	15	2	2	0	19
	Out	11	16	2	0	29

Q4. Steering and throttle entropy





PREFACE

This report is one of a series that describes the second phase of the University of Michigan Transportation Research Institute (UMTRI)'s work on the SAVE-IT project, a federally-funded project for which Delphi serves as the prime contractor and UMTRI as a subcontractor. The overall goal of this project is to collect and analyze data relevant to distracted driving, and to develop and test a workload manager. That workload manager should assess the demand of a variety of driving situations and in-vehicle tasks. Using that information, the workload manager would determine, for each driving/workload situation, what information should be presented to the driver (including warnings), how that information should be presented, and which tasks the driver should be allowed to perform. UMTRI's role is to collect and analyze the driving and task demand data that served as a basis for the workload manager, and to describe that research in a series of reports.

In the first phase, UMTRI completed literature reviews, developed equations that related some road geometry characteristics to visual demand (using visual occlusion methods), and determined the demands of reference tasks on the road and in a driving simulator.

The goals of this phase were to determine: (1) what constitutes normal driving performance, (2) where, when, and how secondary tasks occur while driving, (3) whether secondary tasks degrade driving and by how much, (4) which elements of those tasks produce the most interference, (5) how road geometry and traffic affect driving workload, (6) which tasks drivers should be able to perform while driving as a function of workload, and (7) what information a workload manager should sense and assess to determine when a driver may be overloaded.

In the first report of this phase (Yee, Green, Nguyen, Schweitzer, and Oberholtzer, 2006), UMTRI developed a second-generation scheme to code: (1) secondary driving tasks that may be distracting (eating, using a cell phone, etc.), (2) subtasks of those tasks (grooming, using a tool, etc.), (3) where drivers look while on the road, and (4) other aspects of driving. The scheme was then used to code video data consisting of face clips and forward scenes from the advanced collision avoidance system (ACAS) field operational test (FOT). The ACAS FOT was a major study in which instrumented vehicles collected a combined 100,000 miles of driving data for about 100 drivers, who used those vehicles for everyday use (Ervin, Sayer, LeBlanc, Bogard, Mefford, Hagan, Bareket, and Winkler, 2005).

Oberholtzer, Yee, Green, Nguyen, and Schweitzer (2006) used the second-generation UMTRI coding scheme to determine how often various secondary tasks and subtasks occur as a function of the type of road driven, driver age, driver sex, and other factors. In addition, Yee, Nguyen, Green, Oberholtzer, and Miller (2006) performed an analysis to identify the visual, auditory, cognitive, and psychomotor (VACP) demands of all subtasks observed and determined how often those subtasks were performed. The goal of this analysis was to gain insight on how much, and to what degree, various aspects of subtask demand (VACP dimensions) affect driving.

In a subsequent study, Eoh, Green, Schweitzer, and Hegedus (2006), this report, examine various combinations of measures (e.g., steering wheel angle and throttle) to analyze their joint distribution as a function of road type. This is done by pairing or grouping these measures to identify abnormal driving. By using the nonparametric distributions that describe these measures, pairs of thresholds were used to identify when particular maneuvers (e.g., lane changes) occurred on various road types. Success in this study was truly mixed, with high detection performance in some situations and poor detection in others. Nonetheless, some of these thresholds were descriptive enough to be used for a preliminary workload manager.

To support a more precise description of driving, Green, Wada, Oberholtzer, Green, Schweitzer, and Eoh (2006) developed distribution models that describe many of the driving performance measures examined.

Finally, to help characterize different driving situations and tasks, Schweitzer and Green (2006) asked subjects to rate clips of scenes from the ACAS FOT data relative to 2 anchor clips of expressway driving (1 of light and 1 of heavy traffic). Scenes of expressways, urban roads, and suburban driving were used for these ratings. Subjects also identified whether or not they would manually tune a radio, dial a cell phone, or enter a navigation destination in each of the clips. This data was used to determine the probability that each of the 3 tasks would be performed on each road type as a function of rated workload. In addition, the analysts used the ACAS driving performance data to develop equations that relate workload ratings to the driving situation (e.g., amount of traffic, headway to a lead vehicle).

The next task is for Delphi to use the findings from these reports to develop and test a workload manager.

TABLE OF CONTENTS

INTRODUCTION

Over the last century, motor vehicles have evolved from basic transportation to “living rooms on wheels” with features to enhance comfort, convenience, safety, and capabilities. Increasing feature content can have a down side, making what was simple to operate more like flying an airplane. By providing the driver with more tasks to manage, drivers could be distracted or overloaded, leading to degradation of the primary driving task.

Recognizing this, motor vehicle manufacturers and suppliers have been developing workload managers. These systems assess the driving situation and driving workload, and then alter the set of tasks the driver is allowed to perform (Michon, 1993; Wood, Leivian, Massey, Bieker, and Summers, 2001; Cherri, Nodari, and Toffetti, 2004; Green, 2004). To support the development of such systems, the U.S. Department of Transportation contracted with Delphi to conduct research on this topic and UMTRI has been a part of that team. In the early phases of this project, UMTRI carried out several literature reviews (e.g., Eby and Kostyniuk, 2004; Green and Shah, 2004) and experiments on driver distraction (e.g., Zylstra, Tsimhoni, Green, and Mayer, 2004).

The current phase, as described in the Preface, utilized an UMTRI-developed coding scheme (Yee, Green, Nguyen, Schweitzer, and Oberholtzer, 2006) to examine the type and frequency of secondary tasks that drivers perform while driving (Oberholtzer, Yee, Green, Eoh, Nguyen, and Schweitzer, 2006), and identify the visual, auditory, cognitive, and psychomotor demands of those tasks (Yee, Nguyen, Green, Oberholtzer, and Miller, 2006). Others studies have quantified the distributions of measures of driving for normal and distracted situations (Green, Wada, Oberholtzer, Green, Schweitzer, and Eoh, 2006). Studies have also determined which tasks drivers are willing to do in various situations as a function of workload, which has been quantified as a function of traffic and road geometry (Schweitzer and Green, 2006).

One of the challenges of designing a workload manager is the real-time, moment-to-moment assessment of the demands of the primary driving task. This assessment is of concern because if demand estimates are incorrect by a substantial amount, drivers may not find workload managers useful and could even find them annoying, which may lead drivers to turn them off, not buy vehicles with them, or other negative consequences.

One strategy to develop accurate real-time predictions of demand is to focus initially on situations where demand is clearly excessive. When, then, is it most apparent that drivers should not engage in additional tasks? The answer is when drivers are maneuvering or, in many cases, when drivers are about to maneuver. Maneuvering includes turning at intersections, changing lanes, decelerating in response to a braking lead vehicle or a traffic light, merging, parking, backing up, accelerating from a traffic light, and so forth. These maneuvering situations have seldom been considered in workload studies because they are riskier than other driving situations and exposing drivers to them may create an unacceptable risk.

The focus of this report is to identify situations (1) where drivers are maneuvering and, to a lesser extent, (2) where drivers are about to maneuver, and (3) when drivers are distracted. This is done using data from the Advanced Collision Avoidance System (ACAS) Field Operational Yest (FOT), a major on-the-road study involving 96 drivers and a fleet of vehicles that accumulated over 100,000 miles of naturalistic driving data.

This report also examines the effects of secondary tasks on driving performance, steering wheel angle variability, throttle angle variability, heading angle variability, lane position variability, speed variability, and steering and throttle entropy. Steering entropy is a measure of randomness in a driver's steering control (Boer et. al., 2005). Steering entropy is greater when drivers make larger, erratic steering movements. Similarly, throttle entropy is a measure of randomness throttle position.

More specifically, this report examines the following questions:

1. How are measures of driver input (steering wheel angle, throttle position) and vehicle output (heading, speed, lateral and longitudinal acceleration) distributed as a function of road type?

2. What is the effect of the number of secondary tasks (none, 1, or 2) on measures of driver performance (as listed in question 1) as a function of road type? Does performance differ as a function of the number of tasks?

3. What driving performance measures and thresholds are recommended for a workload manager as a function of road type to identify when the driver is maneuvering (and should not perform secondary tasks)?

4. How effectively do steering and throttle entropy values predict distracted and normal driving? Do age, gender, and their interaction have a significant effect on steering and throttle entropy?

The goal of this workload manager is not to perfectly identify when drivers are overloaded but to reasonably determine overload (a reasonable d-prime) with very few false alarms.

METHOD

To distinguish between normal and distracted driving (defined later), the authors examined driving performance data from the Advanced Collision Avoidance System (ACAS) Field Operational Test (FOT) (Ervin, Sayer, LeBlanc, Bogard, Mefford, Hagan, Bareket, and Winkler, 2005) in detail. In designing that evaluation, a major goal was to make driving completely natural. Subjects used the test vehicles as their own personal vehicles, with the only restriction being that they could not drive outside of the U.S. There is considerable evidence that subjects indeed behaved normally. They drove to work, went on shopping trips, took the test vehicles on vacation (including trips of over a thousand miles), and engaged in personal habits that people do not like to admit they do while driving.

There were 96 drivers (equal numbers of men and women in their 20s, 40s, and 60s) in the test sample, selected to be representative of drivers in southeastern Michigan. Fifteen of the subjects drove for 3 weeks, and 81 drove for 4 weeks. The first week of testing was for baseline, naturalistic data without the ACAS system in operation, which is the data set examined here.

The test fleet consisted of 10 model-year 2002 Buick LeSabres fitted with video cameras to record the driver's face and the forward scene. The forward scene was recorded at 1 Hz by a limited resolution black-and-white camera. A second black-and-white camera recorded the driver's face without audio recording. However, to reduce the data to be stored, only 4-second samples (at 5 Hz) recorded once every 5 minutes were saved.

In addition to the video data, a custom-designed instrumentation package recorded 400 engineering variables (speed, yaw angle, steering wheel angle, throttle percentage, etc.) in real time. In this report, 4 fundamental variables were selected for the most focused analysis: steering wheel angle (degree), throttle percentage (%), in-lane angle (degree), and speed measured by a transmission sensor (meter/second). Driving tasks can be regarded as a two-dimensional control task, where steering wheel angle is the driver's lateral input and throttle percentage is the driver's longitudinal input. Driver input leads to vehicle movement that can be defined as a combination of longitudinal movement (measured using speed as sensed by the transmission controller) and lateral movement (heading in lane). Derivatives of these variables were also analyzed.

The GPS coordinates of the test vehicle, combined with matching map data, permitted identification of the road type and road segment being driven at any given time. The 9 categories of roads in the ACAS database were: (0) ramp, (1) interstate, (2) freeway, (3) arterial, (4) minor arterial, (5) collector, (6) local, (7) unpaved, and (8) unknown. Ramps were excluded from the distraction analyses because they were so infrequent, though they are included in a few other analyses in this report. Excluded from all analyses were (1) unpaved roads as some of the engineering data, such as lane position, was not available for those roads, and (2) unknown roads because the findings could not be linked to a known road type. For additional details on the ACAS data set, see Ervin, Sayer, LeBlanc, Bogard, Mefford, Hagan, Bareket, and Winkler (2005).

The process of reducing the data for analysis was quite complex and is therefore only summarized here. For complete details, see Yee, Green, Nguyen, Schweitzer, and Oberholtzer (2006). In brief, the face video data, the indicator of distraction for this report, was analyzed in 2 passes using custom UMTRI software (Figure 1). In the first pass, some 3,000 clips were coded to determine if drivers were performing any tasks in addition to driving. Distraction was defined as drivers engaging in any secondary activity in addition to just driving (e.g., using a cell phone, conversing). Gaze direction and head orientation were also examined.

Figure 1. Screenshot of the UMTRI Software Used for Data Analysis

The intent was to select clips so there were an equal number in each of the road categories (6), by age groups (3), and by sex groups (2) of interest. Equalizing the cell sizes (rather than sampling based on exposure) maximized the sensitivity of statistical tests concerned with road, age, and sex differences. Even though the data set was large, it turned out that some cells did not contain 83 (~3000/36) useable clips. In those cases, cells were pooled across sex (and re-sampled) because sex was thought to be the least influential factor of the 3 examined.

After the coding began, problems (misaimed or out-of-focus camera, missing engineering data, etc.) were discovered with some of the initially-selected clips. This led to replacing some of the clips sampled, rethinking the coding scheme, and recoding clips in the sample. However, the coding process reached a point at which only a few clips were problematic, and replacing/recoding the entire sample did not make sense. The final sample included 2,914 clips of driver's faces, each 3.8 to 4.0 s in duration.

One of the lessons from pilot tests of the coding process was that it was too difficult to code all of the desired information in 1 pass (tasks, subtasks, eye gaze and head direction, hand location, etc. for each frame). Furthermore, preliminary analysis of the ACAS data (Ervin, Sayer, LeBlanc, Bogard, Mefford, Hagan, Bareket, and Winkler, 2005) suggested that distraction would occur in only 17% of the clips. Thus, 83% of the clips would involve normal driving and the bulk of the analysis time would be analyzing those clips, which were not the clips of primary interest.

Therefore, face clips were analyzed in 2 passes. In the first pass, analysts first viewed the face clips to determine which, if any, of the secondary tasks was present (Table 1) and whether the driver was drowsy. They then viewed the forward-scene clips to determine the road surface condition (dry, wet, slippery) and the weather (sunny, rain, snow).

Table 1. Categories of Secondary Tasks

No.	Name	No.	Name
1	Use cell phone	7	Write
2	Eat/drink	8	Type
3	Smoke	9	Use in-car system
4	Converse	10	Internal distraction
5	Groom	11	Chew gum
6	Read	12	Chew tobacco

In the second pass, face clips were examined frame by frame to determine the exact subtasks evident in each frame (dial phone-hand held, prepare to eat, groom using tool, etc.), where the driver was looking, where their head was pointed, and where their hands were positioned. Eye gaze location was used as an alternative indicator of distraction (looking away from the road to the interior was considered distracted). Head direction was coded because it is thought to be a correlated indicator that is much easier to determine than gaze direction. One of the hidden assumptions of this approach is that all secondary tasks are treated as equally distracting, which the driving research literature shows to be otherwise. However, as a first step in the analysis of the

ACAS data, that was a reasonable assumption, with the understanding that the assumption could be reviewed later.

As was noted earlier, most frames were thought to reflect normal driving. Therefore, to make the best use of the analysts' time, the 823 clips (407 involving distraction and 416 involving normal driving) in Pass 2 were a sample of those in Pass 1. Distraction clips were selected so the frequency of occurrence of a distracting task in Pass 2 was similar to that of Pass 1. For example, if 10% of the distractions in Pass 1 involved a cell phone, then the target was 10% for Pass 2. A total of 15,962 frames were examined in Pass 2.

To support the analysis of the data in this experiment, a number of special files were created in Excel, some for Pass 1, others for Pass 2. Analyses that follow were developed using JMP and MATLAB.

RESULTS

How are measures of driver input and vehicle output distributed as a function of road type?

As a first step toward identifying maneuvers (when secondary tasks should not occur) and differentiating them from other driving situations, the authors examined the input space for vehicle control. Figure 2 shows key variables in that space, namely steering wheel angle and throttle position. To highlight differences between various roads, envelopes (95^{th} percentile bivariate normal ellipses) for each road type are superimposed over the scatter plot, even though they may not accurately fit the underlying distributions. As was shown in Green, Wada, Oberholtzer, Green, Schweitzer, and Eoh (2006), the data are not bivariate normal, and that is also evident here, where the bivariate distributions include regions of negative throttle, which are not physically feasible. Though, in some sense, points well outside the ellipses represent abnormal driving, probably maneuvering, and points well inside represent non-maneuvering situations.

These envelopes highlight the differences among road types. Table 2 shows the road class codes, their corresponding road types, and brief descriptions (see Yee, Green, Nguyen, Schweitzer, and Oberholtzer (2006) for the formal definitions) that are used throughout the report to facilitate data analysis.

Table 2. Road Classes and Corresponding Codes

Class	Name	Description
0	Ramp	Connect roads and limited access roads
1	Interstate	Limited access (U.S. interstate designation)
2	Freeway	Limited access and crossings (U.S. route number)
3	Arterial	Primary road (link minor arterials)
4	Minor arterial	Secondary road (link connectors)
5	Collector	Gather traffic from local roads
6	Local	Residential streets (least traveled)

Interstates and freeways have considerable variability in throttle angle and little variability in steering wheel angle, so their ellipses are tall and narrow. For all practical purposes, as described in the Methods section, expressways and interstates are the same class of road, so small differences between them represent the sampling error in the data. Collector and local roads have very similar steering and throttle characteristics, with greater steering wheel variability than other types of roads. Also note the different envelope for ramps, with the main axis being tilted because most ramps involve a right turn. For this data set, readers are reminded that few data points on ramps were sampled, so the envelope should be used with caution.

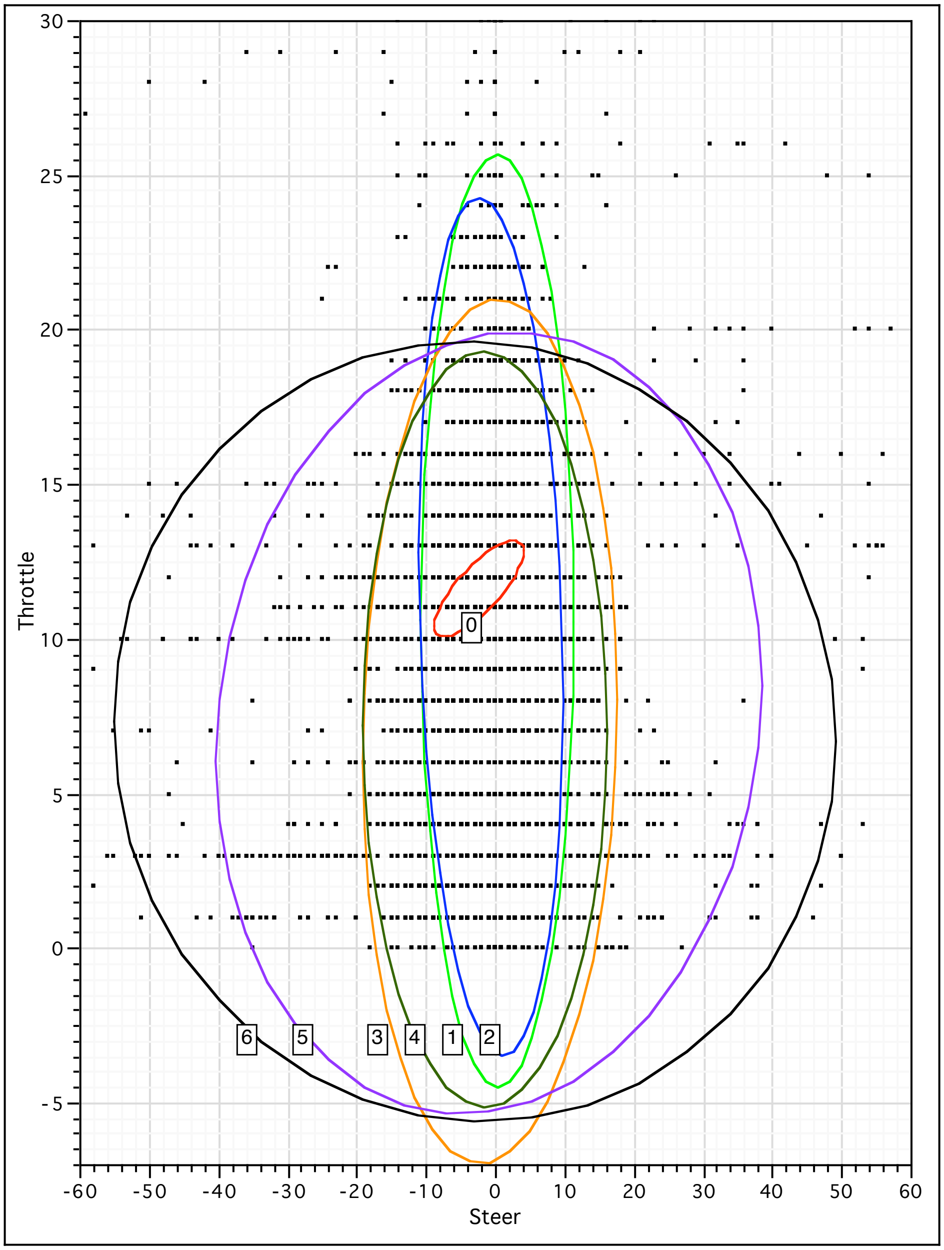


Figure 2. Steering Angle vs. Throttle Angle by Road Class

Figure 3 shows one characterization of the output domain of driving, the bivariate relationship between heading angle and transmission-measured speed. The differences in posted speed limits are reflected in the lack of vertical overlap in the distributions for each road type as indicated by the 95th percentile envelopes. Again, these envelopes were used to highlight differences, not to imply that the underlying distributions are normal. The clustering is freeways and interstates, arterial, minor arterial and collector, local, and ramp. Minor arterials have less variability in speed than do arterials, local roads, and collectors.

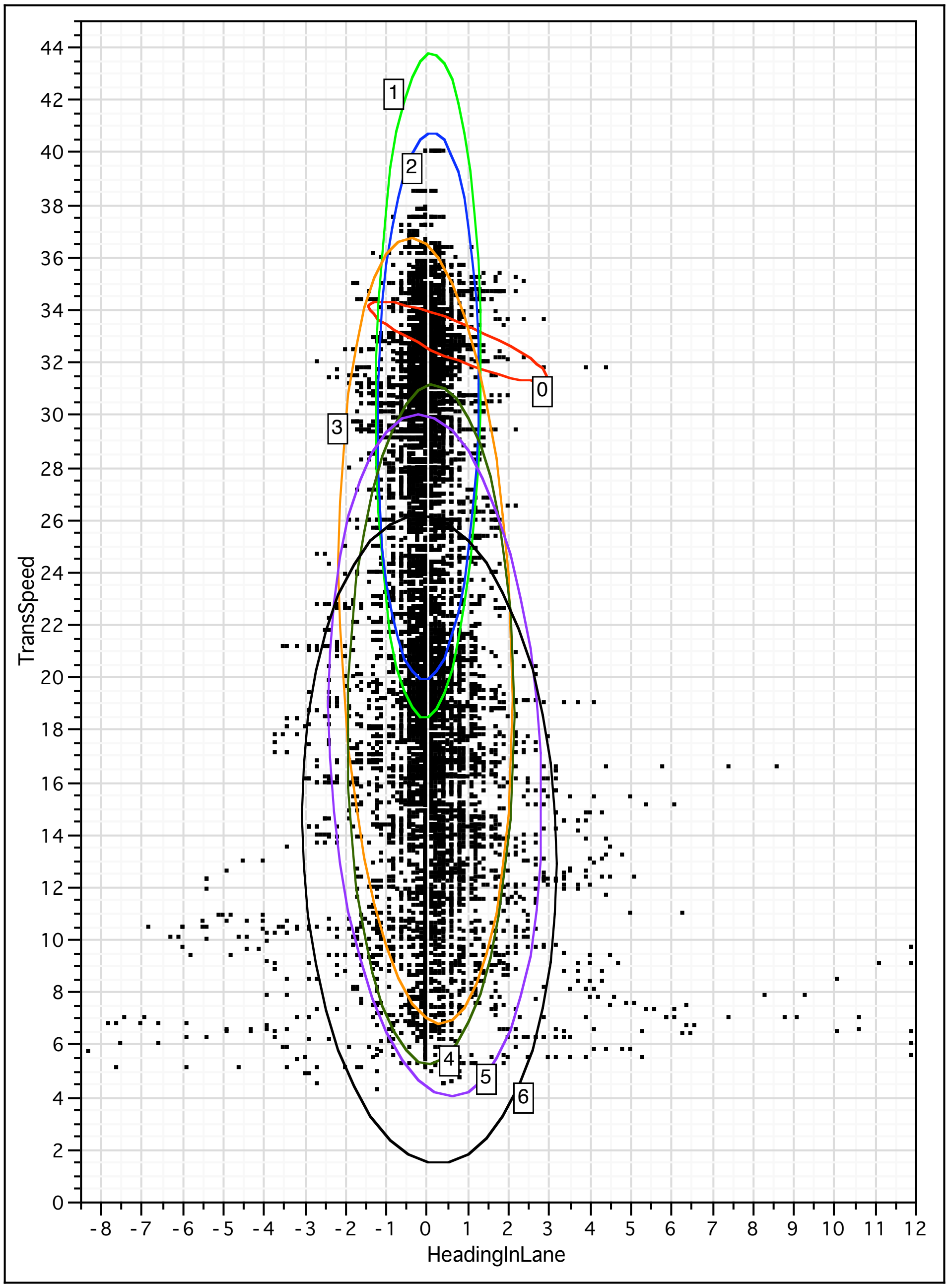


Figure 3. Heading Angle vs. Speed by Road Class

Figures 4 and 5 present derivative spaces for the input (i.e., steering and throttle rate) and output (i.e., heading rate and acceleration) domains, respectively. As in Figure 3, the clustering in Figure 4 is interstates and freeways, arterials and minor arterials, collectors and local roads, and ramps. Collectors and local roads showed greater steering wheel variability than other types of roads. Notice in Figure 5 that the quantization of the acceleration data led to very odd fits of the bivariate normal distributions. This occurred because of the lack of resolution of transmission speed from which the accelerations were derived. This suggests that, if acceleration measurements are used to distinguish between normal driving and maneuvering, resolutions of greater than 0.1 g should be considered.

More generally, this data shows that if driving input and output spaces are to be used to identify maneuvers, then the broad road type being driven must be known. The data also shows that, in many cases, driving performance measures group roads into 4 categories, (1) interstates and freeways, (2) arterials and minor arterials, (3) collectors and local roads, and (4) ramps. However, there are instances where knowing the specific road type may lead to a more accurate classification.

One of the practical implications of these findings is that workload managers (which utilize the maneuvering/non-maneuvering status to determine primary task workload, based on vehicle input and output values) will need to know the road type being driven. Rapidly determining the road type will require data provided by an in-vehicle navigation system.

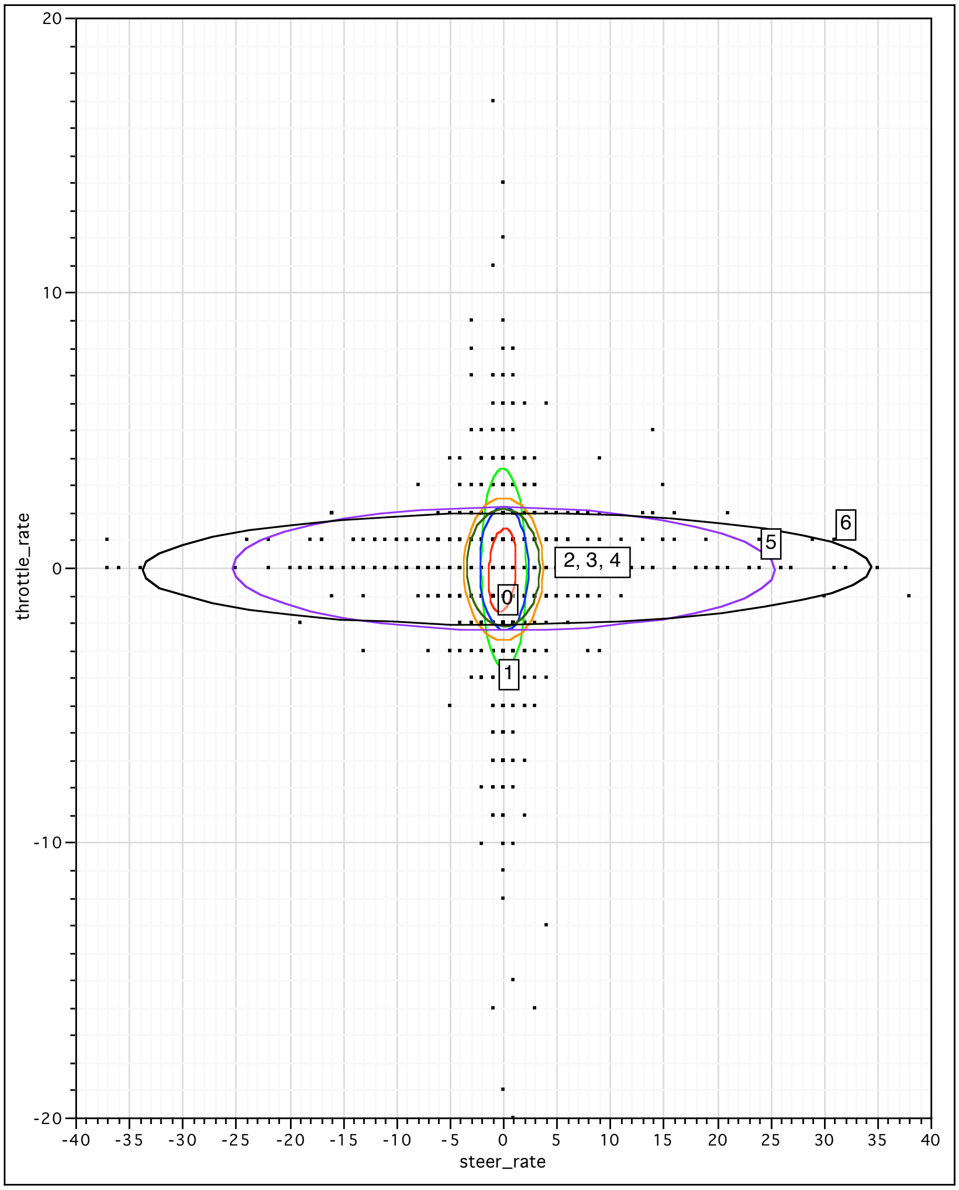


Figure 4. Steering Rate vs. Throttle Rate by Road Class

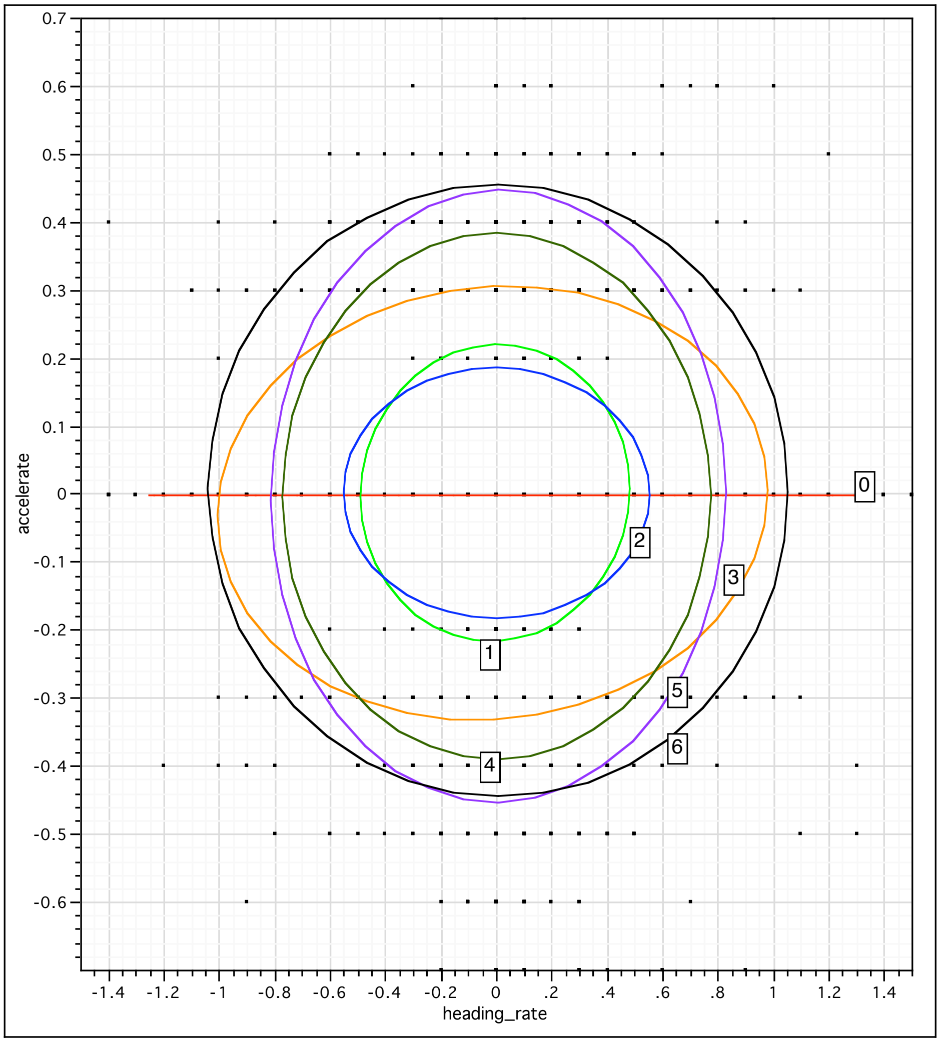


Figure 5. Heading Rate vs. Acceleration by Road Class

What is the effect of the number of secondary tasks (none, 1, or 2) on measures of driver performance as a function of road type?

One might hypothesize that drivers are intelligent in determining when they should perform potentially distracting tasks. If that were true, then multiple tasks would be less likely in more extreme situations (large steering angles, steering rates, accelerations, etc.) because these situations are more likely to be associated with maneuvering. To verify this, scatter plots and bivariate normal ellipses of the number of secondary tasks undertaken were developed for each paired-measure, road-type combination explored in the previous section.

A small gray dot signifies that no secondary task was noted. A black circle indicates 1 task and a black plus sign indicates two tasks. As a further aid, the authors drew 3 bivariate normal ellipses in Figures 6-29 (p = 0.950) distinguishing the number of secondary tasks (orange for no tasks, dark green for 1 task, and blue for 2 tasks).

In brief, the primary finding from this analysis was that distracting secondary tasks were noted in situations where drivers were believed to be maneuvering. The authors did not examine which secondary tasks occurred and their intrusiveness in those situations as that was beyond the scope of this project. However, later sections do consider the addition of thresholds that a workload manager might use to distinguish between maneuvering and non-maneuvering situations, and how those thresholds can be used to identify when secondary tasks should not be performed.

Steering Angle and Throttle Percent

Figures 6 and 7 show how the number of tasks performed while driving on interstates and freeways varies with steering angle and throttle percent. Note the poor fit of the normal distribution, as the ellipses include regions of negative throttle. Also notice there is essentially no difference between no tasks and 1 task in the 95^{th} percentile distributions, and that overall the no-task and 1-task events appear equally distributed. However, situations in which 2 tasks occur are significantly restricted in terms of steering angle. That is, drivers engage in 2 tasks only when they are driving fairly straight, and are much less likely to engage in 2 tasks while maneuvering.

For arterials (Figure 8), the range of steering angles over which 1 task occurs is much lower than that for no tasks. Whereas for minor arterials (Figure 9), the differences are less pronounced. There were no cases of 2 tasks occurring on arterials.

The distributions for no tasks and 1 task were similar for collectors and local roads (Figures 10 and 11). However, the distributions for 2 tasks were substantially restricted, especially in steering wheel angle.

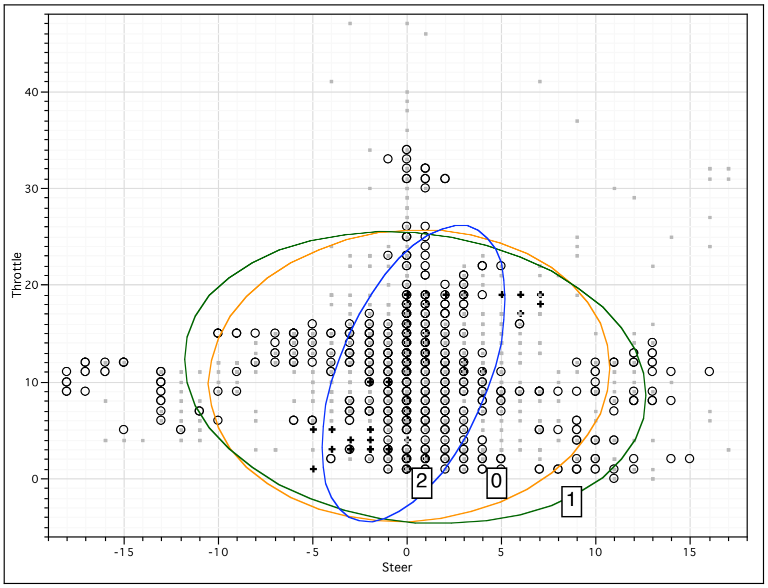


Figure 6. Distribution of Steer and Throttle Angles for Interstates by Number of Secondary Tasks Being Performed (0, 1, 2)

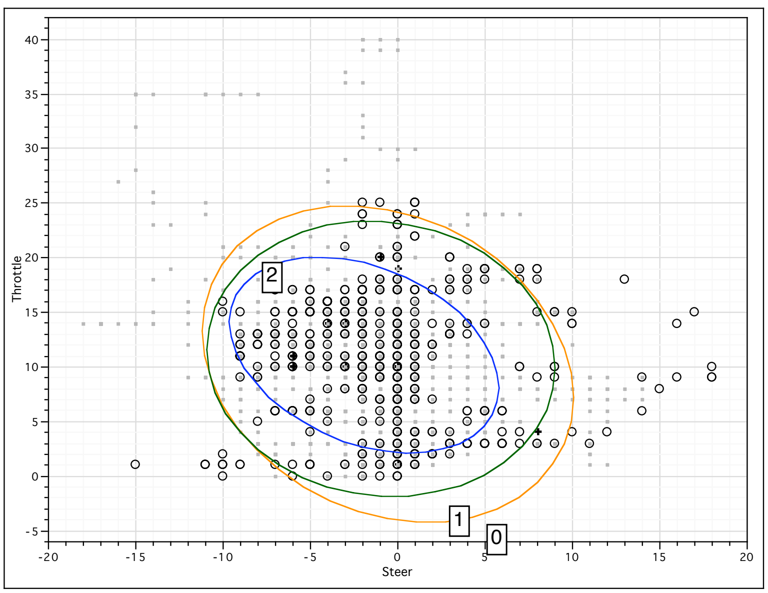


Figure 7. Distribution of Steer and Throttle Angles for Freeways by Number of Secondary Tasks Being Performed (0, 1, 2)

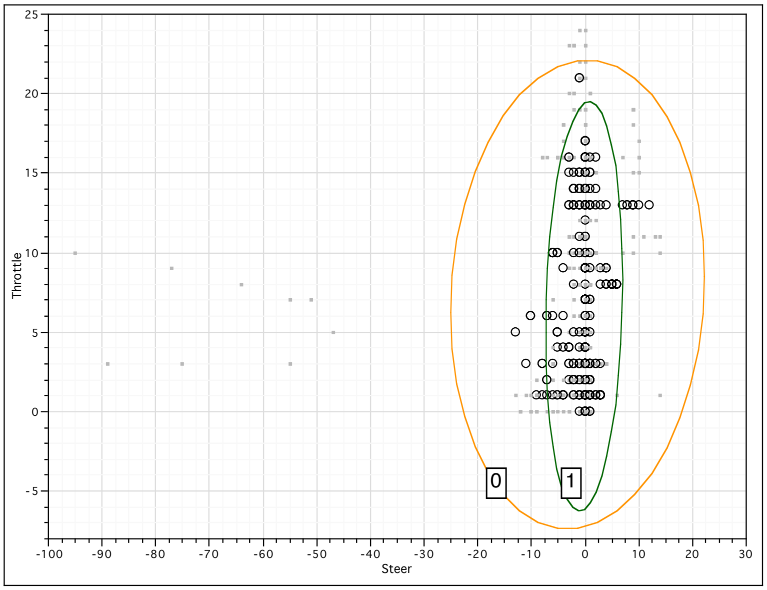


Figure 8. Distribution of Steer and Throttle Angles for Arterials
by Number of Secondary Tasks Being Performed (0, 1, 2)

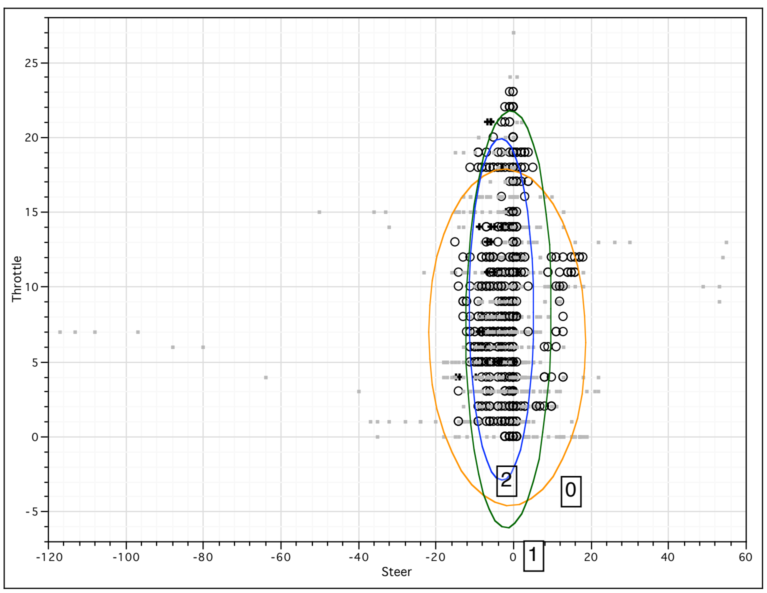


Figure 9. Distribution of Steer and Throttle Angles for Minor Arterials
by Number of Secondary Tasks Being Performed (0, 1, 2)

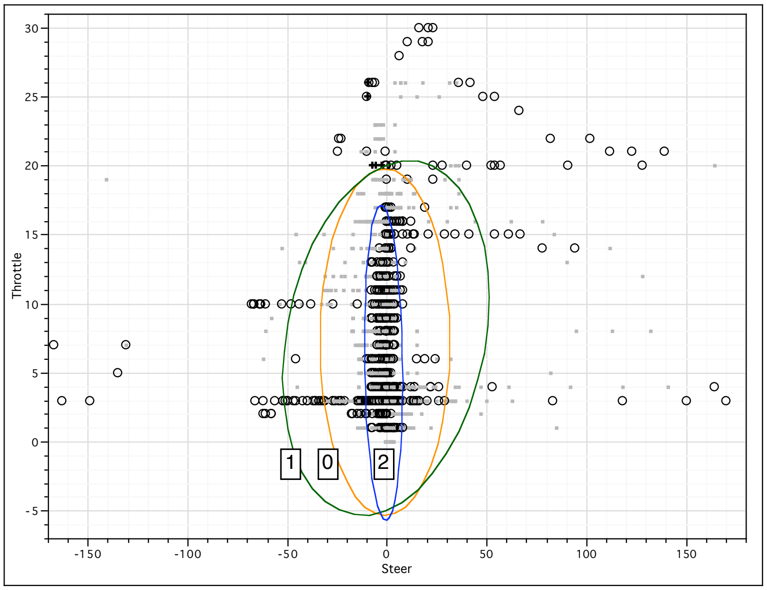


Figure 10. Distribution of Steer and Throttle Angles for Collectors by Number of Secondary Tasks Being Performed (0, 1, 2)

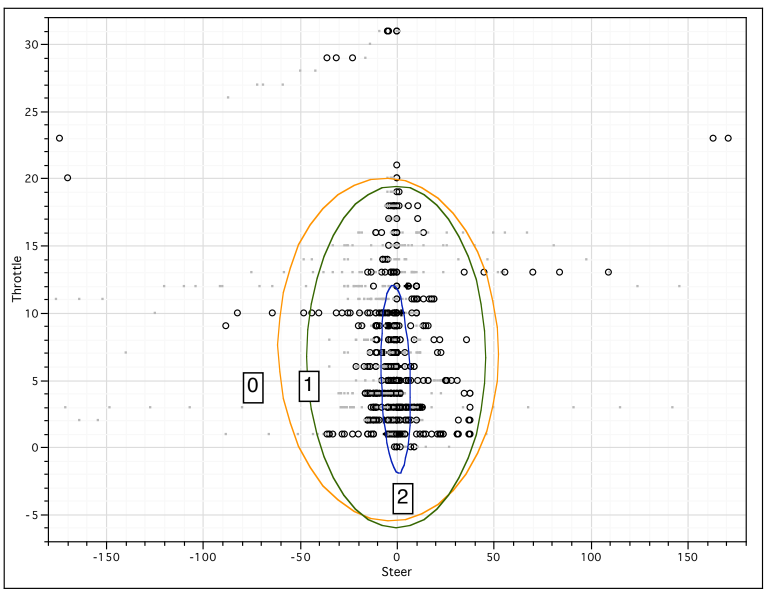


Figure 11. Distribution of Steer and Throttle Angles for Local Roads by Number of Secondary Tasks Being Performed (0, 1, 2)

Heading and Speed

Figures 12-17 show heading vs. speed relationships on each road. While the 2-task cases were gathered on the centerline for the input domain (Figure 6), they were more dispersed in the output domain (Figure 12) on interstates. An analogous relationship was observed on local roads (Figures 11 and 17). On the freeway (Figure 13), the bivariate ellipse for 2 tasks was biased to the right side for both output and input domains. Observations on the arterial road showed similar trends for both input (Figure 8) and output (Figure 14) domains.

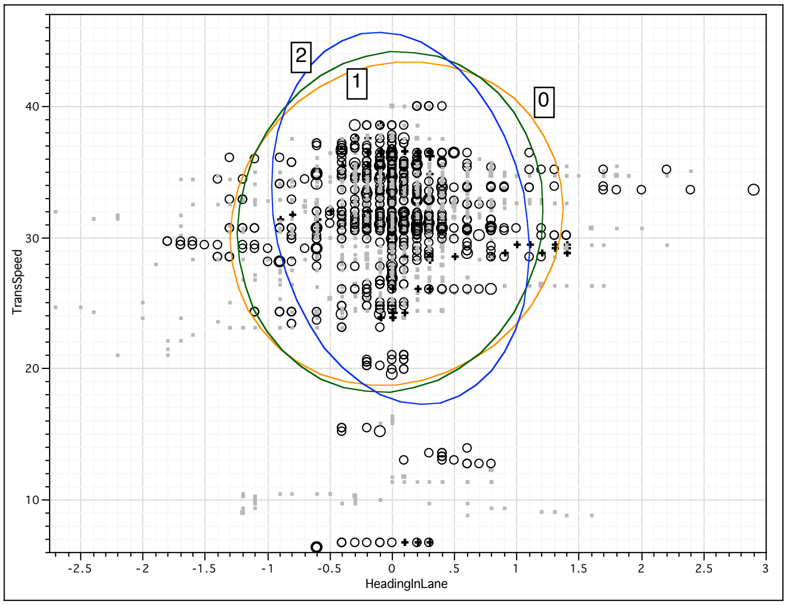


Figure 12. Distribution of Heading and Speed for Interstates by Number of Secondary Tasks Being Performed (0, 1, 2)

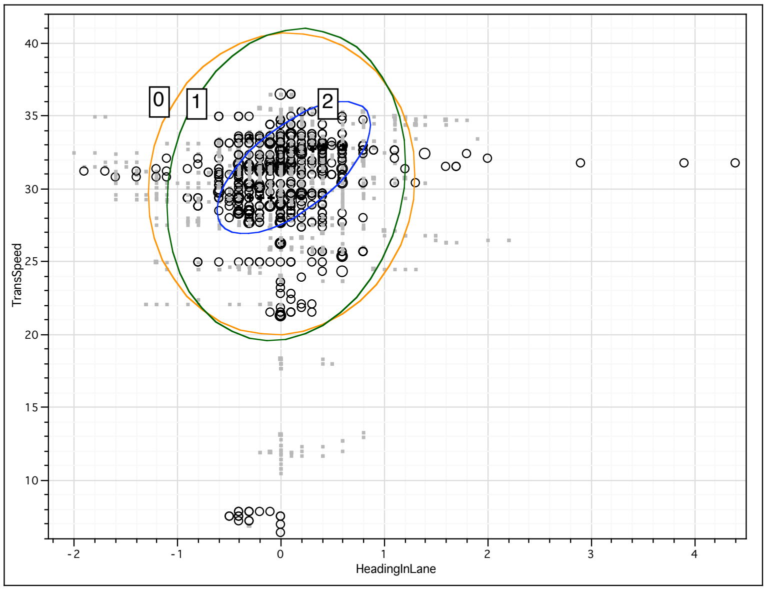


Figure 13. Distribution of Heading and Speed for Freeways by Number of Secondary Tasks Being Performed (0, 1, 2)

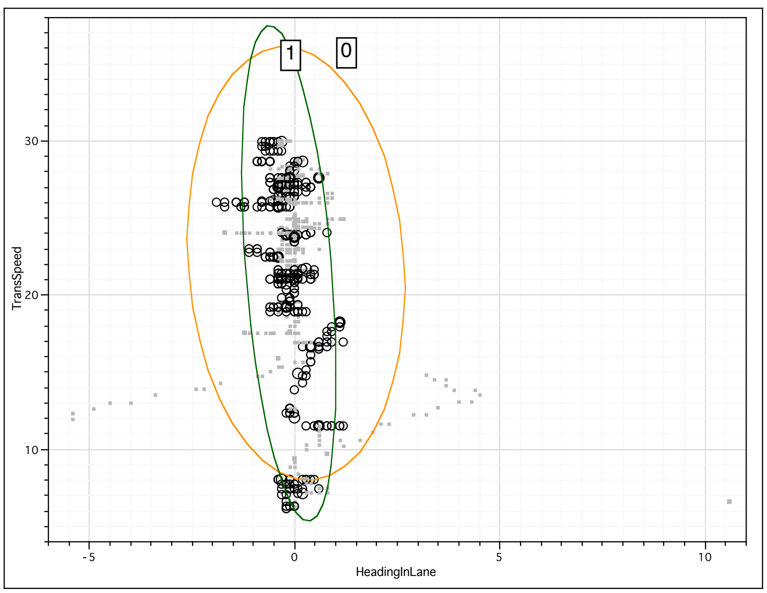


Figure 14. Distribution of Heading and Speed for Arterials by Number of Secondary Tasks Being Performed (0, 1)

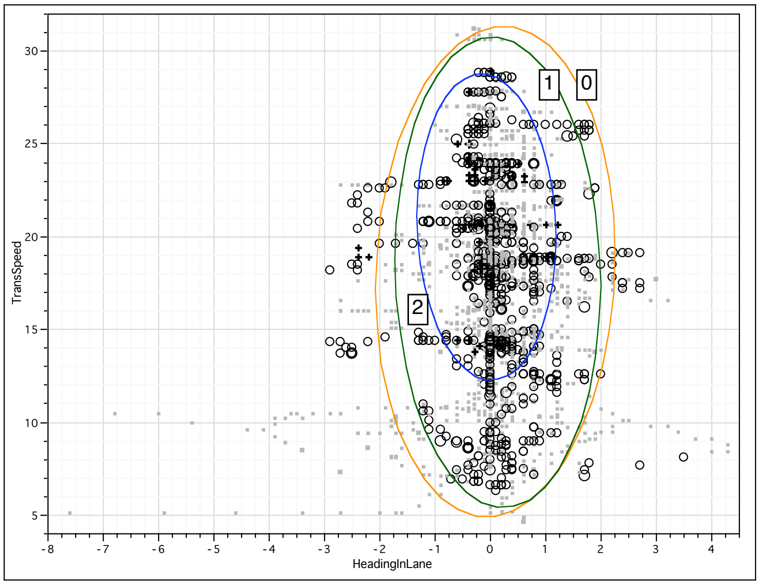


Figure 15. Distribution of Heading and Speed for Minor Arterials by Number of Secondary Tasks Being Performed (0, 1, 2)

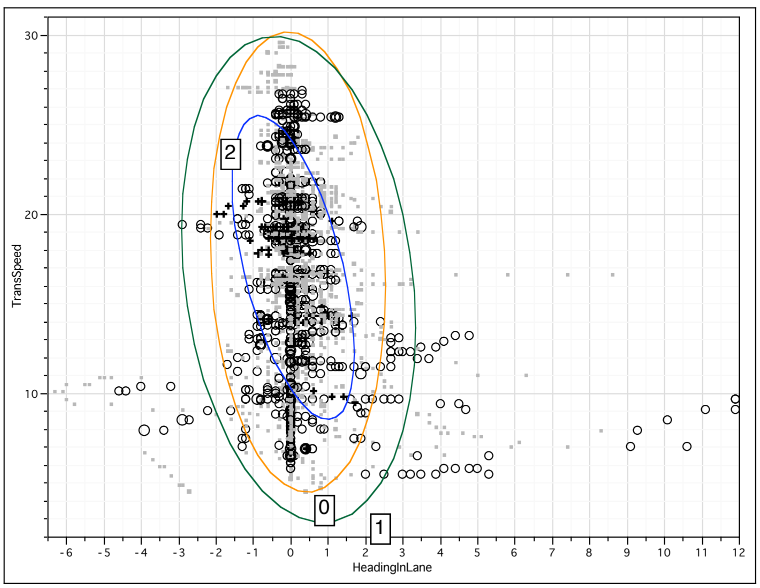


Figure 16. Distribution of Heading and Speed for Collectors by Number of Secondary Tasks Being Performed (0, 1, 2)

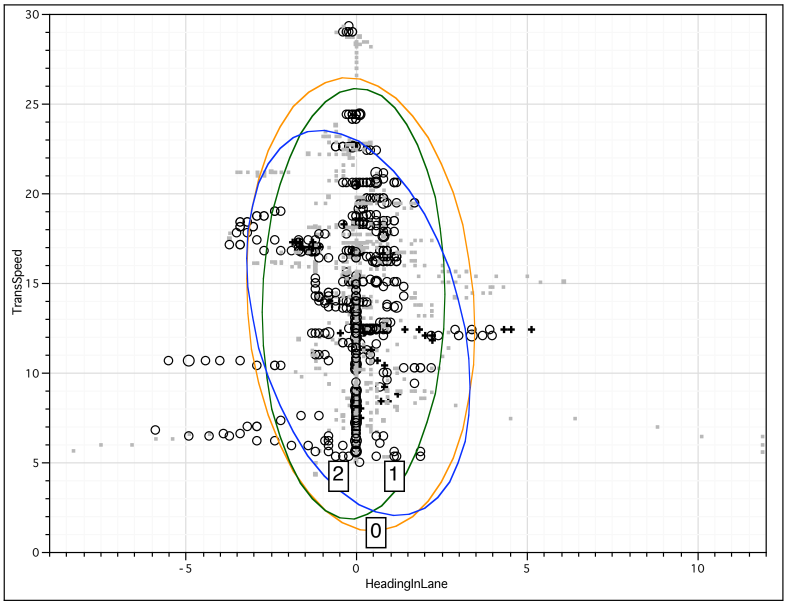


Figure 17. Distribution of Heading and Speed for Local Roads
by Number of Secondary Tasks Being Performed (0, 1, 2)

Steering Rate and Throttle Rate

Figures 18-23 show the relationship between steering rate and throttle rate as a function of the number of tasks. In general, the road type pairs that showed similarities for previous measure pairs were also similar here. In general, there were no differences between the no-task and 1-task conditions. The exceptions were arterials, where steering rate was more variable for the no-task condition and collectors, where steering rate was more variable for the 1-task condition. Again, this data should be viewed with some caution due to the quantization of the underlying data.

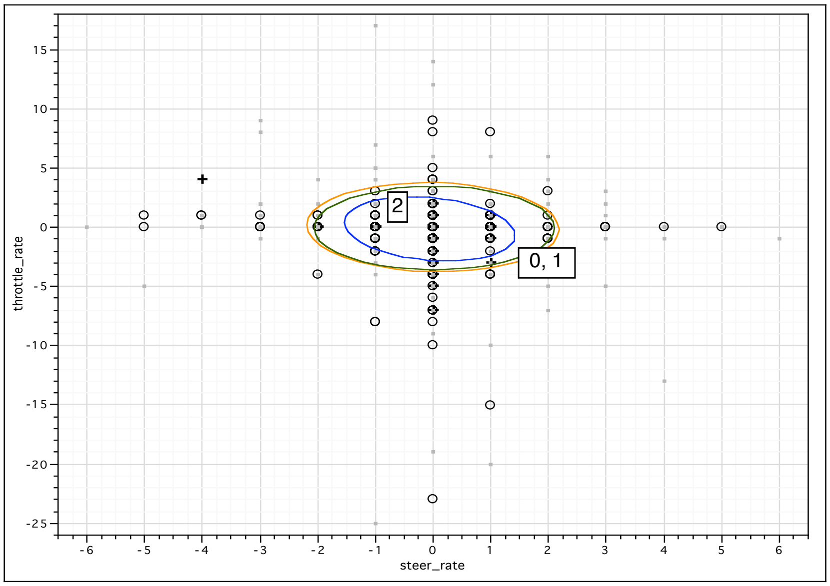


Figure 18. Distribution of Steering Rate and Throttle Rate for Interstates by Number of Secondary Tasks Being Performed (0, 1, 2)

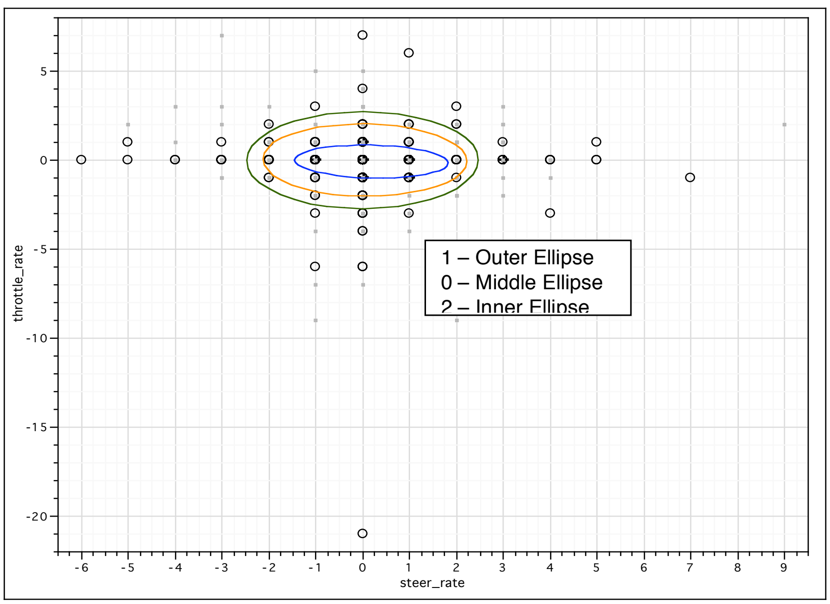


Figure 19. Distribution of Steering Rate and Throttle Rate for Freeways by Number of Secondary Tasks Being Performed (0, 1, 2)

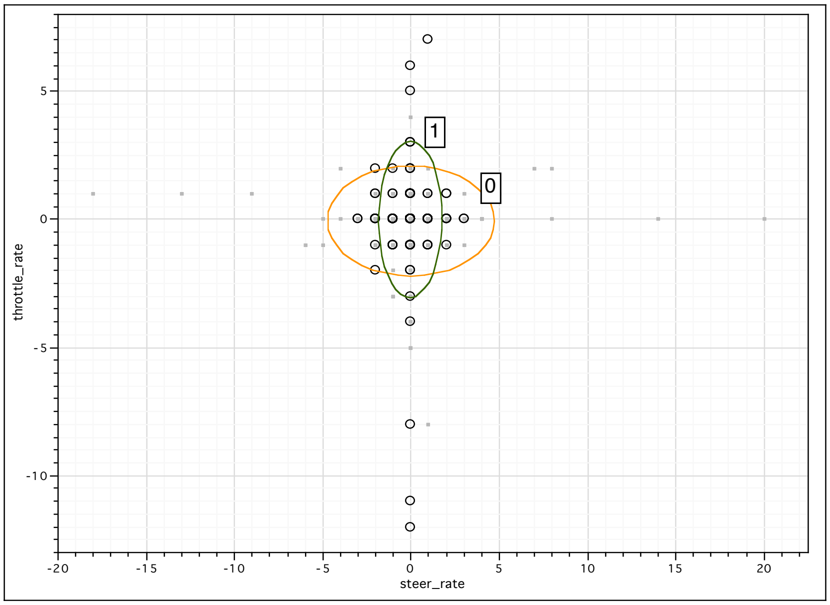


Figure 20. Distribution of Steering Rate and Throttle Rate for Arterials by Number of Secondary Tasks Being Performed (0, 1)

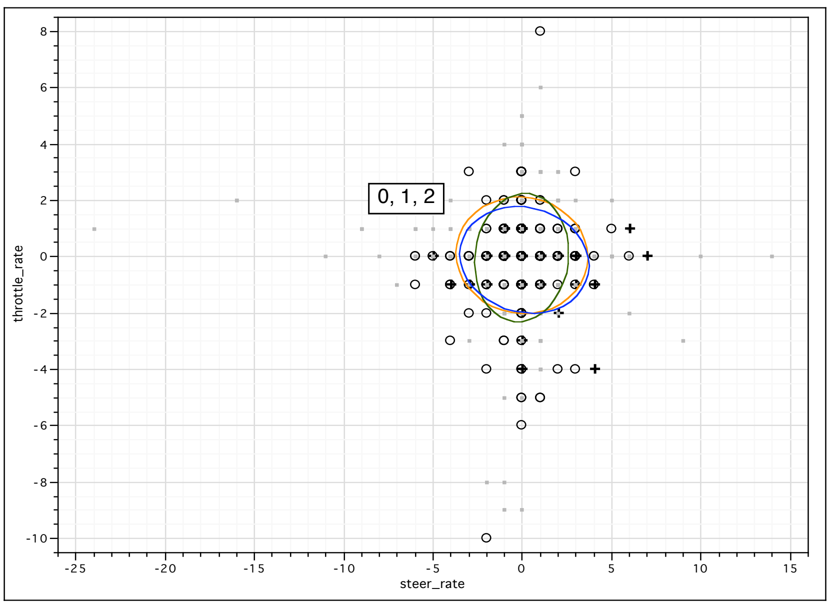


Figure 21. Distribution of Steering Rate and Throttle Rate for Minor Arterials by Number of Secondary Tasks Being Performed (0, 1, 2)

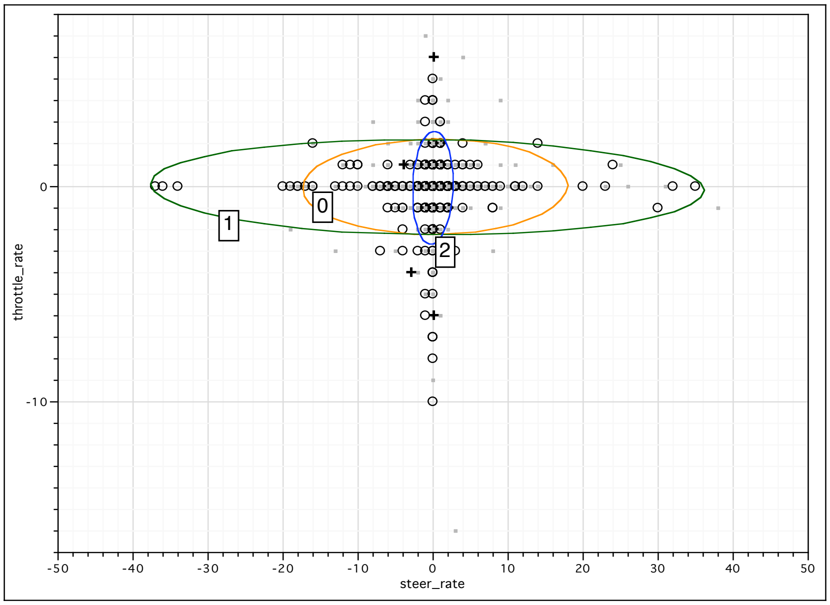


Figure 22. Distribution of Steering Rate and Throttle Rate for Collectors by Number of Secondary Tasks Being Performed (0, 1, 2)

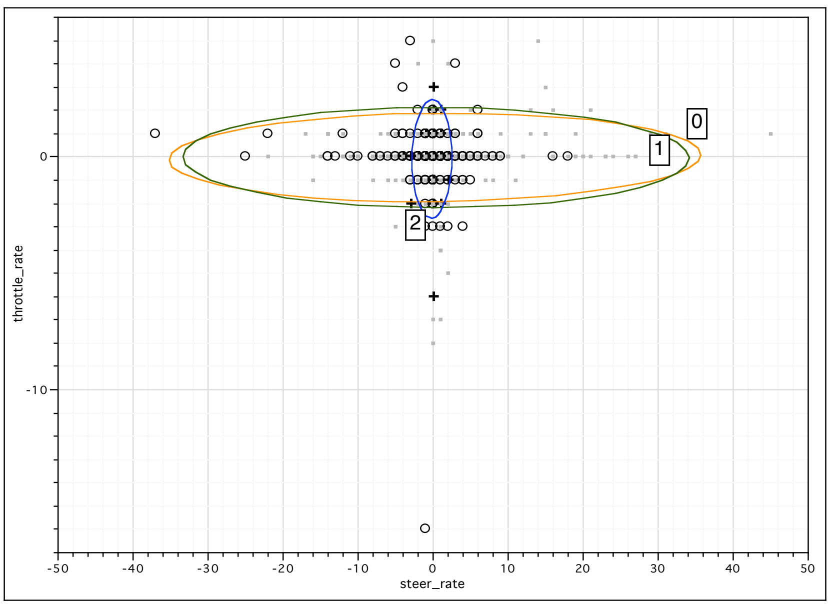


Figure 23. Distribution of Steering Rate and Throttle Rate for Local Roads by Number of Secondary Tasks Being Performed (0, 1, 2)

Heading Rate and Speed Rate (Longitudinal Acceleration)

Figures 24-29 show the relationship between heading rate and speed rate as a function of the number of tasks. Again the distribution of tasks as a function of the measure pairs examined was very similar except for arterials, where steer rate was slightly greater in the no-task condition. As before, the quantization of the data may limit the identifying differences between the no-task and 1-task conditions.

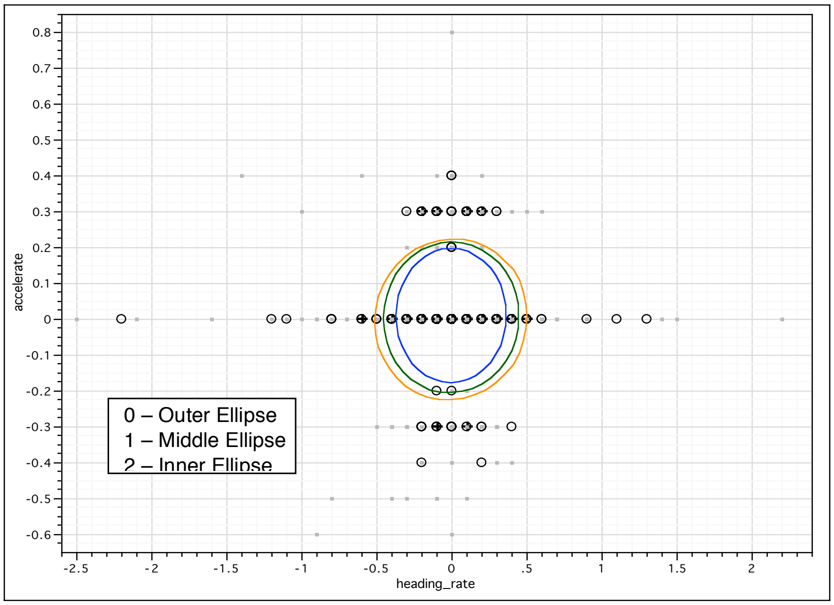


Figure 24. Distribution of Heading Rate and Speed Rate for Interstates by Number of Secondary Tasks Being Performed (0, 1, 2)

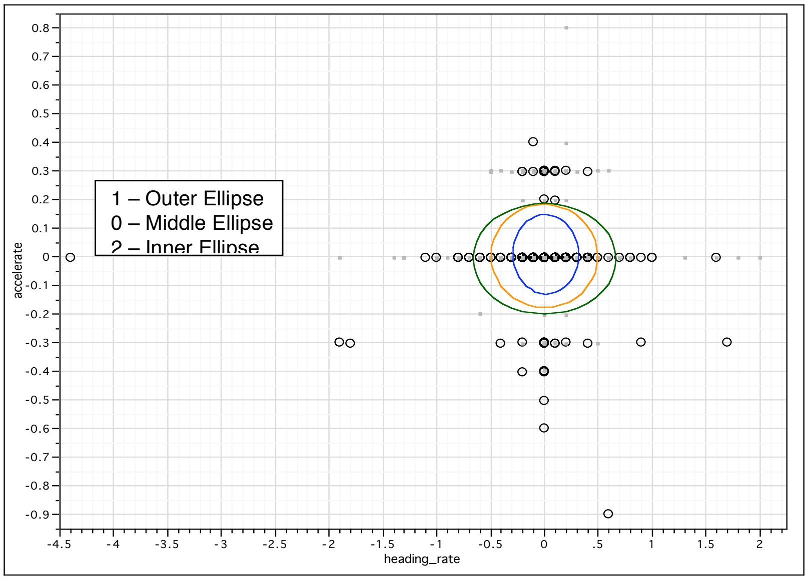


Figure 25. Distribution of Heading Rate and Speed Rate for Freeways by Number of Secondary Tasks Being Performed (0, 1, 2)

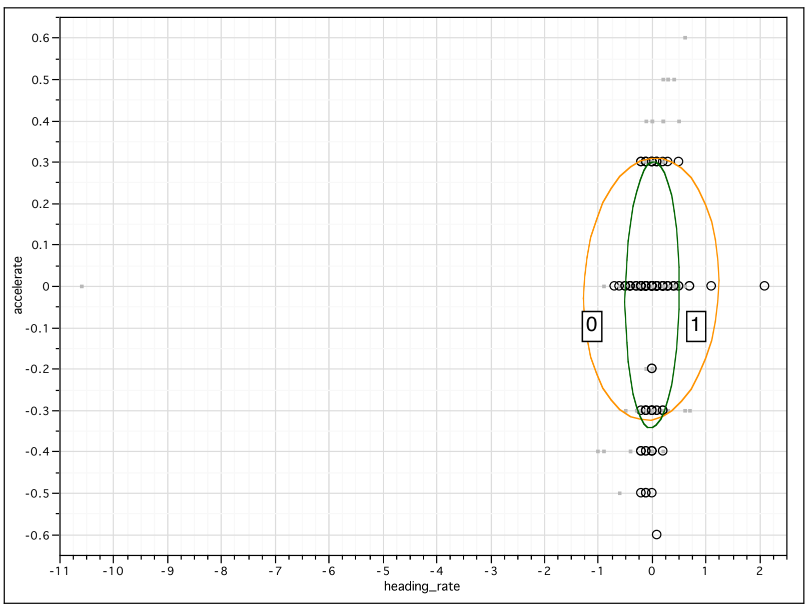


Figure 26. Distribution of Heading Rate and Speed Rate for Arterials by Number of Secondary Tasks Being Performed (0, 1)

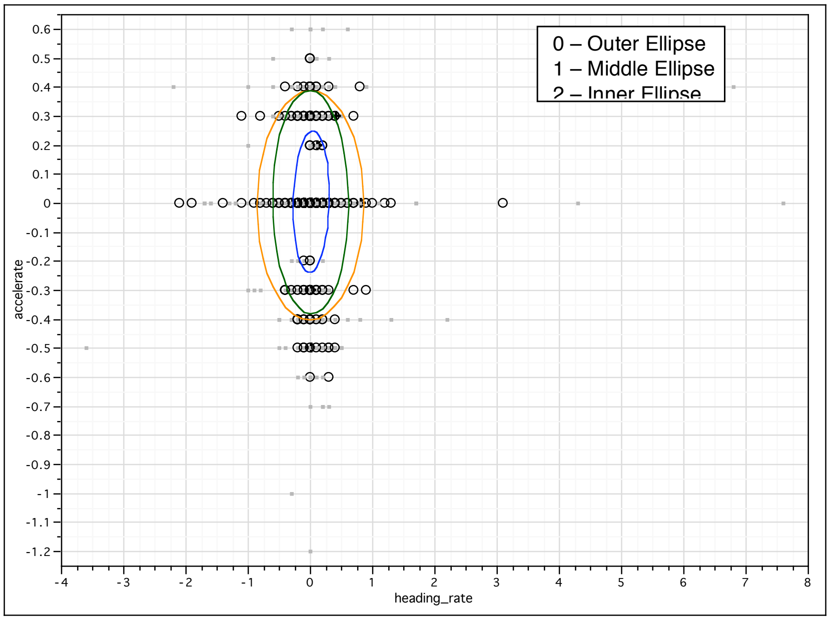


Figure 27. Distribution of Heading Rate and Speed Rate for Minor Arterials by Number of Secondary Tasks Being Performed (0, 1, 2)

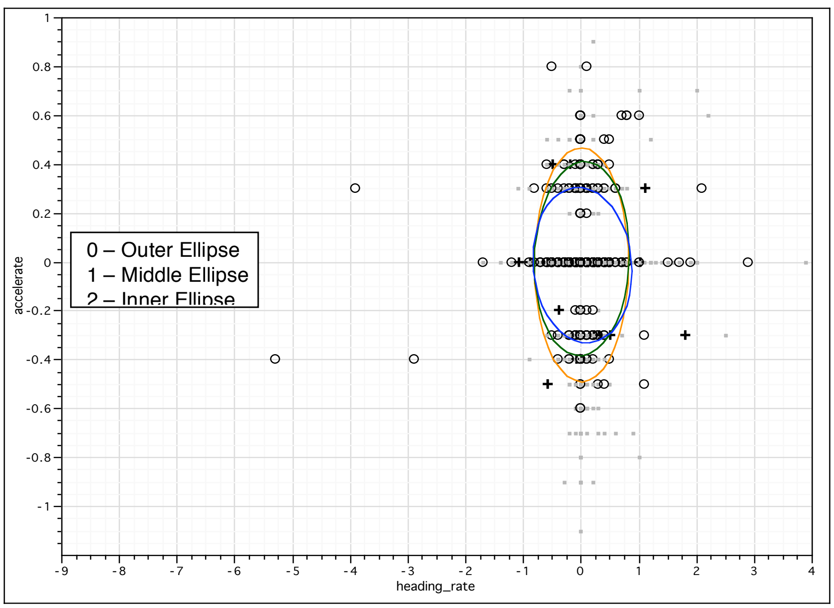


Figure 28. Distribution of Heading Rate and Speed Rate for Collectors by Number of Secondary Tasks Being Performed (0, 1, 2)

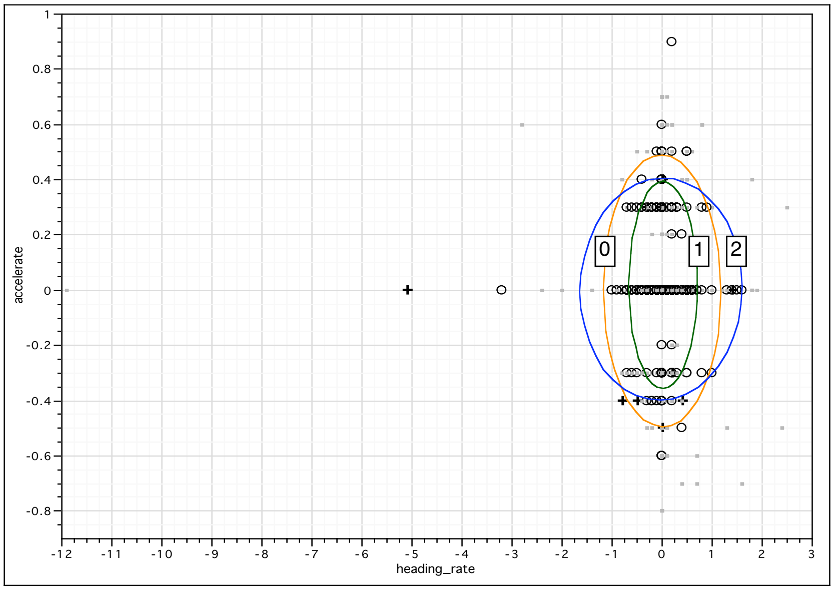


Figure 29. Distribution of Heading Rate and Speed Rate for Local Roads by Number of Secondary Tasks Being Performed (0, 1, 2)

What should be the steering wheel angle and throttle percentage thresholds for maneuver detection?

In previous sections, the data was assumed to be normally distributed, which was generally not true as seen when values that are not physically feasible fell within the ellipses. Appendix A describes a further attempt to fit bivariate normal ellipses to the data by using multiple pairs of performance measures are used for classification and examining what fraction of the data is "abnormal" driving. Given that these models still did not fit the data well, the next logical step was to explore the effects of various thresholds on the data set where there were no distribution assumptions; that is, the data was nonparametric. The previous analyses showed that this could not be done generically, but needed to be tailored for each road class.

Thresholds were developed following two rules:

Rule 1: Draw a simple diagram such as box, triangle, or their combination based on nonparametric density distribution.

Rule 2: Maintain the same or similar shape of the diagram for different road types as much as possible.

Ideally, the domain of the distribution would be a series of vertical and/or horizontal lines in the bivariate distributions. These would be extremely easy to implement in software, requiring only logical operations (if steering wheel angle is greater than x and throttle is greater than y, then... else...), not arithmetic operations. This reduces the cost of the processor needed and the processing time. This is the rationale for the box variant of Rule 1.

Using the same shape for different roads simplifies the software needed to process the data. Where road classifications may be incorrect (for example, due to errors in the database), it can make the workload identification more reliable since there are fewer incorrect categories.

The authors made an effort to determine reasonable, but not necessarily ideal, thresholds. This was done by examining nonparametric density distributions, discussing the data with vehicle dynamics experts at UMTRI, and gathering other evidence. (See Appendix B for details.)

Based on these ideas, initial thresholds (coded as solid lines) were developed for each measurement pairs-road type combination (4 x 6 = 24 figures total). In addition to the thresholds, colored contour lines were drawn based on the density grid table in Appendix C. Warmer colors (near the center) indicate lower percentiles in the distribution. Each contour line is a 5% change, so the outer contour is 95th percentile. Finally, 95th and 99th percentile rings from the bivariate normal distribution have also been superimposed to emphasize the departure from normality.

To validate the thresholds, a random sample of 60 ACAS FOT video clips (30 inside the threshold, 30 outside) was reviewed by one of the report authors for each of the 2 thresholds examined for each variable pair. The clips (all approximately 4 seconds) were classified as maneuvering or non-maneuvering, using Table 3 to identify the type of maneuver, which varied with the type of road. For example, there are no turns at intersections on expressways because there are no intersections.

Table 3. Types of Maneuvers

Demand	Type	Description	Value	Used for Classification
High	Lane	Changing lanes	Left, right, both	All variables
	Merge/exit	Merging, exiting, or changing the road	Merge, exit, lane change	All variables
	Stop	Stopping	Stop	Derivative variables
	High G	Rapid longitudinal acceleration	Accelerate, Decelerate	Derivative variables
	Turn	Turning at the intersection	Left, right, U, Z	All variables
Low	Curve	Driving on a curved road segment	Left, right, S	All variables

Some maneuvers were much easier to identify in some domains than in others. For example, detecting stops and high g acceleration is much easier using speed rather than steer/throttle variable combinations. This validation data was used to develop an improved threshold (coded as a dashed line). Keep in mind that all maneuvers are not equally demanding and maneuver demands vary from situation to situation. For example, the demand of driving a curve depends on the curve radius and speed.

Based on how well the initial thresholds detected maneuvers, the thresholds were adjusted for each maneuver based on analyst judgment, a second set of 60 clips was reviewed, and the detection performance of the second threshold for each maneuver was determined.

Selecting a threshold is a standard signal detection problem (Table 4). In this case, hits were important, but for customer acceptance (not being locked out when a task was important to do), misses were also given priority.

Table 4. Maneuver Identification Options

		Real Situation: Maneuver	Real Situation: Non-Maneuver
Interpretation of Data	Maneuver	Hit	False alarm
	Non-Maneuver	Miss	Correct rejection

Input Space: Steer/Throttle

Figure 30 shows two sets of thresholds superimposed on nonparametric density distribution and bivariate normal ellipses for steering wheel angle and throttle position for interstate highways. Notice that there are some “islands” of data points: about 20% for throttle values and only a few degrees at most for steering wheel angles. The “arm” at –10 degrees steering angle, 10% to 15% throttle, may reflect a leftward lane change, a movement that is probably more rapid than a move to the right. This amorphous distribution shape complicates drawing boundaries to distinguish between normal driving and maneuvering. The solid line represents the initial threshold and the dashed line the improved threshold.

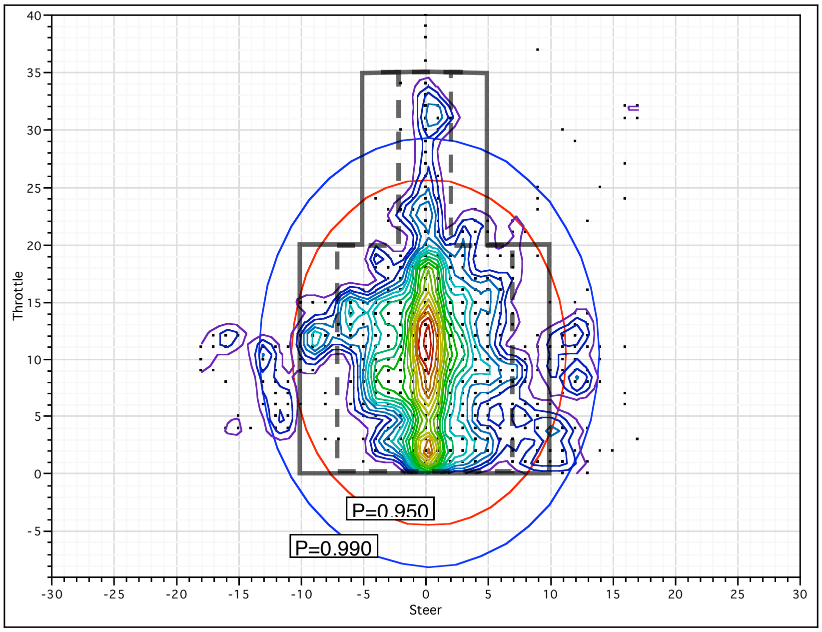


Figure 30. Steering Angle vs. Throttle Angle for Interstates

Table 5 shows the classification of 60 video clips (30 sampled inside the thresholds, 30 sampled outside). Of the 30 “inside” clips in the initial threshold, 19 were maneuvers, whereas of the 30 outside, 29 were maneuvers. Thus, one can be reasonably certain that if the initial threshold is exceeded (or the second threshold for that matter), that the driver is maneuvering. However, most of the maneuvers were driving curves, which are often not high-demand situations on expressways. For curves, the approach before the curves is where the demand is greatest (Tsimhoni and Green, 2004), and failing to notice the beginning of a curve can be fatal. If curve detection is ignored, then 13 of the 30 clips inside the boundaries and 8 of the 30 clips outside involve a maneuver. Interestingly, the second (“improved”) thresholds were not much better than the original thresholds, including all of the lane changes. In fact, neither set of thresholds segregates lane changes.

Table 5. Summary Statistics for Steering Angle vs. Throttle Angle for Interstates

		Maneuver					Non-maneuver	Total	
Threshold	Location	Curve	Lane	Merge /exit	Turn	Sub-total			
Initial	Inside	6	10	3	0	19	11	30	60
	Outside	21	4	4	0	29	1	30	
Second	Inside	7	10	0	0	17	13	30	60
	Outside	25	0	1	1	27	3	30	

Figure 31 shows steering-throttle relationships and the 2 thresholds for freeways, whose nonparametric distribution resembles that of Figure 30. The 95th percentile normal ellipses for Figures 30 and 31 have a strong resemblance and the strongest of all of the figures in this section. In fact, the threshold values were the same for throttle values of less than 20%. Only 2 sets of thresholds were required because of slight differences in the underlying distribution.

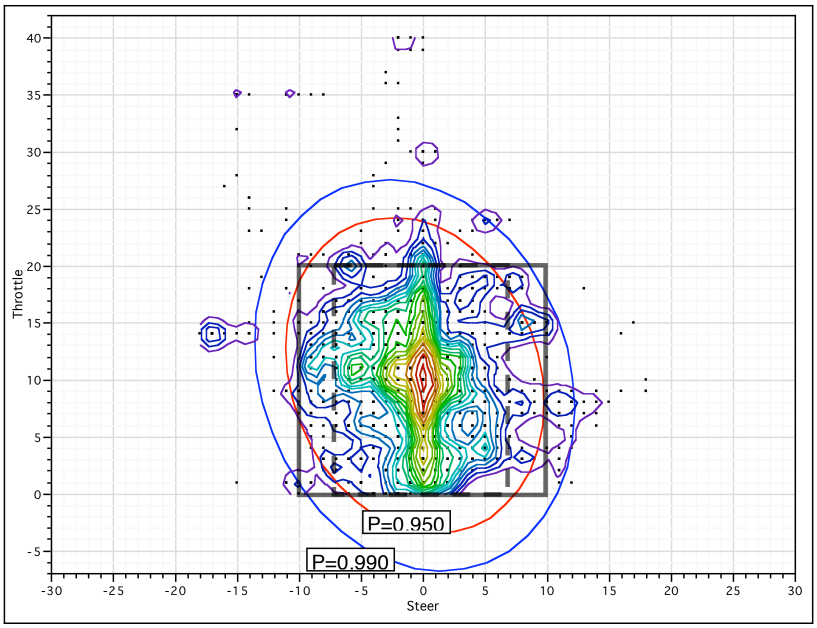


Figure 31. Steering Angle vs. Throttle Angle for Freeways

As shown in Table 6, both sets of thresholds did reasonably well in detecting maneuvers with 28 of 30 being maneuvers outside the thresholds for the initial thresholds and 27 of 30 for the second threshold. Ignoring curves, 14 of the 30 maneuvers are in the outside region for the first threshold, and 11 of 30 are outside for the second. As with interstates, the steer vs. throttle thresholds are missing lane changes, though the thresholds do identify merge/exit maneuvers, especially for freeways. Thus, these pairs of measures by themselves are potentially useful in identifying a limited set of maneuvers.

Table 6. Summary Statistics for Steering Angle vs. Throttle Angle for Freeways

		Maneuver					Non-maneuver	Total	
Threshold	Location	Curve	Lane	Merge /exit	Turn	Sub-total			
Initial	Inside	7	7	1	0	15	15	30	60
	Outside	14	1	13	0	28	2	30	
Second	Inside	10	4	2	0	16	14	30	60
	Outside	16	3	8	0	27	3	30	

Figures 32 (arterial roads) and 33 (minor arterial roads) bear some resemblance to each other, though the steering wheel angle variance is much greater for minor arterials. The initial threshold was the same as that for freeways. In the second threshold set, the steering angle threshold was reduced. Also, note the poor fit of the normal distribution to the steering-throttle data for arterials (Figure 32). Throttle peaks for arterials and minor arterials were on the order of 2%, in contrast to the freeway and expressway distributions, where throttle peaks were on the order of 10% to 12%. The small mean, coupled with positive throttle percentages not being negative, explains why the normal distribution was such a poor fit.

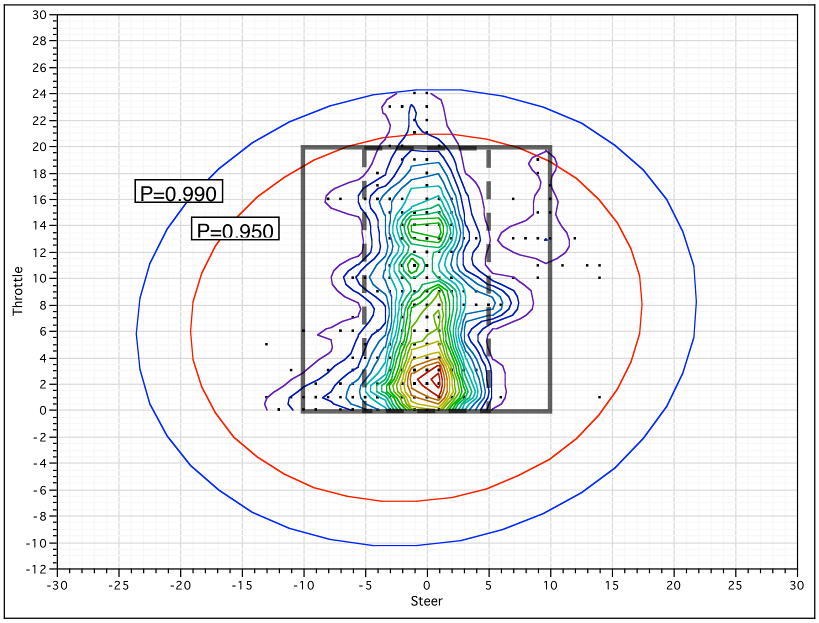


Figure 32. Steering Angle vs. Throttle Angle for Arterials

As shown in Table 7, the initial thresholds did reasonably well in detecting maneuvers. Some 28 of the 30 clips outside the threshold contained a maneuver of some sort, whereas inside the threshold, only 14 of the 30 clips contained maneuvers. Both thresholds were effective at detecting turns but missed many of the lane changes. Thus, for arterials, steering angle vs. throttle thresholds will only detect some of the types of maneuvers reasonably well. Of the 2, the initial thresholds are preferred.

Table 7. Summary Statistics for Steering Angle vs. Throttle Angle for Arterials

		Maneuver					Non-maneuver	Total	
Threshold	Location	Curve	Lane	Merge /exit	Turn	Sub-total			
Initial	Inside	8	6	0	0	14	16	30	60
	Outside	9	3	1	15	28	2	30	
Second	Inside	2	10	0	2	14	16	30	60
	Outside	9	2	0	9	20	10	30	

For minor arterials (Figure 33), the initial threshold was the same as that for freeways. However, in contrast to the arterials model, the range of steering values accepted expanded in the second threshold, reflecting the broader distribution of steering wheel angles on minor arterials.

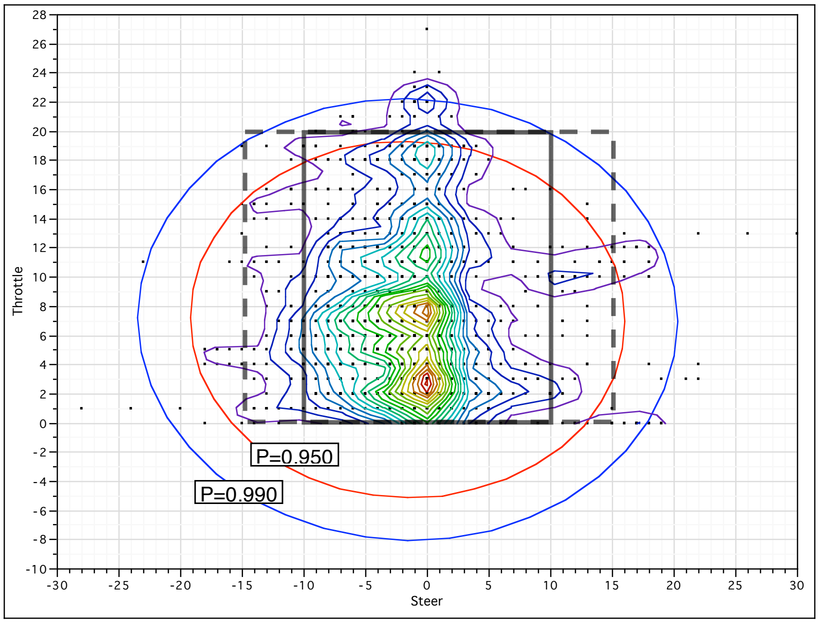


Figure 33. Steering Angle vs. Throttle Angle for Minor Arterials

As shown in Table 8, both thresholds showed similar performance in detecting maneuvers. All clips outside of the second threshold were maneuvers and 26 of the 30 clips outside the initial threshold were maneuvers. Inside their respective thresholds, the initial threshold missed 8 maneuvers and the second model missed 9 maneuvers. Both models did reasonably well in detecting turns and very well in detecting curves, which is of secondary importance. Both thresholds failed to detect lane changes accurately.

Table 8. Summary Statistics for Steering Angle vs. Throttle Angle for Minor Arterials

		Maneuver					Non-maneuver	Total	
Threshold	Location	Curve	Lane	Merge /exit	Turn	Sub-total			
Initial	Inside	3	2	0	3	8	22	30	60
	Outside	13	1	0	12	26	4	30	
Second	Inside	0	7	0	2	9	21	30	60
	Outside	5	0	0	25	30	0	30	

Figure 34 shows 2 sets of thresholds for collectors in a two-lobe configuration, necessary to capture low speed driving. The lower speeds and greater amount of steering angles are reflected by the concentration of the data much closer to 0 percent throttle. The shape of the upper lobe is similar to that for arterials.

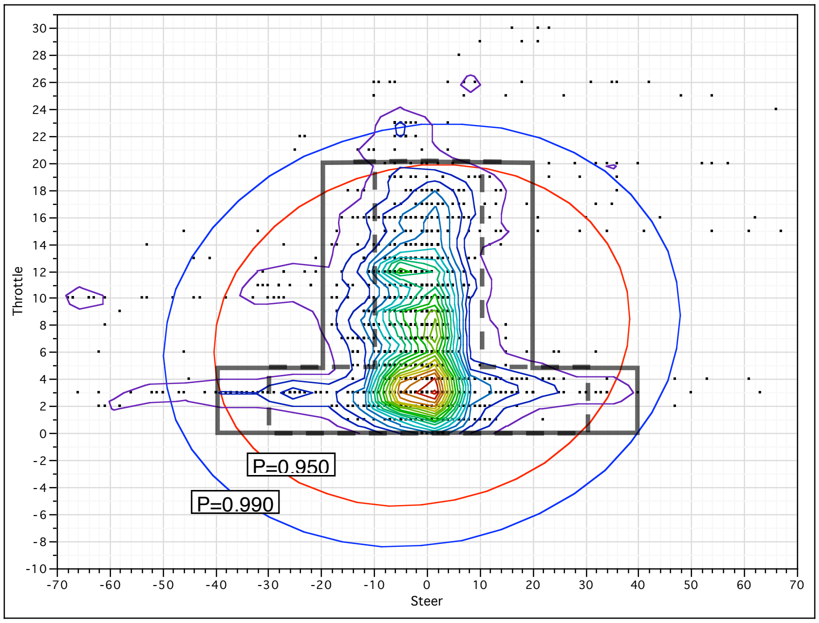


Figure 34. Steering Angle vs. Throttle Angle for Collectors

As shown in Table 9, all clips outside of the initial threshold were maneuvers and 27 of 30 clips outside of the second threshold were maneuvers. The detection performance for maneuvers for the initial threshold is less than 3 to 1 overall and the ratio for the second threshold is 4.5 to 1. Both thresholds did well in detecting turns and poorly in detecting lane changes.

Table 9. Summary Statistics for Steering Angle vs. Throttle Angle for Collectors

		Maneuver					Non-maneuver	Total	
Threshold	Location	Curve	Lane	Merge /exit	Turn	Sub-total			
Initial	Inside	9	2	0	0	11	19	30	60
	Outside	6	0	0	24	30	0	30	
Second	Inside	5	1	0	0	6	24	30	60
	Outside	12	0	0	15	27	3	30	

As shown in Figure 35, the authors established thresholds differently for local roads than for other roads, primarily because of the much greater steering wheel angles at low throttle settings.

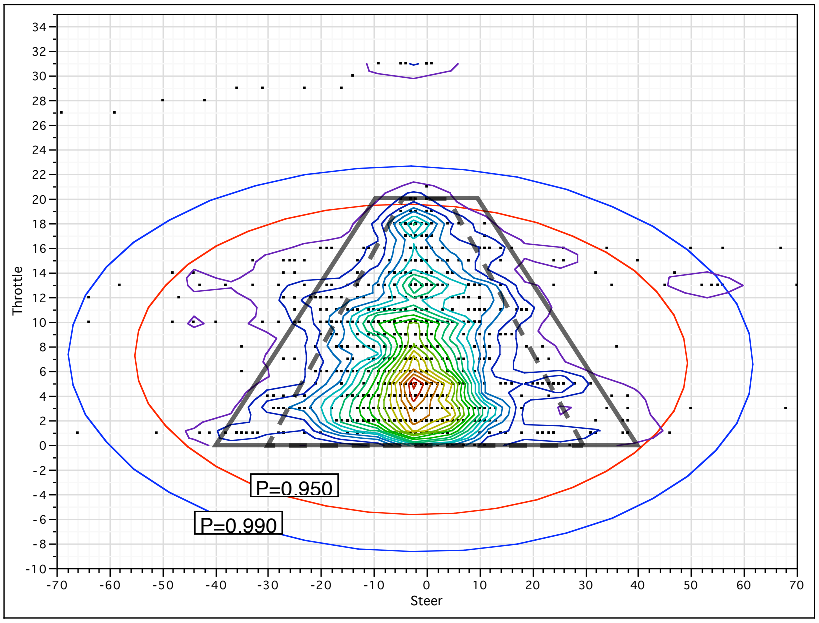


Figure 35. Steering Angle vs. Throttle Angle for Local Roads

Table 10 shows the classification performance of the two models using trapezoidal thresholds. Both thresholds did equally well, detecting all of the turns and most of the curves. There were too few lane changes to accurately judge that maneuver, and no merge/exits were observed. Either threshold yields acceptable performance in distinguishing between maneuvers and non-maneuvers.

Table 10. Summary Statistics for Steering Angle vs. Throttle Angle for Local Roads

		Maneuver					Non-maneuver	Total	
Threshold	Location	Curve	Lane	Merge/ exit	Turn	Sub-total			
Initial	Inside	5	1	0	0	6	24	30	60
	Outside	10	0	0	20	30	0	30	
Second	Inside	5	0	0	0	5	25	30	60
	Outside	11	1	0	16	28	2	30	

Figure 36 shows the nonparametric contour plot for steering wheel angle versus throttle for ramps. This odd distribution occurred because there are only 14 data points for the ramp out of the 15,962 total samples. The authors did not calculate thresholds for any of the ramp data because of the small sample size. Readers should exercise caution in making decisions based on these few points.

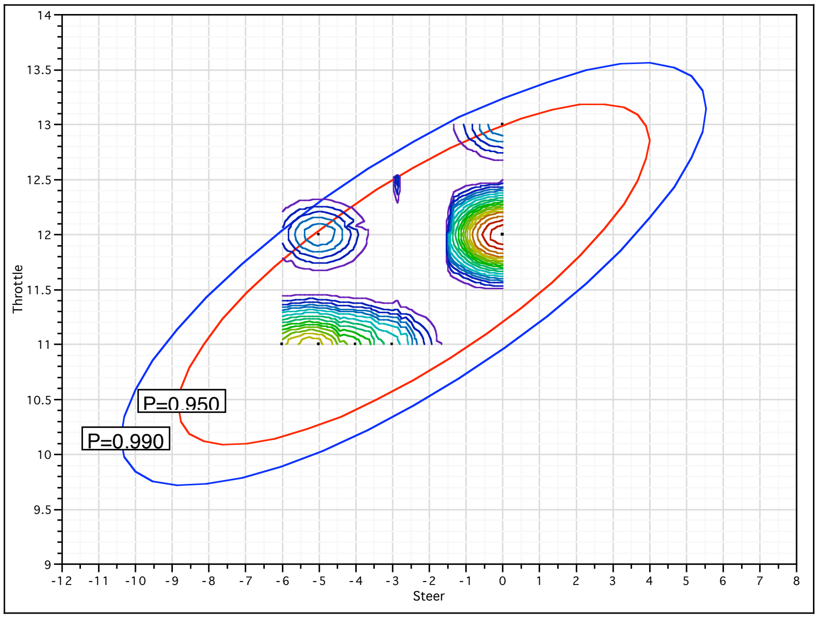


Figure 36. Steering Angle vs. Throttle Angle for Ramps

Overall, steering and throttle data could be used to fairly accurately detect and identify maneuvers. The data performed best when detecting turns, average when detecting curves, and poorly when detecting lane changes. Almost all road classes had different thresholds due to the need to fit thresholds to different sets of data. Collectors and local roads required differently-shaped thresholds to fit the data. A practical implication of this result is that a maneuver-based workload manager that uses steering wheel and throttle data to classify driving performance will need to know the road class driven to work effectively. For contemporary products, this means the workload manager will need to have access to data from a navigation system.

What should be the heading and speed thresholds for maneuver detection?

As an alternative or supplement to steering wheel angle and throttle percentage, the authors examined detection performance of heading and speed. As before, the differences among roads required different thresholds for each road class.
The sample had a limited number of stopped cases because it was designed to examine vehicles in motion. This led to poor detection of high g and stop maneuvers, which were omitted.

There are 2 different thresholds used for interstates (Figure 37), 1 with curved thresholds, dependent on speed (based on the bivariate normal ellipse for the 95th percentile), and 1 with vertical thresholds for heading, an easier model to implement.

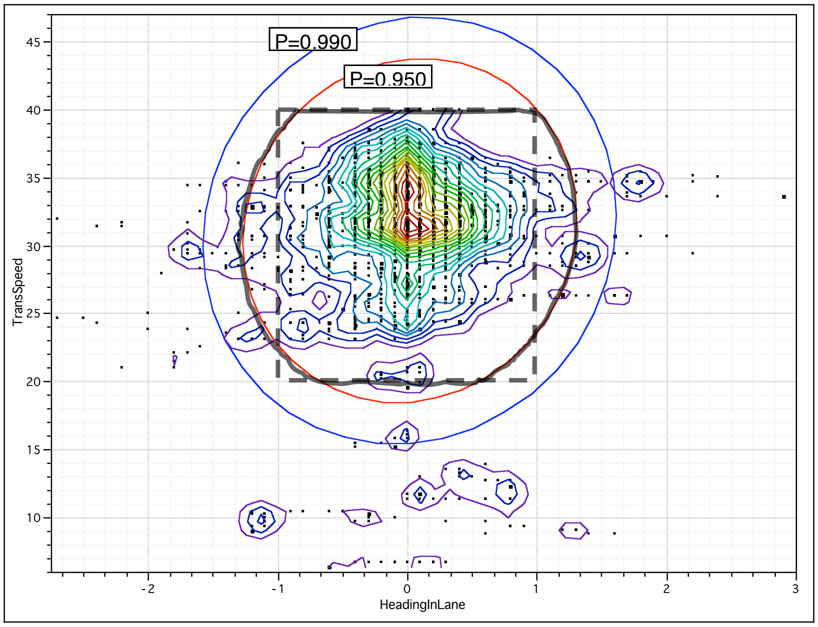


Figure 37. Heading vs. Speed for Interstates

Both thresholds did equally well, as seen in Table 11, detecting nearly all of the maneuvers outside of the threshold and half of those inside. They were good at detecting lane changes, but detection performance for other maneuvers was inconsistent. Why the 2 thresholds had such drastically different performance in detection curves and merge/exits is uncertain given they were so similar in coverage.

Table 11. Summary Statistics for Heading vs. Speed for Interstates

		Maneuver					Non-maneuver	Total	
Threshold	Location	Curve	Lane	Merge /exit	Turn	Sub-total			
Initial	Inside	10	3	2	0	15	15	30	60
	Outside	3	18	6	0	27	3	30	
Second	Inside	9	1	2	0	12	18	30	60
	Outside	12	14	1	0	27	3	30	

Figure 38 shows the models examined for freeways. The initial threshold was the same as that for interstates, though the maximum speed was reduced from 40 to 35 m/s. The second threshold has expanded boundaries for heading. The road types are very similar, so the heading vs. speed distributions should also be similar.

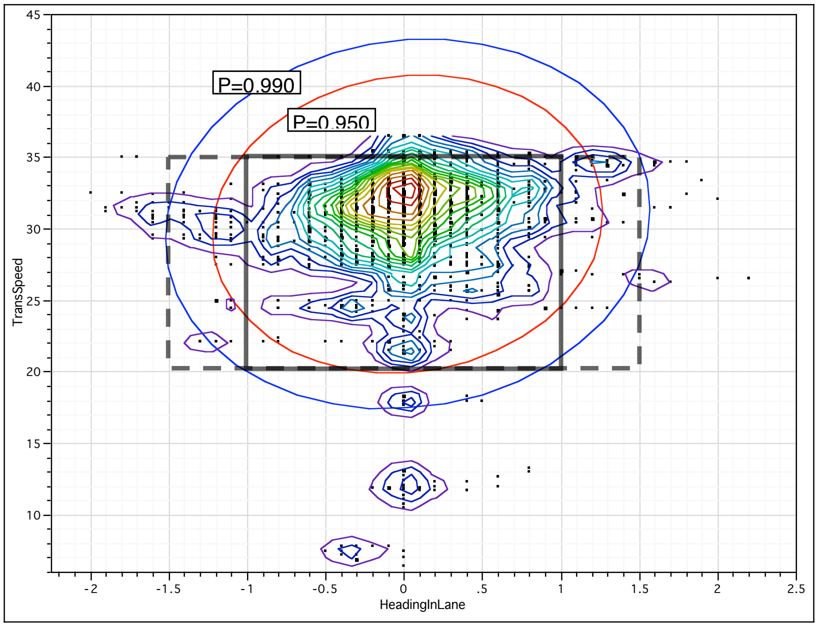


Figure 38. Heading vs. Speed for Freeways

Although the second threshold covered 50 percent more area than the initial threshold, only 1 more instance of maneuvering was detected (Table 12), though they were independent samples. Both thresholds did quite well detecting lane changes and below average detecting curves. There were too few samples to make a definitive judgment for merges/exits. Both thresholds were roughly equal in overall detection performance.

Table 12. Summary Statistics for Heading vs. Speed for Freeways

		Maneuver					Non-maneuver	Total	
Threshold	Location	Curve	Lane	Merge /exit	Turn	Sub-total			
Initial	Inside	12	1	2	0	15	15	30	60
	Outside	10	14	4	0	28	2	30	
Second	Inside	15	2	2	0	19	11	30	60
	Outside	11	16	2	0	29	1	30	

As shown in Figure 39, the overall speed for arterials was lower than that for interstates and freeways, so the speed thresholds reduced to 30 m/s maximum and to 5 m/s minimum. Heading thresholds were similar to those on interstates and freeways. (Note that the scaling of the x-axis is shifted to accommodate the data.)

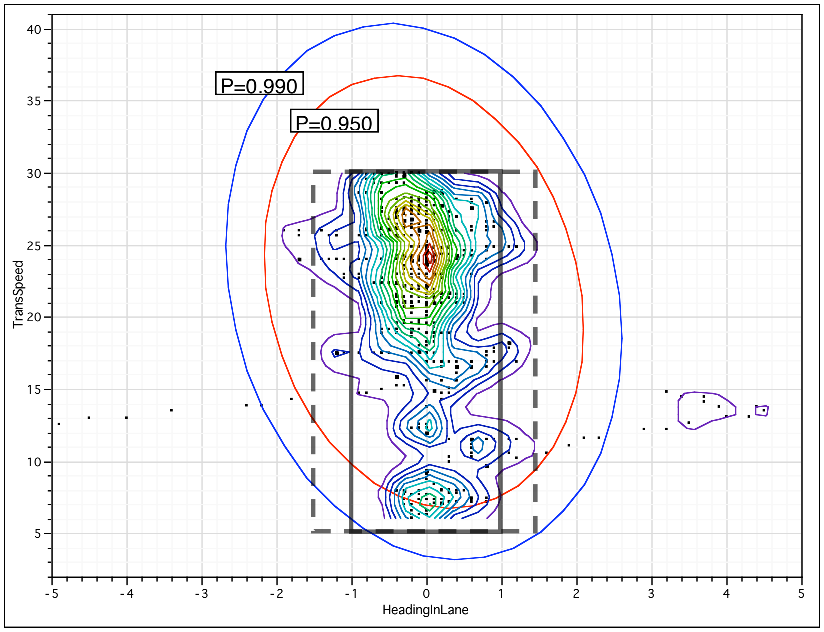


Figure 39. Heading vs. Speed for Arterials

Though both models are above average (Table 13), the initial model performed better than the second at detecting lane changes. Both models performed below average at detecting curves. The detection performance of other maneuvers could not be addressed because of a lack of data.

Table 13. Summary Statistics for Heading vs. Speed for Arterials

		Maneuver					Non-maneuver	Total	
Threshold	Location	Curve	Lane	Merge /exit	Turn	Sub-total			
Initial	Inside	7	1	0	1	9	21	30	60
	Outside	8	13	0	1	22	8	30	
Second	Inside	5	7	0	3	15	15	30	60
	Outside	3	23	1	1	28	2	30	

Figure 40 shows the results for minor arterials. The thresholds examined were the same as those for arterials.

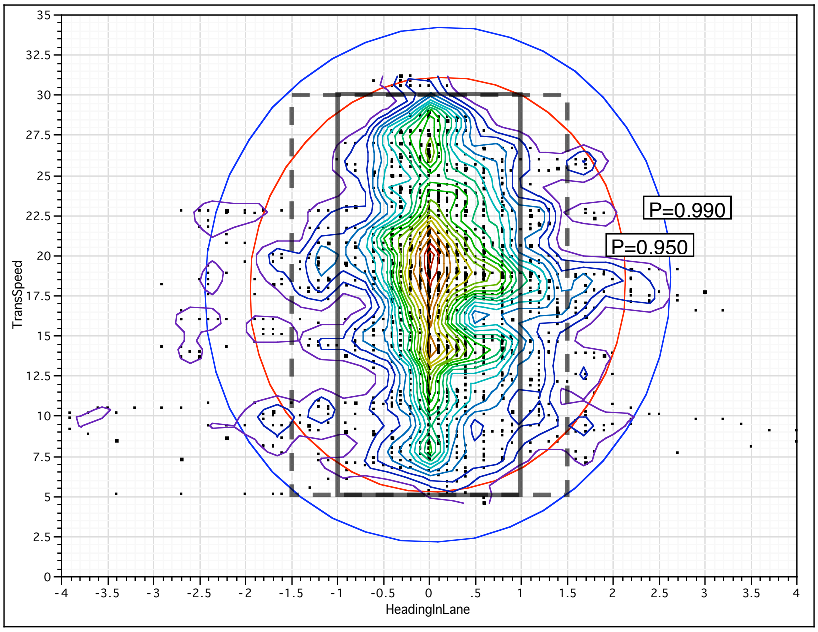


Figure 40. Heading vs. Speed for Minor Arterials

As shown in Table 14, the initial threshold was much better at detecting maneuvers (23:4) than the second threshold (27:14), for turns, lane changes, and curves. However, of the instances where the heading and speed exceeded the second threshold, "non-maneuvers" were rare (3/30 cases).

Table 14. Summary Statistics for Heading vs. Speed for Minor Arterials

		Maneuver					Non-maneuver	Total	
Threshold	Location	Curve	Lane	Merge /exit	Turn	Sub-total			
Initial	Inside	3	1	0	0	4	26	30	60
	Outside	10	11	0	2	23	7	30	
Second	Inside	9	4	0	1	14	16	30	60
	Outside	7	16	0	4	27	3	30	

As shown in Figure 41, the distribution of heading vs. speed for collectors is not symmetric among a significant number of situations with headings on the order of 2 degrees at speeds of about 13 m/s. A notch removes combinations of large positive headings with high speeds from inclusion within the threshold. The solid line diagram has an asymmetric form to fit the nonparametric distribution. The dashed line diagram was identical to the arterial and minor arterial diagrams.

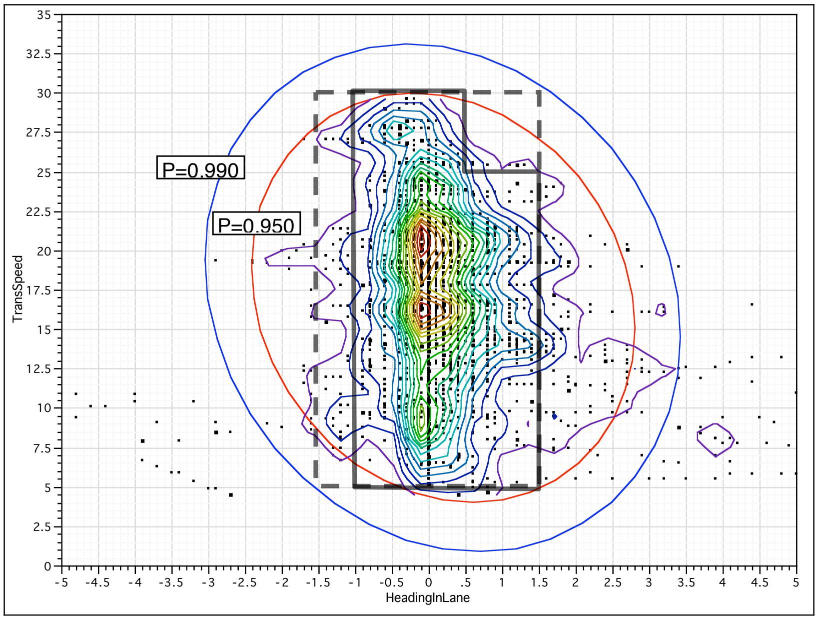


Figure 41. Heading vs. Speed for Collectors

As shown in Table 15, the initial threshold (23:5) detected performance slightly better than the second threshold (27:8). Both had average performances in detecting curves, lane changes, and turns. However, for the second threshold, any value exceeding that threshold was highly likely to be a maneuver.

Table 15. Summary Statistics for Heading vs. Speed for Collectors

		Maneuver					Non-maneuver	Total	
Threshold	Location	Curve	Lane	Merge /exit	Turn	Sub-total			
Initial	Inside	3	0	0	2	5	5	30	60
	Outside	14	7	0	2	23	7	30	
Second	Inside	3	2	0	3	8	2	30	60
	Outside	13	11	0	3	27	3	30	

Figure 42 shows the results for local roads. The boundaries for heading thresholds are larger for local roads than any other road types.

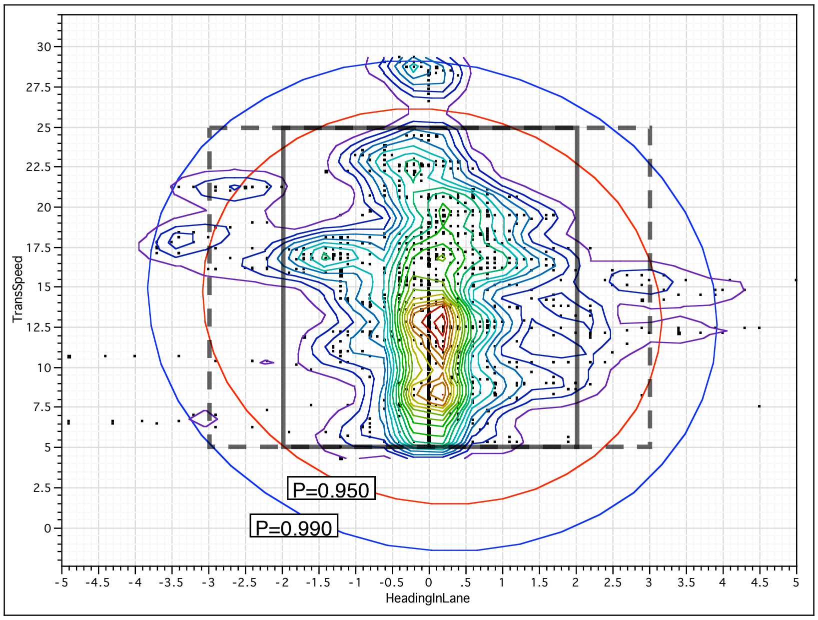


Figure 42. Heading vs. Speed for Local Roads

Table 16 shows the results for local roads. Both thresholds did above average detecting curves and lane changes, with the initial thresholds slightly outperforming the second ones in detecting turns. Maneuvers outside the second threshold were extremely rare (3/30 cases).

Table 16. Summary Statistics for Heading vs. Speed for Local Roads

		Maneuver					Non-maneuver	Total	
Threshold	Location	Curve	Lane	Merge /exit	Turn	Sub-total			
Initial	Inside	5	0	0	9	14	16	30	60
	Outside	16	1	0	8	25	5	30	
Second	Inside	4	2	0	9	15	15	30	60
	Outside	18	5	0	4	27	3	30	

As before, the data for ramps looks odd, reflecting the small sample size (Figure 43).

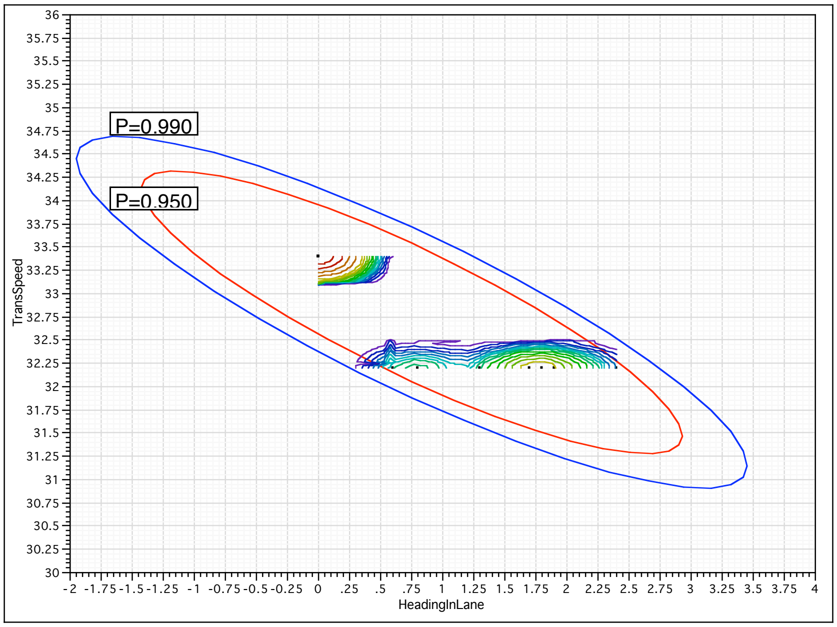


Figure 43. Heading vs. Speed for Ramps

What should be the steering rate and throttle rate thresholds for maneuver detection?

The authors investigated derivative variables to detect rapid changes of vehicle movements including rapid acceleration, deceleration, or stopping as well as rapid lane change and turning at an intersection, etc. At least 3 models were examined for each road type but only the best model is presented. Simple rectangular thresholds were adopted for models of all derivative variables for ease of implementation.

As seen in Figures 44-49, which show the thresholds, all of the steering rate versus throttle rate distributions, the derivative of steering wheel angle and throttle percent data, are composed of multiple islands. This is because the limited resolution of the original data limits the number of possible values that can be computed.

Initially, thresholds for throttle rate used 95th percentile boundaries to help detect high g and stop maneuvers, which they were not able to do. Setting vertical thresholds (throttle rate thresholds) to values larger than the boundaries of nonparametric density distribution for all road types did not improve detection performance either.

Figure 44 shows the thresholds examined for interstates.

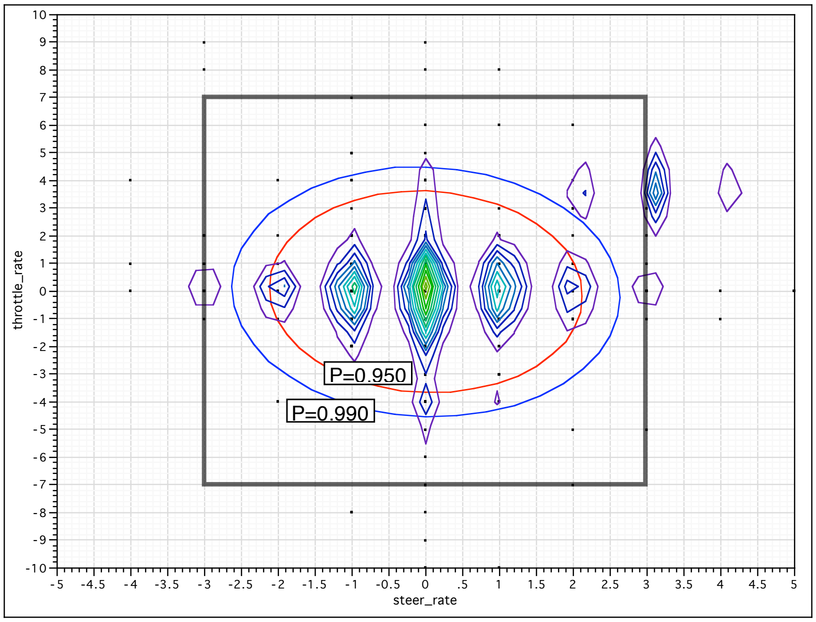


Figure 44. Steering Rate vs. Throttle Rate for Interstates

As shown in Table 17, these thresholds were reasonably effective (28:6 overall) at detecting curves, lane changes, and merge/exit maneuvers. There were too few maneuvers of other types to be certain of their detection performance. “Non-maneuver” situations outside the threshold were rare (2/30 cases).

Table 17. Summary Statistics for Steering Rate vs. Throttle Rate for Interstates

	Maneuver							Non-maneuver	Total	
Location	Curve	High G	Lane	Merge /exit	Stop	Turn	Sub-total			
Inside	3	1	2	0	0	0	6	24	30	60
Outside	13	3	8	4	0	0	28	2	30	

As shown in Figure 45, the thresholds for freeways were set to the same values as those for interstates. Thresholds for throttle rate, ±7 %, are larger than twice the vertical boundary of the nonparametric density distribution. Note that the horizontal axis in Figure 45 has been shifted left and not aligned with Figure 43 so the island can appear.

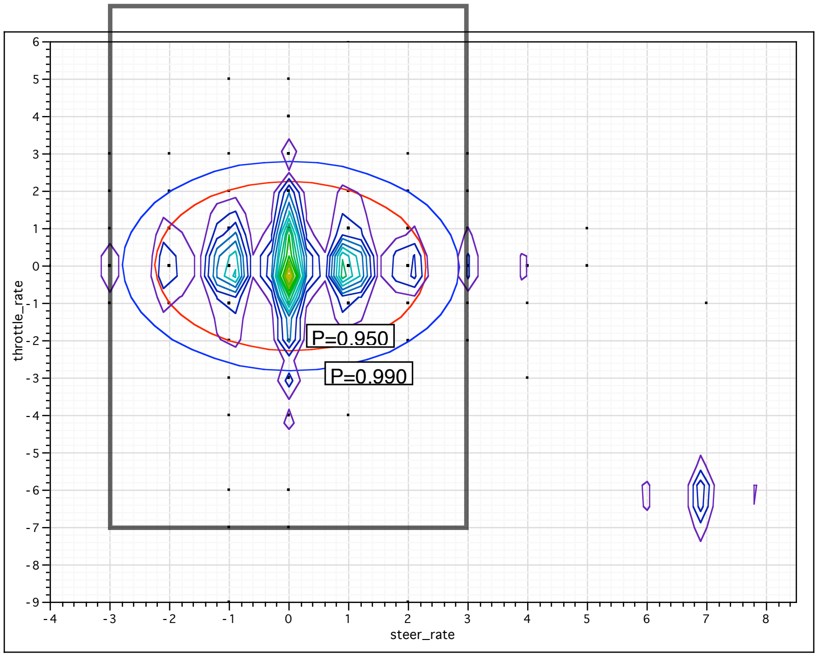


Figure 45. Steering Rate vs. Throttle Rate for Freeways

As shown in Table 18, the thresholds performed above average in detecting curves, lane changes, and merges/exits. The thresholds were not able to detect high g maneuvers. “Non-maneuver” situations outside the threshold were uncommon (4/30 cases).

Table 18. Summary Statistics for Steering Rate vs. Throttle Rate for Freeways

	Maneuver							Non-maneuver	Total	
Location	Curve	High G	Lane	Merge /exit	Stop	Turn	Sub-total			
Inside	6	2	0	0	0	0	8	22	30	60
Outside	10	0	5	10	0	1	26	4	30	

Figure 46 shows the thresholds for arterials, which are narrower than those for expressways.

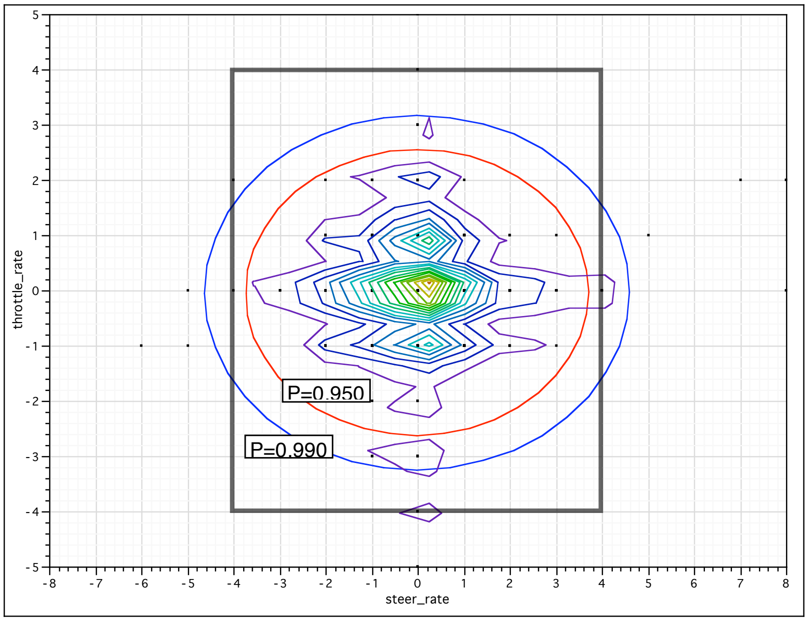


Figure 46 Steering Rate vs. Throttle Rate for Arterials

As shown in Table 19, the thresholds for arterials detected all turns, but performed below average detecting other maneuvers. Nonetheless, “non-maneuver” situations outside the threshold were uncommon (4/30 cases)

Table 19. Summary Statistics for Steering Rate vs. Throttle Rate for Arterials

	Maneuver							Non-maneuver	Total	
Location	Curve	High G	Lane	Merge /exit	Stop	Turn	Sub-total			
Inside	2	9	1	0	2	0	14	16	30	
Outside	1	6	2	0	0	17	26	4	30	60

Figure 47 shows the minor arterials thresholds for steering rate, which were broader than those for arterials.

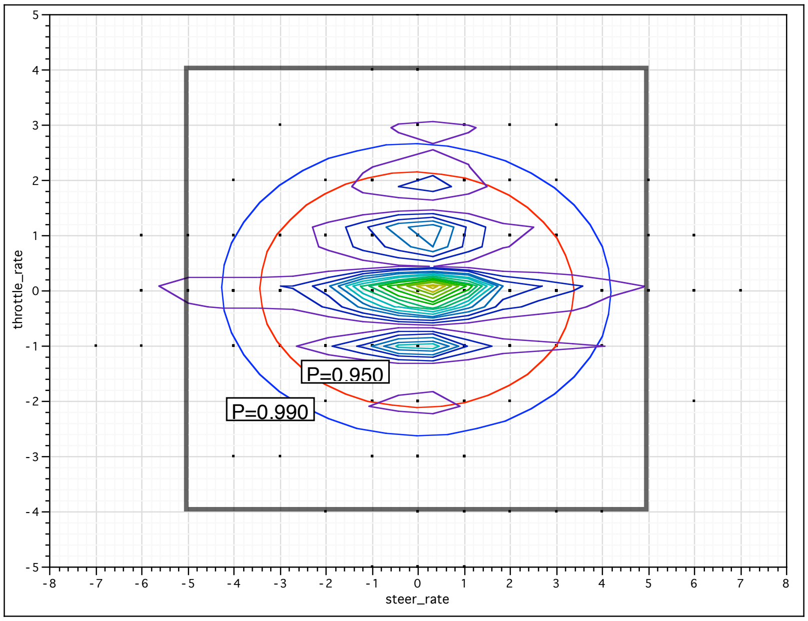


Figure 47. Steering Rate vs. Throttle Rate for Minor Arterials

Table 20 shows that the threshold performed perfectly in detecting turns, lane changes, and curves. The threshold was not effective at detecting high g and stop maneuvers. Interestingly, there were no instances of "non-maneuver" outside of the threshold.

Table 20. Summary Statistics for Steering Rate vs. Throttle Rate for Minor Arterials

	Maneuver							Non-maneuver	Total	
Location	Curve	High G	Lane	Merge /exit	Stop	Turn	Sub-total			
Inside	0	8	0	0	4	0	12	18	30	
Outside	2	1	4	0	0	23	30	0	30	60

Figure 48 shows the threshold model for collectors. The steering rate thresholds were broader than those for arterials and the throttle rate thresholds were less inclusive than those for arterials. Note that the steering rate thresholds were much lower than the larger percentiles of the steering rate distribution.

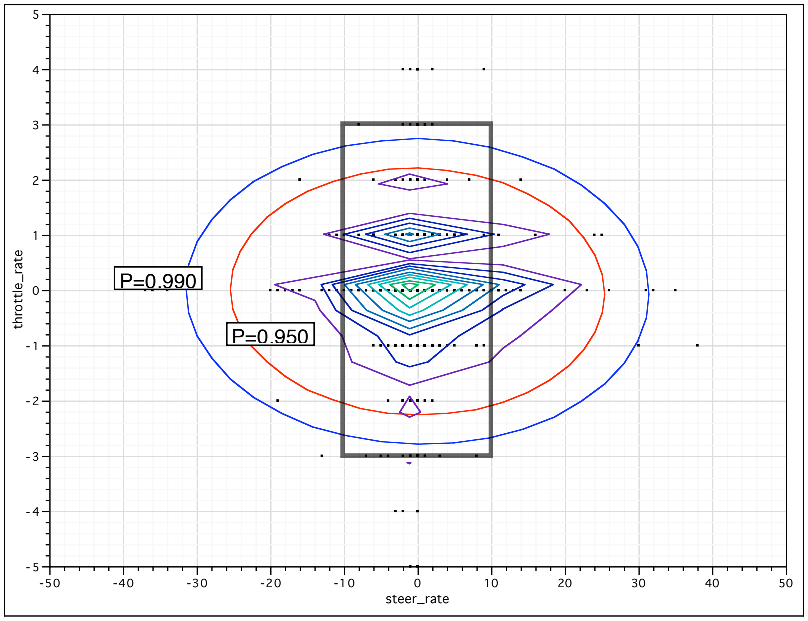


Figure 48. Steering Rate vs. Throttle Rate for Collectors

As shown in Table 21, the thresholds detected all turns but performed below average in detecting all other maneuvers. There was only 1 instance of “non-maneuver” outside of the threshold.

Table 21. Summary Statistics for Steering Rate vs. Throttle Rate for Collectors

	Maneuver							Non-maneuver	Total	
Location	Curve	High G	Lane	Merge /exit	Stop	Turn	Sub-total			
Inside	3	11	3	0	4	0	21	9	30	60
Outside	1	1	1	0	3	23	29	1	30	

As shown in Figure 49, the threshold model for local roads was the same as that for collectors, ±10 deg/s for steering rate and ±3%/s for throttle rate.

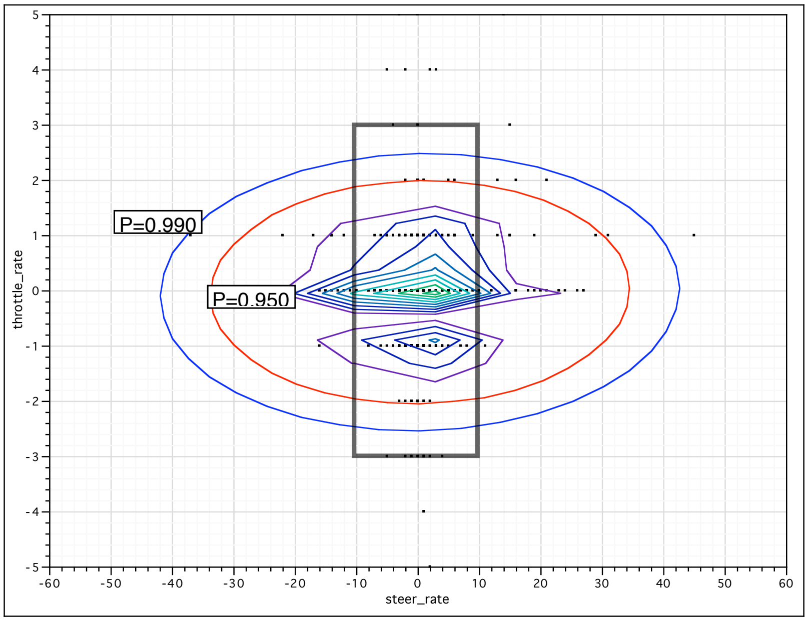


Figure 49. Steering Rate vs. Throttle Rate for Local Roads

As shown in Table 22, the thresholds detected all turns but performed below average in detecting other maneuvers. There were no instances of “non-maneuver” outside of the threshold.

Table 22. Summary Statistics for Steering Rate vs. Throttle Rate for Local Roads

	Maneuver							Non-maneuver	Total	
Location	Curve	High G	Lane	Merge /exit	Stop	Turn	Sub-total			
Inside	2	11	1	0	3	0	17	13	30	60
Outside	3	4	1	0	0	22	30	0	30	

As shown in Figure 50, thresholds were not set for ramps due to the lack of data.

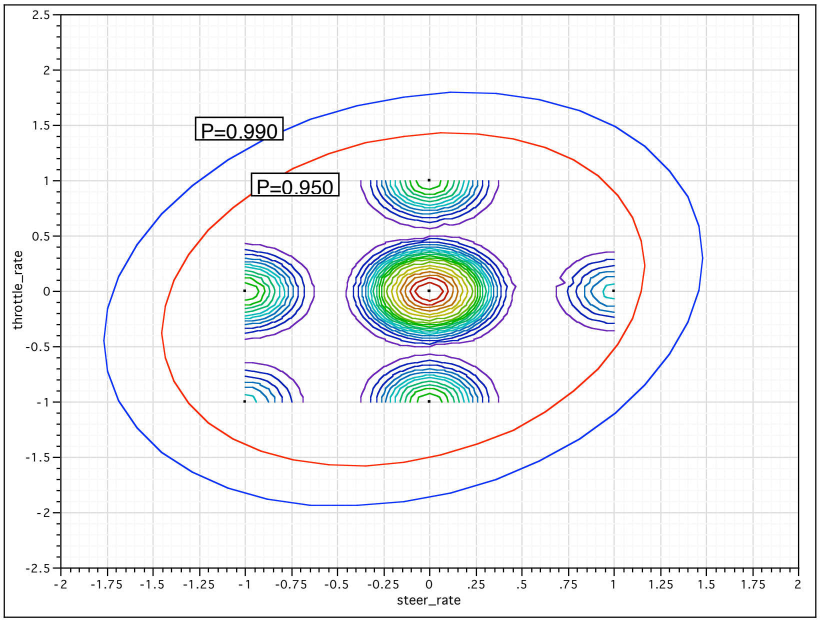


Figure 50. Steering Rate vs. Throttle Rate for Ramps

Using the data, the overall steering rate and throttle rate seem to be poor indicators of high g acceleration and deceleration. This may be due to the precision of the data analyzed.

What should be the heading rate and speed rate (acceleration) thresholds for maneuver detection?

Similar to the steering rate vs. throttle rate pair, the authors examined several models but only discuss the most effective case. Simple rectangular thresholds were used in all cases for ease of implementation. The largest percentile of the nonparametric distribution was used to place the thresholds. Figure 51 shows the thresholds for interstates. Thresholds for heading rate and speed rate were ±0.6 deg/s and ±0.4 m/s^2, respectively. Again, there is a high degree of quantization due to limited precision of the original measurements.

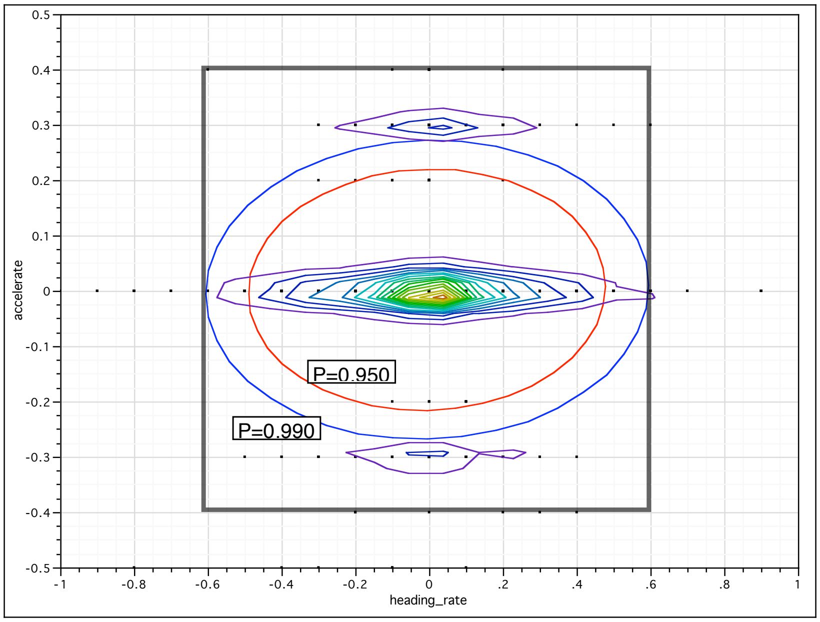


Figure 51. Heading Rate vs. Speed Rate for Interstates

As shown in Table 23, the thresholds selected detected nearly all high g, lane, and merge/exit maneuvers but only detected 1 out of 8 curves. There were 2 instances of "non-maneuver" outside of the threshold.

Table 23. Summary Statistics for Heading Rate vs. Acceleration for Interstates

	Maneuver							Non-maneuver	Total	
Location	Curve	High G	Lane	Merge /exit	Stop	Turn	Sub-total			
Inside	7	0	1	0	0	0	8	22	30	
Outside	1	12	8	7	0	0	28	2	30	60

As shown in Figure 52, thresholds for freeways were set to the same values as those for interstates.

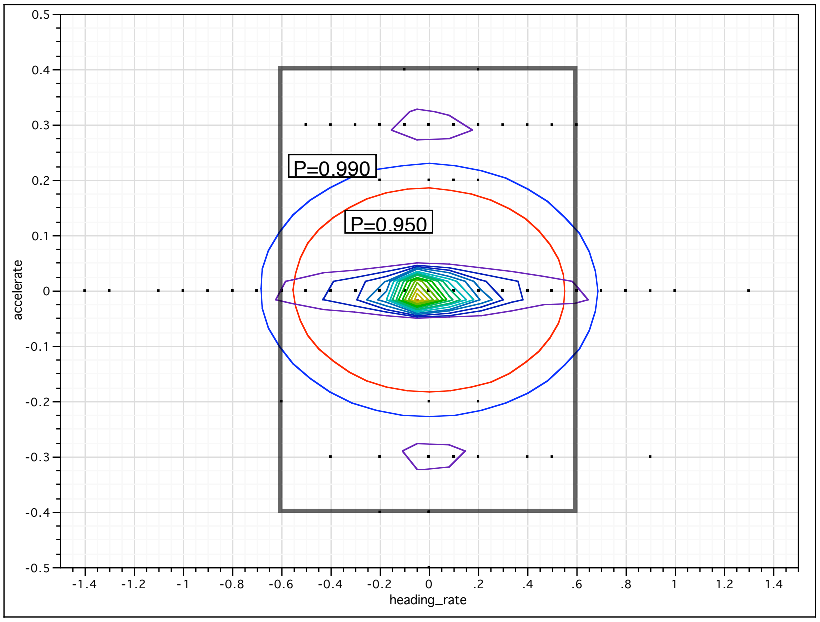


Figure 52. Heading Rate vs. Speed Rate for Freeways

As shown in Table 24, the thresholds detected all high g, merge/exit, and stop maneuvers. In contrast to results for interstates, the thresholds for freeways were only average at detecting lane changes. There was 1 instance of non-maneuvering outside of the threshold.

Table 24. Summary Statistics for Heading Rate vs. Acceleration for Freeways

	Maneuver							Non-maneuver	Total	
Location	Curve	High G	Lane	Merge /exit	Stop	Turn	Sub-total			
Inside	8	0	2	0	0	0	10	20	30	
Outside	6	12	3	7	1	0	29	1	30	60

As shown in Figure 53, the speed rate threshold values used for arterials were the same as those for interstates and freeways. The heading rate thresholds were broader, set to ±1.0 deg/s.

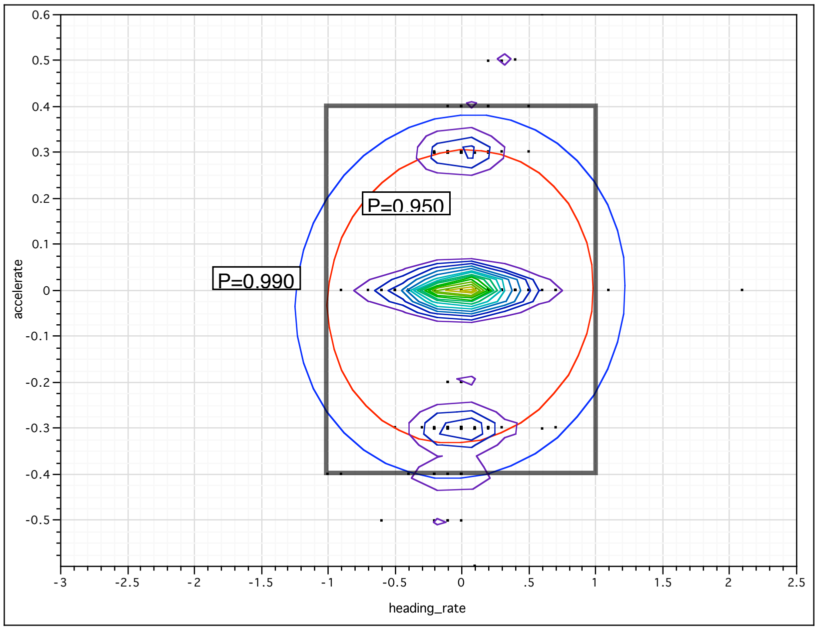


Figure 53. Heading Rate vs. Speed Rate for Arterials

As shown in Table 25, only three events were detected inside the thresholds, all of which were curves. The thresholds detected all high g maneuvers, lane changes, and turns. There were no instances of non-maneuvering outside of the threshold.

Table 25. Summary Statistics for Heading Rate vs. Acceleration for Arterials

	Maneuver							Non-maneuver	Total	
Location	Curve	High G	Lane	Merge /exit	Stop	Turn	Sub-total			
Inside	3	0	0	0	0	0	3	27	30	
Outside	1	20	4	0	1	4	30	0	30	60

As shown in Figure 54, the heading rate threshold values for minor arterials were the same as those for arterials. Speed rate thresholds were decreased to ±0.5 m/s^2

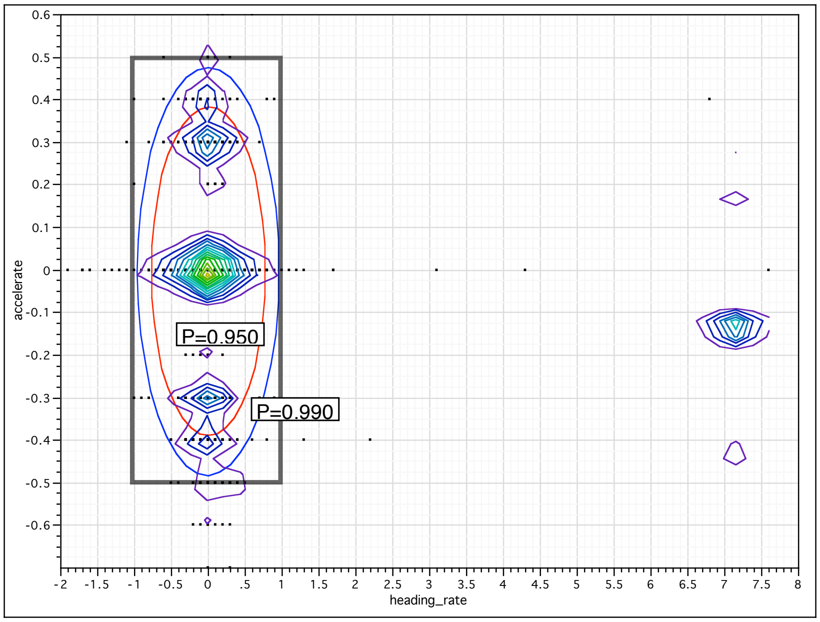


Figure 54. Heading Rate vs. Speed Rate for Minor Arterials

As shown in Table 26, only 2 maneuvers were detected inside the thresholds. The thresholds detected all high g maneuvers, stops, and turns, and they performed above average in detecting lane changes. There were 2 instances of non-maneuvering outside of the threshold.

Table 26. Summary Statistics for Heading Rate vs. Speed Rate for Minor Arterials

	Maneuver							Non-maneuver	Total	
Location	Curve	High G	Lane	Merge /exit	Stop	Turn	Sub-total			
Inside	1	0	1	0	0	0	2	28	30	60
Outside	1	14	3	0	3	8	29	2	30	

As shown in Figure 55, the same heading rate thresholds used for the previous 2 road types were used for collectors. Speed rate thresholds were set to ±0.6 m/s^2.

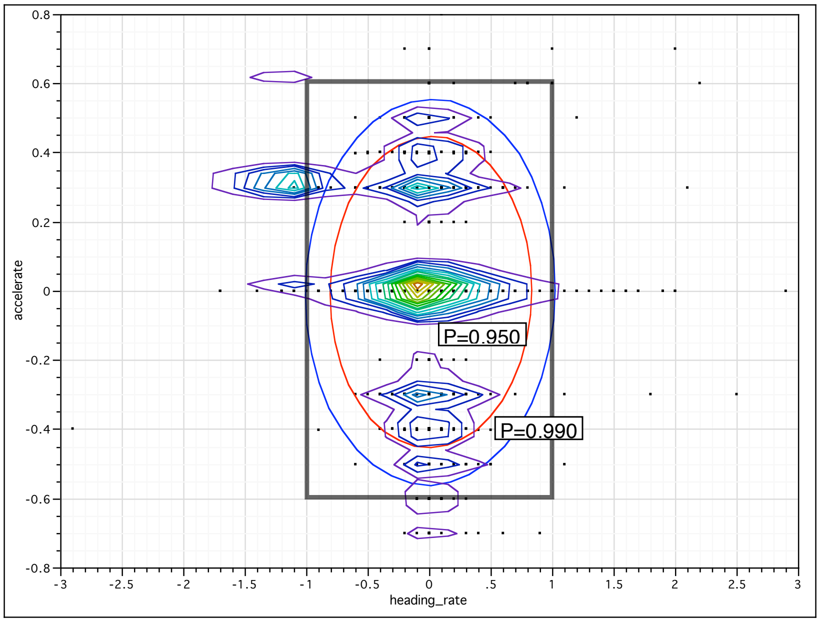


Figure 55. Heading Rate vs. Speed Rate for Collectors

As shown in Table 27, 4 maneuvers (all curves) were detected inside the threshold. The thresholds detected all high g maneuvers, stops, and turns. There were no instances of “non-maneuver” outside of the threshold.

Table 27. Summary Statistics for Heading Rate vs. Acceleration for Collectors

	Maneuver							Non-maneuver	Total	
Location	Curve	High G	Lane	Merge /exit	Stop	Turn	Sub-total			
Inside	4	0	0	0	0	0	4	26	30	60
Outside	0	8	0	0	7	15	30	0	30	

As shown in Figure 56, the thresholds for local roads were the same as those for collectors. (Steering rates and throttle rates were ±1.0 deg/s and ±0.6 m/s^2, respectively.)

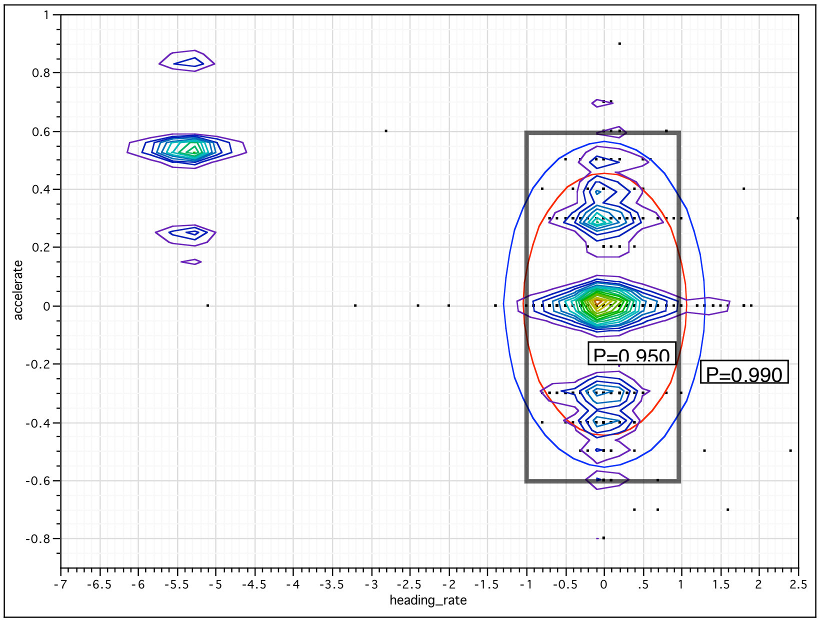


Figure 56. Heading Rate vs. Speed Rate for Local Roads

As shown in Table 28, 4 of the 5 maneuvers detected inside the thresholds were curves. The thresholds performed nearly perfectly in detecting high g maneuvers, stops, and turns. There was 1 instance of non-maneuvering outside the threshold.

Table 28. Summary Statistics for Heading Rate vs. Acceleration for Local Roads

	Maneuver							Non-maneuver	Total	
Location	Curve	High G	Lane	Merge /exit	Stop	Turn	Sub-total			
Inside	4	0	0	0	0	1	5	25	30	60
Outside	2	9	0	0	4	14	29	1	30	

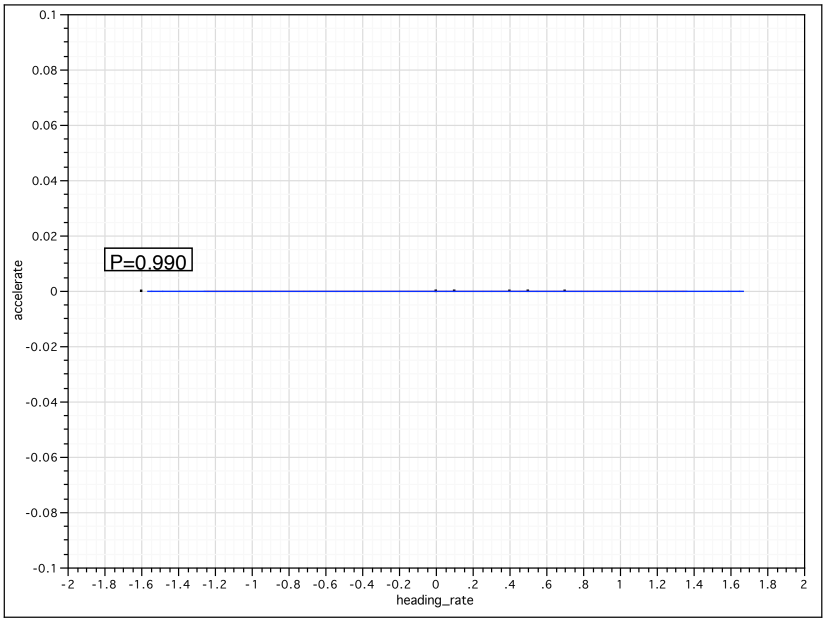


Figure 57. Heading Rate vs. Speed Rate for Ramps

Although some distributions for other roads resemble one another, differences among roads are sufficient to require unique identification if driving input and output measures are to be used to reliably determine whether drivers are driving normally or maneuvering. The implication is that if maneuvering is to be reliably determined, a workload manager needs to know the type of road being used, but this data is currently available only from a navigation system. Thus, a reliable workload manager requires interaction with a navigation system.

Finally, if rates (steering rate, heading rate, throttle rate, speed rate) are used to distinguish maneuvering from non-maneuvering situations, greater precision is required than was present in the original ACAS data.

How effectively do steering and throttle entropy predict distracted and normal driving? Do age, gender, and their interaction have a significant effect on steering and throttle entropy?

Figure 58 shows a general view of the process to analyze the steering wheel data.

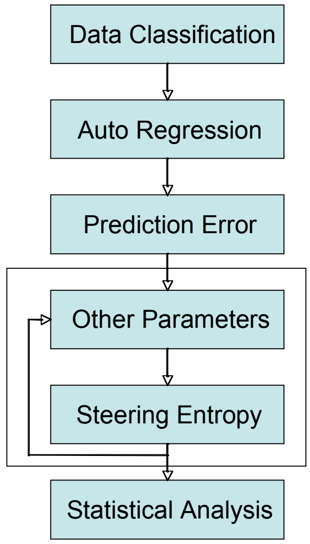


Figure 58. Analysis Procedure

The first step was to clarify the data set into a form that could be readily analyzed using JMP 5.0. The data set consists of 4 s discrete clips. Although Erwin Boer's new method suggests a sampling rate of 4 Hz, the data was left at a rate of 5 Hz. The maximum data length ranged from 18-20 frames. Thex total of 831 clips (including 8 showing drowsy drivers) was comprised of 15,962 frames.

Calculating the exact difference of the steering angles in the transition phase is difficult. The transition phase is where the steering angle passes the 180 degree mark, from a positive angle to a negative angle. The angle difference becomes exaggerated when the angle passes the transition phase. For example, the actual difference of the angles -170 degrees and 170 degrees is 20 but the calculated difference is 340. Due to this error, 19 clips had to be eliminated since the volume of data was too large to manually compute each steering angle difference.

After elimination, the remaining 792 clips contained 395 normal clips and 397 distraction clips. As shown in Table 29, they are reasonably balanced by Age * Sex.

Table 29. Number of Observations for Each Age Group by Gender and Driving Type

Condition	Normal		Distracted		Subtotal
Sex / Age	Male	Female	Male	Female	
20s	73	69	83	66	291
40s	74	53	84	53	264
60s	62	64	48	63	237
Subtotal	209	186	215	182	792

Next, auto regression was implemented using MATLAB 7.2.

To get more sensitive results, Boer changed his prediction model from a Taylor series expansion (2000) to an autoregressive model (2005). The same third-order AR-model was used in this study. In Boer's study, the steering time series $\{s_n\}$ is defined as:

$$s_n = -a_1 s_{n-1} - a2 s_{n-2} - a3 s_{n-3} + pe_n$$

The Burg algorithm was used to estimate a_i coefficients. The MA-PE generating filter, which is derived from the above AR-model, has the following form (Boer, 2000):

$$pe_n = s_n + a_1 s_{n-1} + a2 s_{n-2} + a3 s_{n-3}$$

A reference data set is a part of the data set used to estimate the AR-model parameters (a_i). It is a subset of the baseline data. In his study, Boer (2005) got the separate AR-model parameters for each subject. Since his data was sufficiently large (approximately 2 minutes of baseline data for each subject), he was able to use half of the data to get AR-model parameters and half to get the steering entropy. In this study, the mean length of the baseline data was only 16.5 s and was not continuous. This was not enough data to obtain the AR-model parameters and steering entropy. The authors estimated the AR-model parameters for each age group by gender. As shown in Table 29, the number of normal driving clips varied from 53 to 74. Among these, the first 25 clips with steering angles of less than 40 degrees were selected as the reference data set.

Prediction errors of normal and distracted driving were estimated using the following equations. MA-PE generating filters are estimated for mth Age * Sex groups.

$$pe_n^{bas_m^{ref}} = s_n^{bas_m^{ref}} + a_1^{bas_m^{ref}} s_{n-1}^{bas_m^{ref}} + a_2^{bas_m^{ref}} s_{n-2}^{bas_m^{ref}} + a_3^{bas_m^{ref}} s_{n-3}^{bas_m^{ref}}$$

Prediction errors for normal driving of m^th Age * Sex groups could be estimated with the MA-PE generating filter and steering angle data for normal driving.

$$pe_n^{bas_m} = s_n^{bas_m} + a_1^{bas_m^{ref}} s_{n-1}^{bas_m} + a_2^{bas_m^{ref}} s_{n-2}^{bas_m} + a_3^{bas_m^{ref}} s_{n-3}^{bas_m}$$

Prediction errors for distracted driving of m^th Age * Sex groups could also be estimated with the same MA-PE generating filter and steering angle data for distracted driving.

$$pe_n^{cond_m} = s_n^{cond_m} + a_1^{bas_m^{ref}} s_{n-1}^{cond_m} + a_2^{bas_m^{ref}} s_{n-2}^{cond_m} + a_3^{bas_m^{ref}} s_{n-3}^{cond_m}$$

According to Boer et al. (2005), all parameters (including the re-sampling frequency, the alpha value, the number of bins, and whether a Taylor expansion or an AR-model based prediction filter is used) can be freely selected. In this study, the sampling rate (5 Hz) and prediction model (AR-model) were fixed. The authors then set the number of bins to 10 since the maximum number of the data points in one clip was 20, if the same 14 bins were used, there must be empty bins for most of clips. Also, using 4-8 bins would have yielded less sensitive results. Coefficients for each bin also changed slightly. The set of lower bin bounds is:

$$\{-1000.0, -5pe_\alpha, -2.5pe_\alpha, -1pe_\alpha, -0.5pe_\alpha, 0, 0.5pe_\alpha, 1pe_\alpha, 2.5pe_\alpha, 5pe_\alpha\}$$

The set of upper bounds is:

$$\{-5pe_\alpha, -2.5pe_\alpha, -1pe_\alpha, -0.5pe_\alpha, 0, 0.5pe_\alpha, 1pe_\alpha, 2.5pe_\alpha, 5pe_\alpha, 1000.0\}.$$

The terms pe_α and α have the following relationship:

$$pe_\alpha = 0.5\left[\left|\arg_{pe}\{CDF(pe)=\alpha\}\right| + \left|\arg_{pe}\{CDF(pe)=1-\alpha\}\right|\right]$$

The alpha value was explored to find most significant setting.

The steering entropy step was implemented using Matlab 7.2.

Both old and new versions of steering entropy equations were used.

Old equation: $H^{cond_m} = \sum_{k=1}^{10}\left\{-p_k^{cond_m}\log_{10}(p_k^{cond_m})\right\}$

New equation: $H^{cond_m} = \dfrac{\sum_{n=1}^{N^{cond_m}} -\log_2(p^{bas_m^{ref}}(pe^{cond_m}))}{N^{cond_m}} = \sum_{k=1}^{10}\left\{-p_k^{cond_m}\log_2(p_k^{bas_m^{ref}})\right\}$

The data set was not obtained from a controlled experiment. The number of observations for each Age* Sex* Task group was not equally balanced (see Table 29).

Steering Entropy Analysis

Figure 59 presents the difference of the prediction errors between normal driving and distracted driving. Compared to normal driving, distracted driving showed a larger number of high-prediction error values.

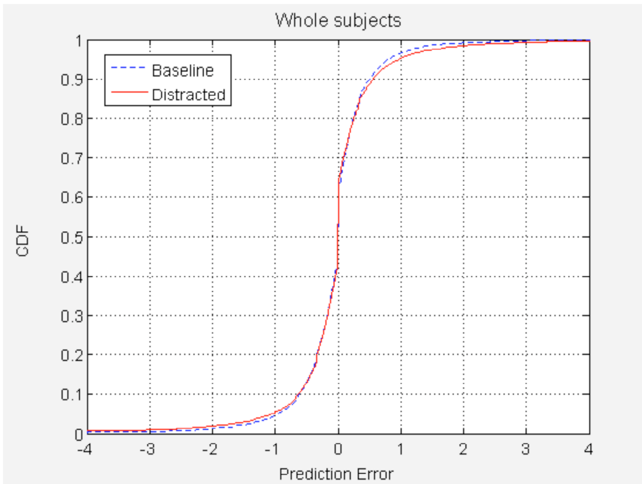
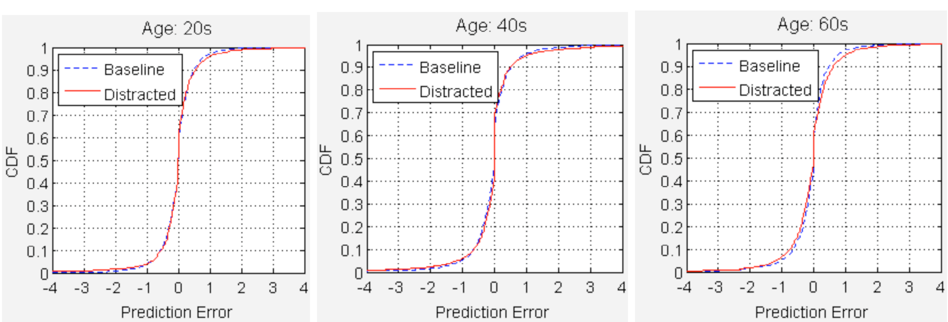


Figure 59. Prediction Error Distributions for Data Set

The same relationships were observed when the data set was classified by age groups and by gender groups (see Figure 60).



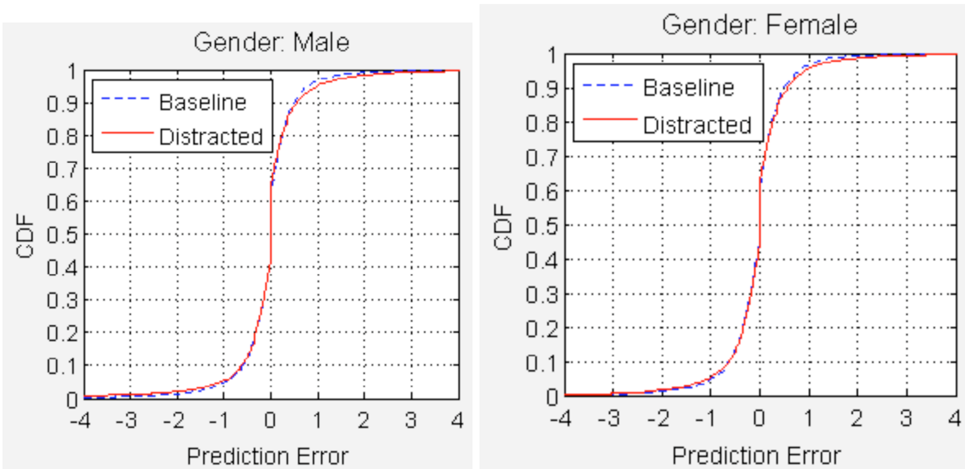


Figure 60. Prediction Error Distributions for Each Age and Gender Group

Using the data set of this study, the original equation for steering entropy showed better results than the new equation. Alpha values of 0.05 (used in the original method) and 0.2 (used in the revised method) were used to set the bin boundaries and obtain the steering entropies.

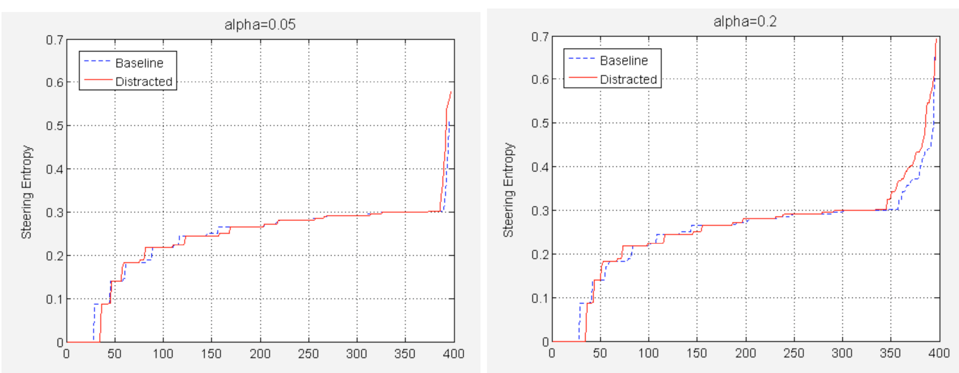


Figure 61. Steering Entropy Plot with Boer's (2000, 2005) Alpha Values

As shown in Figure 61, both results showed only a small difference between normal driving and distracted driving. The difference was larger, however, when the alpha value was 0.2 rather than 0.05. Thus several more alpha values were tested.

Figure 62 shows steering entropy plots for alpha values from 0.3 to 0.6 in increments of 0.1.

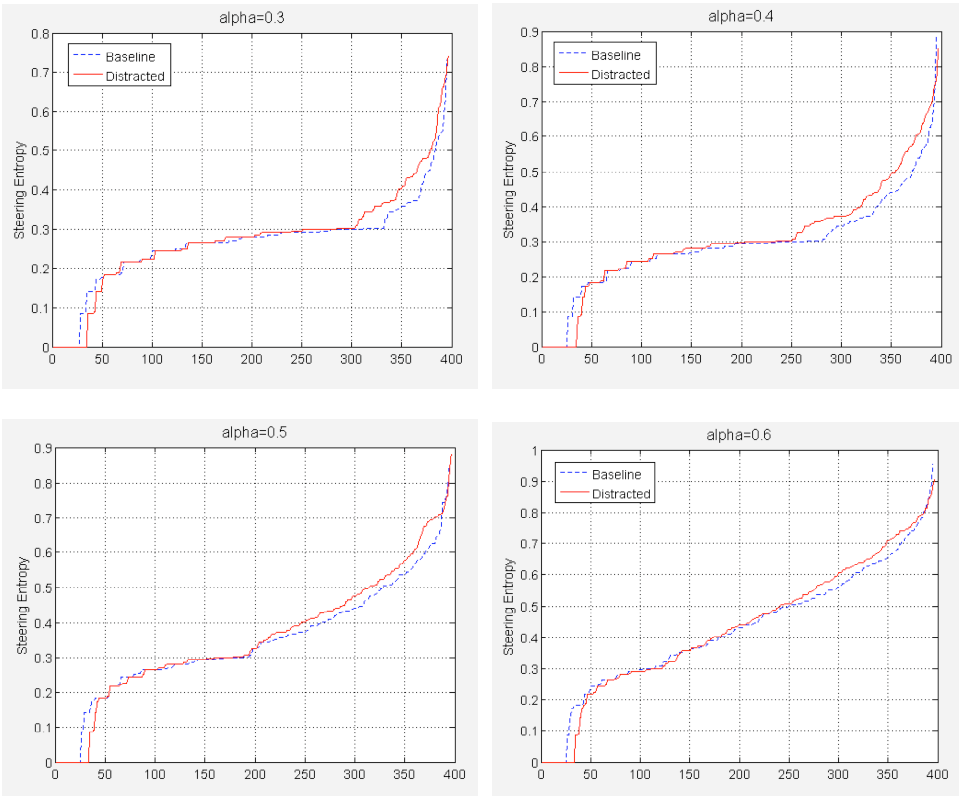


Figure 62. Steering Entropy Plots with Various Alpha Values

The difference between normal driving and distracted driving was largest when the alpha value was 0.4. A statistical analysis was performed for the results of this case.

To examine steering entropy in detail, ANOVA was used with Age, Sex, and Distraction included in the model, as well as 2-factor interactions. Because of missing cells, replacing Distraction with Task did not make sense. In that ANOVA, Age ($p<.0001$), Age*Sex ($p<.0005$), and Distraction ($p=.035$) were all statistically significant. However, the factors in the ANOVA only accounted for 5% of the variance, in part because individual differences due to subjects were not isolated. Keep in mind that the data were selected to balance out age, sex, and road type effects overall, but constraining tasks (so each subject did each task) would probably have made it impossible to find suitable data. The key finding is that steering entropy increased with distraction, with means of 0.291 for normal driving and 0.312 for distracted driving.

However, as shown in Figure 63, steering entropy did not always increase. Although not statistically different, the mean steering entropy values for eating/drinking and cell phone use were lower than that of the no-task scenario (Figure 64). Chewing tobacco and smoking had similar values. The steering entropy values for the other 5 tasks were greater than the no-task scenario. This may be due to confounding noted earlier. Again, differences to due road and subject were confounded with tasks. This was unavoidable because the primary purpose of the data was to examine differences in task frequency when the number of instances of driver Age * Sex * Road class were equal, not to equalize the frequency of tasks, in particular by subject, to facilitate the analysis of steering entropy.

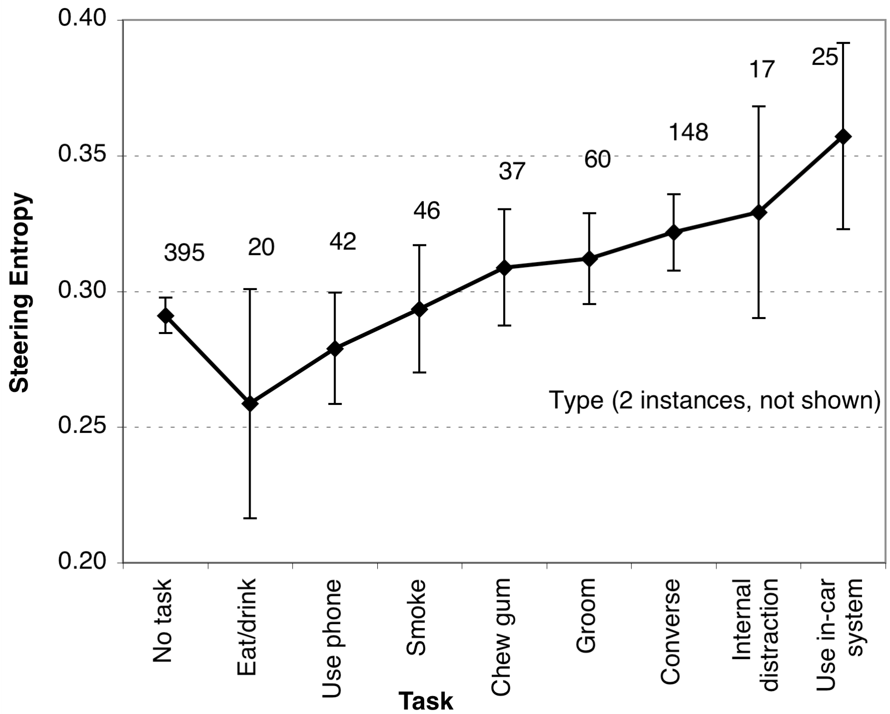


Figure 63. Types of Distraction vs. Steering Entropy
Note: Values above error bars are the number of instances.

Figure 64 shows the Age * Sex interaction effect. For the 40s age range and 60s age range, steering entropies of females were larger than those of males. The 20s age range showed an opposite trend. Statistical significance among 6 levels is represented at the right side of Figure 65. This outcome may be due to confounding as well.

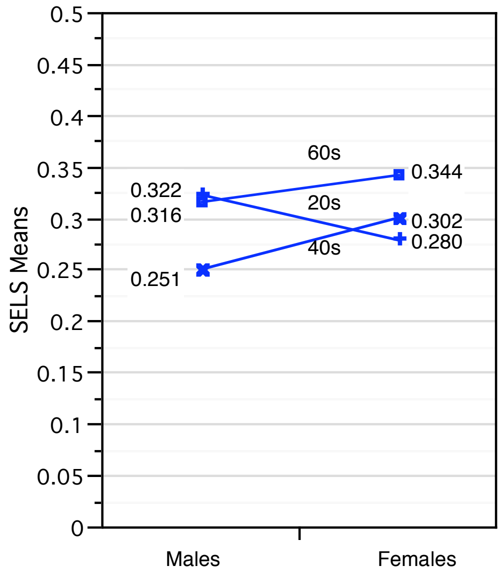


Figure 64. Age * Sex Interaction

Throttle Entropy Analysis

Since both the throttle percentage and the steering wheel angle constituted the input domain for the workload manager threshold settings, the application of the entropy concept to throttle percentage was also analyzed. Throttle entropy has been given very little attention in the literature. Development procedures and related models are the same as those used for steering entropy.

Figure 65 represents the difference of the prediction errors between normal driving and distracted driving. The baseline and distracted driving lines are nearly identical.

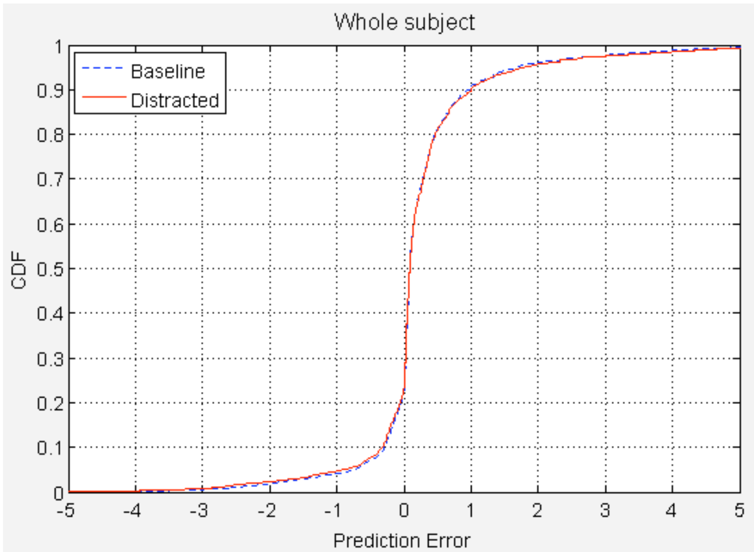


Figure 65. Prediction Error Distributions for the Data Set

Throttle entropy values, calculated with various alpha values (0.05 and 0.2 to 0.9 in 0.1 increments), did not show obvious differences between normal and distracted driving.

In an manner similar to that for steering entropy, an ANOVA of throttle entropy was computed with Age, Sex, and Distraction as the main effects, along with all 2-factor interactions. Age ($p<.05$), Sex ($p<.0001$), and their interaction ($p<.001$) were significant, but Distraction was not ($p=0.26$). Figure 66 shows the effect of task differences on throttle entropy. Interestingly, steering entropy and throttle entropy were highly correlated ($r=0.99$). However, in contrast to the steering entropy data, the range of the throttle entropy is much less. Again, what this could be reflecting are underlying differences due to roads and subjects, with which task differences were confounded.

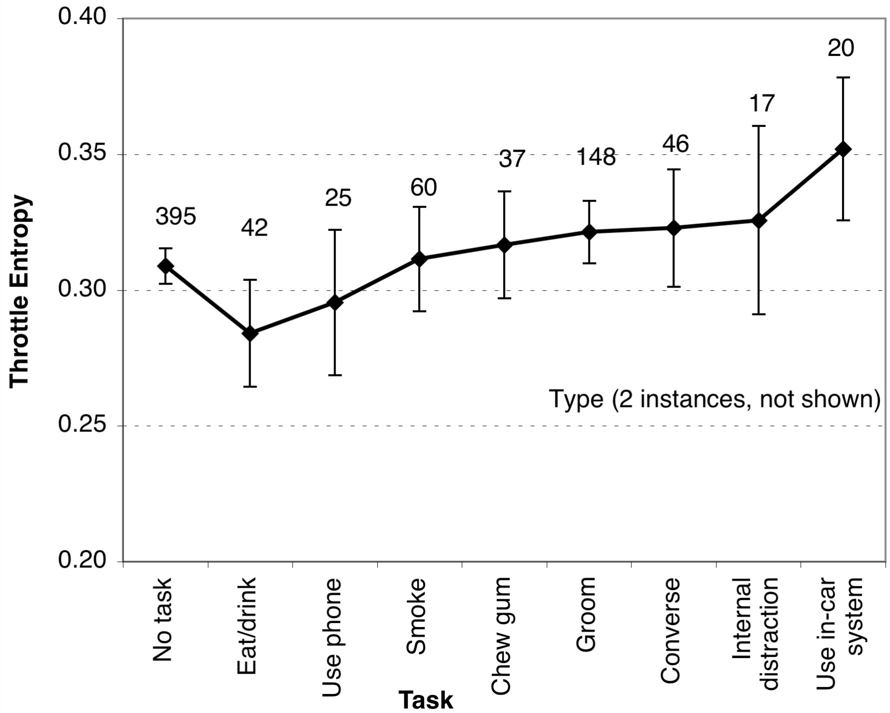


Figure 66. Types of Distraction vs. Throttle Entropy
Note: Values above error bars are the number of instances.

CONCLUSIONS

1. How are measures of driver input and vehicle output distributed as a function of road type?

Bivariate distributions were used to examine the spatial relationship between longitudinal movements (throttle percentage as an input variable, transmission speed as an output variable) and lateral movements (steering wheel angle as an input variable, heading angle as an output variable). Analysis showed that neither of the pairs of measures was well fit by bivariate normal distributions, either overall or by road type. However, there were other patterns in the data.

Driver Input

Based on the data in Figure 2, the steering angle versus throttle angle distributions fell into 4 groups of similar distributions: (1) interstates and freeways, (2) arterials and minor arterials, (3) collectors and local roads, and (4) ramps. Table 30 shows the upper and lower bounds for the distributions of each of the road groups interpolating between the pairs of envelopes when appropriate. Interstates and freeways had the largest range for throttle angle, distributed from -4 to +25 degrees (even though the throttle had a minimum angle of 0 degrees). Ramps had the smallest range for throttle angle, distributed from +10 to +13 degrees. Collectors and local roads had the largest distribution for steering angle, from approximately -49 to +50 degrees. Ramps had the smallest distribution, from -9 to +4 degrees, in part because of the very small sample size. Keep in mind that these distributions are rough approximations in that the bivariate normal distributions did not fit the data very well. An example is that negative throttle percentages, which are included in the ellipses, are not physically possible.

Table 30. Steering and Throttle Angle Upper and Lower Bounds for Road Groups Based on 95th Percentile Envelopes

Measure	Road Group			
	Interstates / freeways	Arterials / minor arterials	Collectors / local	Ramps
Steering angle upper (deg)	10	18	45	4
Steering angle lower (deg)	-10	-20	-45	-9
Throttle angle upper (deg)	25	20	19	13
Throttle angle lower (deg)	-4	-7	-5	10

The steering rate versus throttle rate distributions had the same road groups as the steering angle versus throttle angle distributions (as shown in Figure 3). Table 31 shows the upper and lower bounds for steering rate and throttle rate for each road group. Collectors and local roads had a range of -28 to +28 degree change for steering rate, 7 times larger than the next largest group. All groups had similar ranges for throttle rate.

Table 31. Steering and Throttle Rate Upper and Lower Bounds for Road Groups Based on 95th Percentile Envelopes

Measure	Road Group			
	Interstates / freeways	Arterials / minor arterials	Collectors / local	Ramps
Steering rate upper (deg/s)	3	4	28	1
Steering rate lower (deg/s)	-3	-4	-28	-1
Throttle rate upper (deg/s)	4	3	3	2
Throttle rate lower (deg/s)	-4	-3	-3	-2

Vehicle Output

For heading angle versus speed (see Figure 4), roads were grouped into 5 categories: (1) interstates and freeways, (2) minor arterials and collectors, (3) ramps, (4) arterials, and (5) local. The differences among road classes were much more distinct than those of steering angle and throttle. Table 32 shows the upper and lower bounds for the distributions of speed and heading angle for each road group, again for the 95th percentile envelopes. Arterials showed the largest variability for speed, from approximately 7 to 37 m/s. Local roads showed the largest variability in heading angle, from approximately -3.1 to +3.1 degrees. This varied the most because local roads had the lowest upper bound for speed, which allows a greater heading angle while remaining in control.

Table 32. Speed and Heading Angle Upper and Lower Bounds for Road Groups Based on 95th Percentile Envelopes

Measure	Road Group				
	Interstates / freeways	Arterials	Minor arterials / collectors	Local	Ramps
Heading angle upper (deg)	1.2	2.0	2.0	3.1	3.0
Heading angle lower (deg)	-1.2	-2.0	-2.1	-3.1	-1.8
Speed upper (m/s)	42	37	30	26	34
Speed lower (m/s)	19	7	5	2	31

For heading angle versus acceleration (see Figure 5), the roads were grouped into the same 5 categories as heading angle versus speed, though overall there was much less differentiation. Table 33 shows the upper and lower bounds for the distributions of each road group. Particularly noteworthy was the mirror imaging of the acceleration data, indicating that exposure to g levels for braking and acceleration are similar. One very important thought to keep in mind about both the heading rate and the acceleration data is the resolution of the data. For example, the acceleration data was plotted to the nearest 0.1 m/s^2. Since 9.8 m/s^2 is 1 g, the resolution of the data is 0.01 g. For the clips examined, the largest values reported were +/-0.6 m/s^2 or 0.06 g, a fairly mild change in speed.

Table 33. Acceleration and Heading Rate Bounds for Road Groups

Measure	Road Group				
	Interstates / freeways	Arterials	Minor arterials / collectors	Local	Ramps
Heading rate upper (deg)	0.5	1.0	0.8	1.1	1.4
Heading rate lower (deg)	-0.5	-1.0	-0.8	-1.1	-1.3
Longitudinal acceleration upper (m/s^2)	0.2	0.3	0.4	0.5	~0
Longitudinal acceleration lower (m/s^2)	-0.2	-0.3	-0.4	-0.5	~0

Since workload managers may use these measures to classify driving performance, this suggests that perhaps only a general classification of the type of road is needed.

Although some distributions for other roads resemble one another, differences among roads are sufficient enough that they need to be uniquely identified if driving input and output measures are to be used to reliably determine if drivers are driving normally or maneuvering.

Finally, if rates (steering rate, heading rate, throttle rate, speed rate) are used to distinguish maneuvering from non-maneuvering situations, greater precision is required when measuring the original ACAS variables. For example, if speed was measured 10 times per second, the acceleration would only be measured 5 times per second. This larger time increment between measurements led to islands of data in the distributions of the rate variables, which is not accurate. Furthermore, if acceleration is to be used to trigger a workload manager, and 3 samples are required to compute acceleration and the acceleration were sudden, then identification of the large acceleration would lag the event by as much as 2 sample intervals, which at 10 Hz is 200 ms. If response times are on the order of a second or so, then the penalty of slow sampling is a 20 percent increase in response time.

2. What is the effect of the number of secondary tasks (none, 1, or 2) on measures of driver performance as a function of road type?

There was essentially no difference between no task and 1 task in the 95th percentile distributions for steering angle versus throttle angle and heading angle versus speed for interstates, freeways, minor arterials, collectors, and local roads. Interestingly, there was less variability of steering versus throttle angle and heading angle versus speed when subjects performed 2 tasks. (There were 2 cases of 3 tasks being performed together, too few for analysis.) The diminished variability in the 2-secondary-tasks situation could be because drivers choose to perform 2 tasks only when the primary task demands are very low or because they reduce the number of control actions when heavily distracted, reducing the associated variability.

However, situations in which 2 tasks occur are significantly restricted in terms of steering angle. The maximum range of steering wheel angle at which 2 task events appear is largest for local roads, at approximately -10 to +10 degrees. This is still relatively small compared to the maximum range for no-task and 1-task events, which is largest for local roads at values from -50 to 50 degrees. That is, drivers engage in 2 tasks only when they are driving fairly straight, and they are much less likely to be maneuvering when doing so. Again, the rate data (steering rate, heading rate, throttle rate, speed rate) should be viewed with some caution due to the quantization of the underlying data.

3. What driving performance measures and thresholds are recommended for a workload manager as a function of road type to identify when the driver is maneuvering?

Since the purpose of this project is to build a workload manager, a key to its success is identifying measures and thresholds that reliably differentiate between maneuvers and non-maneuvers. Maneuvers, such as lane changes, parking, turning at intersections, etc., are almost always events of high demand on the driver, and not times when drivers should be engaged in other non-driving activities. Hence, reliably identifying such maneuvers would be very useful for a workload manager.

Maneuver/non-maneuver thresholds were developed to satisfy 2 rules. Rule 1, draw a simple diagram (usually a box) that includes the 95th percentile nonparametric density distribution and Rule 2, maintain a similar shape of the diagram for different road types as much as possible.

To validate the thresholds developed, ACAS FOT video clips, associated with 30 sample events inside and outside of each of the thresholds, were identified. Since the purpose of this evaluation was to examine how well reasonable thresholds generally might work, not to identify an ideal threshold, 2 thresholds were examined for each measure. The initial threshold was set based on discussion with vehicle dynamics experts and a review of the data. Subsequently, based on the detection performance of the first threshold, a second case was examined.

Table 34, aggregated from tables in the results of the steering wheel angle-throttle angle data, shows the performance of various thresholds for identifying curves, lane changes, merges/exits, and turns for 6 road classes. To assist in identifying reasonably effective thresholds (situations where (1) there were at least 5 events, (2) the detection ratio was at least 2:1, and (3) the detection was in the expected direction (e.g., curves should have larger steering angles and be outside the threshold)) are shown in bold. Other criteria could have been used, but 5 events suggest enough data for some small degree of confidence (for example, it is the minimum cell size in a Chi-Square test), and 2:1 seems to be as reasonable a confidence level as any.

Also shown in bold are cases where the overall ratio of maneuvers to non-maneuvers outside the threshold was 5:1. Of course, there are many other reasonable criteria as well. For those who wish to explore them, the data in Table 36 is formatted appropriately.

Table 34. Detection Performance of Various Steering Wheel Angle - Throttle Angle Combinations (in deg)

Road class	Threshold (steer, throttle)	Location	Curve	Lane	Merge /exit	Turn	Non-maneuver
Interstate	Initial (±10, 0 to 20); (±5, 20 to 35)	Inside	**6**	10	3	0	11
		Outside	**21**	4	4	0	**1**
	Second (±7, 0 to 20); (±2, 20 to 35)	Inside	**7**	10	0	0	13
		Outside	**25**	0	1	1	**3**
Freeway	Initial (±10, 0 to 20)	Inside	**7**	7	1	0	15
		Outside	**14**	1	13	0	**2**
	Second (±7, 0 to 20)	Inside	10	4	2	0	14
		Outside	16	3	8	0	**3**
Arterial	Initial (±10, 0 to 20)	Inside	8	6	0	**0**	16
		Outside	9	3	1	**15**	**2**
	Second (±7, 0 to 20)	Inside	**2**	10	0	**2**	16
		Outside	**9**	2	0	**9**	10
Minor arterial	Initial (±15, 0 to 20)	Inside	**3**	2	0	**3**	22
		Outside	**13**	1	0	**12**	**4**
	Second (±10, 0 to 20)	Inside	**0**	7	0	**2**	21
		Outside	**5**	0	0	**25**	**0**
Collector	Initial (±40, 0 to 4); (±20, 4 to 20)	Inside	9	2	0	**0**	19
		Outside	6	0	0	**24**	**0**
	Second (±20, 0 to 4); (±10, 4 to 20)	Inside	**5**	1	0	**0**	24
		Outside	**12**	0	0	**15**	**3**
Local road	Initial (See below)	Inside	**5**	1	0	**0**	24
		Outside	**10**	0	0	**20**	**0**
	Second (See below)	Inside	**5**	0	0	**0**	25
		Outside	**11**	1	0	**16**	**2**

Initial: ±40, 0 to ±10, 20; Second: ±30, 0 to ±10, 20 (both are trapezoidal shapes)

Notice that both road-specific thresholds proposed for all 6 road classes were reasonably effective in detecting curves and turns except for interstates and freeways, where there were too few data points. As a rough rule of thumb, when steering wheel angles are more than 5 to 10 degrees for expressways, interstates, and minor arterials, drivers are likely to be driving curves (maneuvering). For collectors, when the steering wheel angle is greater than 20 degrees (for 0 to 4% throttle) or 10 degrees (for 4 to 20% throttle), drivers are likely to be on curves. For local roads, the thresholds form a trapezoid shape with a steering wheel angle threshold of 10 to 40 degrees, depending on the throttle.

More importantly, overall, except for the second threshold for arterials, one could be reasonable certain that if the threshold was exceeded, the driver was not maneuvering. Keep in mind that these values are for the 2002 Buick LeSabres tested, and other vehicles with a different throttle response or steering-angle-to-tire angle mapping could have slightly different thresholds.

Table 35 shows the effectiveness of using various thresholds for heading and speed to detect selected maneuvers. For all roads except local roads, either of the 2 class-specific thresholds examined (typically 1 to1.5 degrees of heading) was able to identify lane changes. Again the criterion was at least 5 data points and a detection ratio of 2:1. In most cases, the ratio was far greater (e.g., 11:1). Also, keep in mind that lane changes are not relatively less common on local roads than on other types of roads, so detecting them is less critical. Interestingly, heading angle and speed were reliable indicators of driving curves for local roads, which occurred for headings of 2 to 3 degrees. Finally, situations where the maneuver to non-maneuver ratio outside the threshold was at least 5:1 are shown in bold. That occurred for all cases except the initial thresholds for arterials, minor arterials, and collectors.

Table 35. Detection Performance of Various Heading Angle (deg) and Speed (m/s) Combinations

Road class	Threshold (heading, speed)	Location	Curve	Lane	Merge /exit	Turn	Non-maneuver
Interstate	Initial (curve, 20 to 40)	Inside	10	**3**	**2**	0	15
		Outside	3	**18**	**6**	0	**3**
	Second (+/1, 20 to 40)	Inside	9	**1**	2	0	18
		Outside	12	**14**	1	0	**3**
Freeway	Initial (±1, 20 to 35)	Inside	12	**1**	2	0	15
		Outside	10	**14**	4	0	**2**
	Second (±1.5, 20 to 35)	Inside	15	**2**	2	0	11
		Outside	11	**16**	2	0	**1**
Arterial	Initial (±1, 5 to 30)	Inside	7	**1**	0	1	21
		Outside	8	**13**	0	1	8
	Second (±1.5, 5 to 30)	Inside	5	**7**	0	3	15
		Outside	3	**23**	1	1	**2**
Minor arterial	Initial (±1, 5 to 30)	Inside	3	**1**	0	0	26
		Outside	10	**11**	0	2	7
	Second (±1.5, 5 to 30)	Inside	9	**4**	0	1	16
		Outside	7	**16**	0	4	**3**
Collector	Initial (see below)	Inside	**3**	**0**	0	2	5
		Outside	**14**	**7**	0	2	7
	Second (±1.5, 5 to 30)	Inside	**3**	**2**	0	3	2
		Outside	**13**	**11**	0	3	**3**
Local road	Initial (±2, 5 to 25)	Inside	**5**	0	0	9	16
		Outside	**16**	1	0	8	**5**
	Second (±3, 5 to 25)	Inside	**4**	2	0	9	15
		Outside	**18**	5	0	4	3

Derivative variables were investigated to detect rapid changes of vehicle movements including rapid acceleration, deceleration, or stopping as well as lane changes and turning at intersections, etc. Simple rectangular thresholds were adopted for models of all derivative variables for ease of implementation.

Table 36 shows the detection performance using steering rate (deg/s) and throttle rate (deg/s) as the selection measures. Keep in mind that the thresholds selected may be specific to the steering maps and throttle maps of 2002 Buick LeSabres that served as the test vehicles.

Table 36. Detection Performance of Various Steering Rate (deg/s) and Throttle Rate (deg/s) Combinations

Road class, threshold	Location	Curve	High G	Lane	Merge /exit	Stop	Turn	Non-Maneuver
		Maneuver						
Interstate ±3, -7 to 7	Inside	**3**	1	**2**	**0**	0	0	24
	Outside	**13**	3	**8**	**4**	0	0	**2**
Freeway ±3, -7 to 7	Inside	**6**	2	**0**	**0**	0	0	22
	Outside	**10**	0	**5**	**10**	0	1	**4**
Arterial ±4, -4 to 4	Inside	2	9	1	0	2	**0**	16
	Outside	1	6	2	0	0	**17**	**4**
Minor arterial, ±5, -5 to 5	Inside	0	8	0	0	4	**0**	18
	Outside	2	1	4	0	0	**23**	**0**
Collector ±10, -3 to 3	Inside	3	11	3	0	4	**0**	9
	Outside	1	1	1	0	3	**23**	**1**
Local road ±10, -3 to 3	Inside	2	11	1	0	3	**0**	13
	Outside	3	4	1	0	0	**22**	**0**

Based on this data, curves, lane changes, and merges/exists can reliably be identified if the steering rate exceeds ±3 deg/s for expressways and freeways. For arterials, minor arterials, collectors, and local roads, turns are reliably identified for steering rates in excess of ±4, ±5, ±10, and ±10 deg/s, respectively.

Table 37 shows that heading rate and longitudinal acceleration can be used to detect high g maneuvers for all road types (almost by definition), lane changes for interstates (but surprisingly, not as well for freeways (though there are only a few data points)), stops for collectors, and turns for minor arterials, collectors, and local roads. These 2 variables may be useful for detecting other maneuvers, but in many cases there was no data. Thresholds used were 0.4 m/s^2 for interstates, freeways, and arterials; 0.5 m/s^2 for minor arterials; and 0.6 m/s^2 for collectors and local roads. Since 1 g is 9.8 m/s^2, these correspond to approximately 0.04, 0.05, and 0.06 g.

Table 37. Detection Performance of Various Heading Acceleration (deg/s^2) and Longitudinal Acceleration (deg/s^2) Combinations

		Maneuver						
Road Class, Threshold	Location	Curve	High G	Lane	Merge /exit	Stop	Turn	Non-Maneuver
Interstate ±0.5, -.4 to .4	Inside	7	**0**	**1**	**0**	0	0	22
	Outside	1	**12**	**8**	**7**	0	0	**2**
Freeway ±.6, -.4 to .4	Inside	8	**0**	2	**0**	0	0	20
	Outside	6	**12**	3	**7**	1	0	**1**
Arterial ±1, -0.4 to 0.4	Inside	3	**0**	0	0	0	0	27
	Outside	1	**20**	4	0	1	4	**0**
Minor Arterial ±1, -0.5 to 0.5	Inside	1	**0**	1	0	0	**0**	28
	Outside	1	**14**	3	0	3	**8**	**2**
Collector ±1, -0.6 to 0.6	Inside	4	**0**	0	0	**0**	**0**	26
	Outside	0	**8**	0	0	**7**	**15**	**0**
Local Road ±1, -0.6 to 0.6	Inside	4	**0**	0	0	0	**1**	25
	Outside	2	**9**	0	0	4	**14**	**1**

4. How effectively do steering and throttle entropy predict distracted and normal driving? Do age, gender, and their interaction have a significant effect on steering and throttle entropy?

For steering entropy, the main effects of Distraction, Age, and the interaction effect of Age × Sex were statistically significant. When drivers engaged in a distracting situation, the steering entropy generally increased.

For throttle entropy, Age, Sex, and their interaction were statistically significant, but the effect of distraction was not, in part because the range of throttle entropies was much less.

What is noteworthy and curious is the very high correlation between steering and throttle entropy, r=0.99. One could interpret this to mean that performing a secondary task results in a general loss of control, so one would expect both to be affected.

However, in this report, data were sampled so the number of clips in each driver age*sex*road superclass would be roughly equal initially, with subsequent sample from that sample equalizing the number of distracted and nondistracted clips examined. This process was followed so how task frequency varied with driver age, sex, and road type could be examined. However, this meant that for the analysis of steering and throttle entropy, task type was confounded with subject, driver age, and road type. Thus, the differences noted here could be due to those effects, in whole or in part, especially road type, not task differences.

Closing Thoughts

Distraction can be thought of in a number of ways. Distraction can be the consequence of the driver being drawn to complete that task because it attracts the driver, causing them not to pay attention to the primary task of driving. Distraction, as it is commonly used, can also refer to a situation where the combined demands of several tasks, one of which is the primary task of driving, exceed the drivers' capabilities to perform them all concurrently. If the primary task is not protected, performance of that task degrades.

Situations pertaining to distraction can be identified at least 3 ways. First, one could compare normal driving performance with performance while performing a secondary task, and from the driving data (steering wheel angle, accelerations, etc.), develop a function that discriminates between the 2 situations. Second, one could monitor where the driver is looking, and if they are not looking at the road, they may be distracted. Third, one can monitor how a person is driving, and when they are engaged or about to engage in a maneuver (changing lanes, merging, turning at intersections, etc.) have the workload manager respond in some way. When maneuvering or planning a maneuver, it is widely accepted one should not be also be engaged in a secondary task.

Each of those 3 approaches was either examined or utilized in the SAVE-IT project. In this report, univariate measures and bivariate measures of driving performance were examined. Detection of distraction with that approach was not very good. Often there was no difference in performance between baseline driving and when a single secondary task was performed. In fact, driving (primary task) performance was sometimes better when there were 2 secondary tasks.

How can drivers appear to do better when there is greater load? In contrast to simulator or experimenter-monitored on-the-road experiments, in the ACAS FOT drivers were free to perform tasks whenever they wanted. Although it has not been verified, it is believed subjects chose to do tasks when driving conditions were more stable, when roads were straighter, when there was less traffic, when they were not approaching traffic lights or stop signs, etc. Accordingly, one would expect fewer steering wheel movements, less speed variance, etc., that is, better driving performance. That does not mean secondary tasks have no safety or performance consequences, only that on-average, drivers may have elected to do them at more opportune times.

In Green, Wada, Oberholtzer, Green, Schweitzer, and Eoh (2006), a report parallel to this one, differences between normal and distracted driving were examined, but in that case, head orientation (was the head not pointed to the road) was used to identify situations where the driver was probably distracted. Head orientation was easier to

determine than direction of gaze, which for technical reasons sometimes could not be determined from video clips.
Finally, this report examined candidate thresholds for bivariate combinations to detect when drivers were maneuvering. For many maneuvers, detection performance was reasonably good. A huge advantage of this approach is that the workload manager will intervene at times when drivers most need it, and as a consequence, customer acceptance is likely to be high.

Thus, this approach found that some approaches worked well and others did not. Whatever approach is applied, it is apparent that detection performance will only be reliable the situation and driver can be specified in detail. For the situation, one needs to know the road class, if the section is straight or curved, the lane being driven, the distance to lead vehicles, the amount of traffic nearby, if a merge is about to occur, etc. For the subject, at least the age group and sex are needed. As a practical matter, this means a workload manager will need information from an ACC or FCW radar, from a navigation system, possibly from a lane departure system, and many other sources. Given the types of vehicles for which a workload manager will first be targeted, this is feasible.

The next step is to develop a workload manager based on the data in this and other SAVE-IT reports, and test it.

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APPENDIX A – USING BIVARIATE NORMAL PAIRS OF MEASURES TO IDENTIFY THE "ABNORMAL" FRACTION OF DATA

Development of bivariate envelope equations for steering vs. throttle and heading vs. speed

Although the data is not bivariate normally distributed, it was assumed to be so as part of an exercise to examine multiple classification criteria. In some situations, it might be computationally efficient for a workload manager to attempt to use bivariate normal classifications for discriminating between normal and abnormal driving.

As was evident from the figures shown earlier, some of the envelopes for the performance measure pairs were not always centered near the origin, and some of their primary axes were tilted. Transformations were developed accordingly, as shown in Figure 67 and Equation 1.

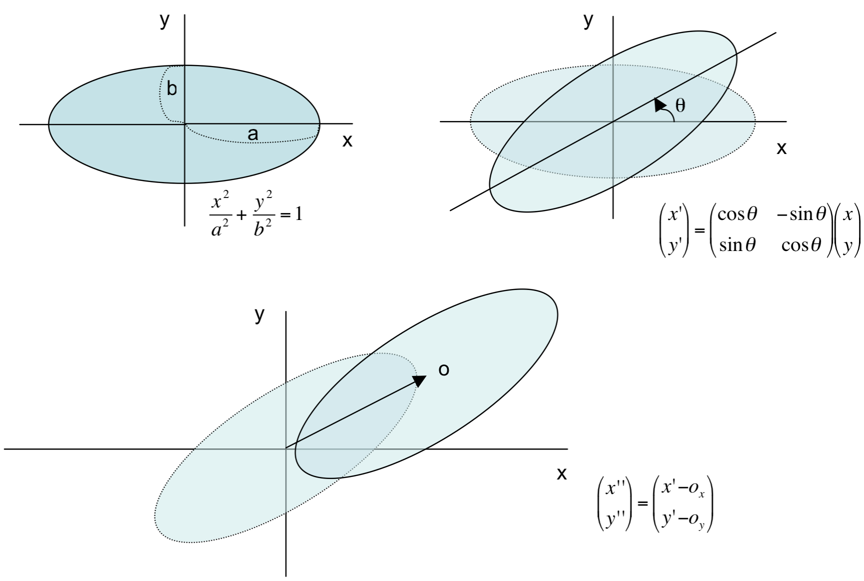

Figure 67. Derivation of the Bivariate Normal Ellipse

$$\frac{\{\cos\theta\cdot(x-o_x)+\sin\theta\cdot(y-o_y)\}^2}{a^2}+\frac{\{-\sin\theta\cdot(x-o_x)+\cos\theta\cdot(y-o_y)\}^2}{b^2}=1 \quad \text{(Equation 1)}$$

In addition, equations were also developed in JMP to classify data points as being inside ("normal") or outside ("abnormal") the ellipse. In those equations, calculated values lower than 1 are inside the ellipse. Parameters of 95th percentile ellipses for 6 road types are presented in Tables 38 and 39. All ellipses were only slightly tilted except for ramps and for steering angle vs. throttle on freeways. The reason for the tilt of the distribution for freeways is uncertain.

Table 38. 95th Percentile Ellipse Parameters for Steering Angle vs. Throttle

No.	Road type	a	b	o_x	o_y	θ
0	Ramp	6.6	1.6	-2.4	11.7	32.3
1	Interstate	11.1	15.1	0.2	10.6	0.0
2	Freeway	10.7	14.0	-0.7	10.4	9.1
3	Arterial	18.3	14.0	-0.9	7.0	-2.7
4	Minor arterial	17.3	12.2	-1.6	7.1	-0.5
5	Collector	39.3	14.0	-1.1	7.3	0.7
6	Local road	52.2	12.6	-3.1	7.0	-0.3

Table 39. 95th Percentile Ellipse Parameters for Heading in Lane vs. Speed

No.	Road type	a	b	o_x	o_y	θ
0	Ramp	2.6	0.7	0.8	32.8	-31.8
1	Interstate	1.3	12.7	0.0	31.1	-0.1
2	Freeway	1.2	10.4	0.0	30.4	-1.1
3	Arterial	2.2	14.9	0.0	21.8	1.8
4	Minor arterial	2.1	13.0	0.1	18.1	0.0
5	Collector	2.6	13.0	-0.2	17.0	1.8
6	Local road	3.2	12.3	0.0	13.8	2.2

Given the nature of these distributions, changing the percentile of the envelope only changes the “a” and “b” values in the equation. Those values, for the 50th, 60th, 70th, 80th, 90th, and 99th percentile, appear in Appendix D (page 105). Using those equations, odds ratios (included/excluded) and percent-excluded values for steer vs. throttle and heading vs. speed were obtained (Appendix D). Figures 68 and 69 show percent-excluded plots by road type for input space and output space, respectively. Although the raw data was not bivariate normally distributed, the estimated percent-excluded values were quite well matched to the inclusion level. Regardless of the road type, percent-excluded values for 90% and 95% inclusion levels at the output domain were close to the 10% and 5% levels, respectively (Figure 69), though there were substantial differences among road types at lower percentage values.

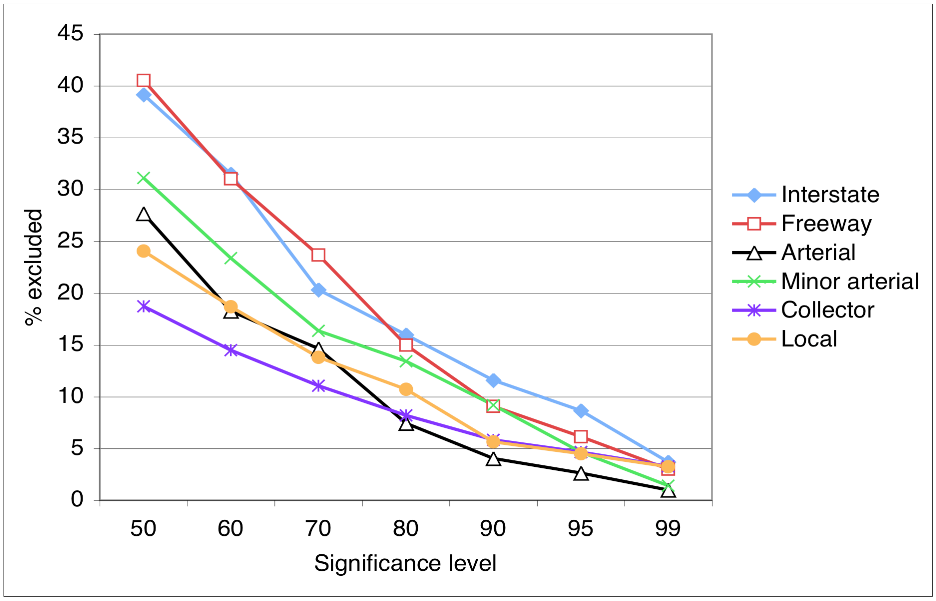

Figure 68. Percent-Excluded for Steer vs. Throttle Angle

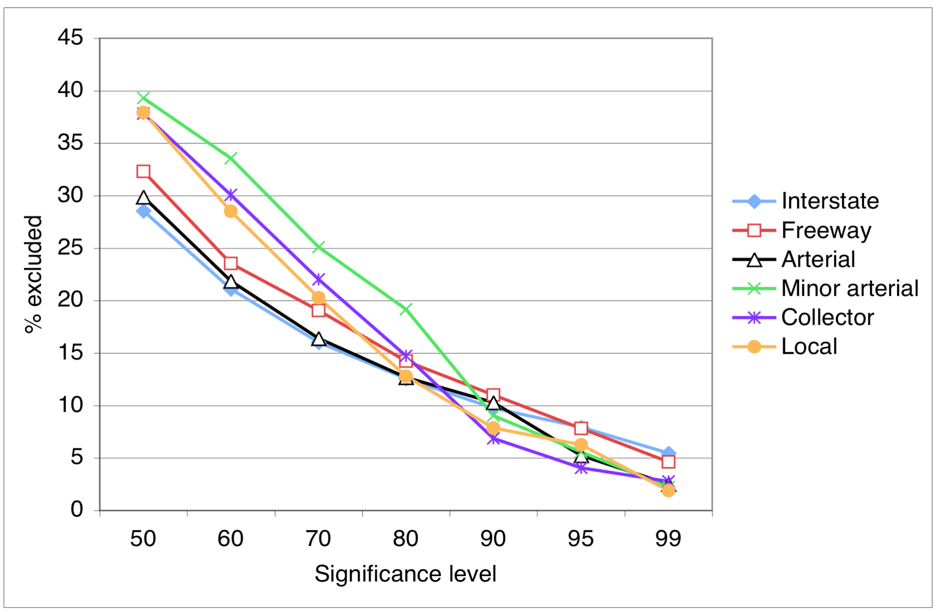

Figure 69. Percent-Excluded for Heading vs. Speed

Bivariate envelope equations for steer rate vs. throttle rate and heading rate vs. speed rate (longitudinal acceleration)

For the derivative space, all the bivariate normal ellipses, except for ramps, have 0 degree angles. Furthermore, all of their center points are at the origin of the x-y axes. Thus, Equation 1 can be simplified into Equation 2. See Tables 40 and 41 for the 95th percentile ellipses for all road types.

$$\frac{x^2}{a^2} + \frac{y^2}{b^2} = 1 \quad \text{(Equation 2)}$$

Table 40. 95th Percentile Ellipse Parameters for Steering Rate vs. Throttle Rate

No.	Road type	a	b	ox	oy	θ
0	Ramp	1.4	1.6	-0.1	-0.1	-14.3
1	Interstate	2.1	3.6	0	0	0
2	Freeway	2.2	2.3	0	0	0
3	Arterial	3.8	2.6	0	0	0
4	Minor arterial	3.5	2.1	0	0	0
5	Collector	25.3	2.2	0	0	0
6	Local road	34.3	2.0	0	0	0

Table 41. 95th Percentile Ellipse Parameters for Heading Rate vs. Acceleration

No.	Road type	a	b	ox	oy	θ
0	Ramp	1.33	0.00	0.05	0	0
1	Interstate	0.48	0.22	0	0	0
2	Freeway	0.55	0.18	0	0	0
3	Arterial	1.00	0.32	0	0	0
4	Minor arterial	0.77	0.38	0	0	0
5	Collector	0.82	0.44	0	0	0
6	Local road	1.05	0.45	0	0	0

As before, ”a” and “b” values were determined for each road type and were used to determine the percent-excluded for various percentile values (50th, 60th, 70th, 80th, 90th, 95th, and 99th percentiles). The actual estimates appear in Appendix D (page 105). Using those equations, odds ratios (included/excluded) and percent-excluded values for steering rate vs. throttle rate (Figure 68, input space) and heading rate vs. acceleration (Figure 69, output space) were calculated. Data was excluded in the derivative space to a lesser extent than in the space from which the values were derived. Less than 20% of the data was excluded even when the inclusion level was set to 50%. This is mainly caused by the concentration of data around the center point of this space.

As shown in Figure 70, there were no differences in exclusion between 50% and 60% (except for local roads), and between 70% and 80% (for all roads). Sometimes this occurred because of the distribution of a single measure and sometimes because of both measures (e.g., steering angle and throttle percent for local roads). Regardless of these problems, the predictions were quite good for the 95th percentiles.

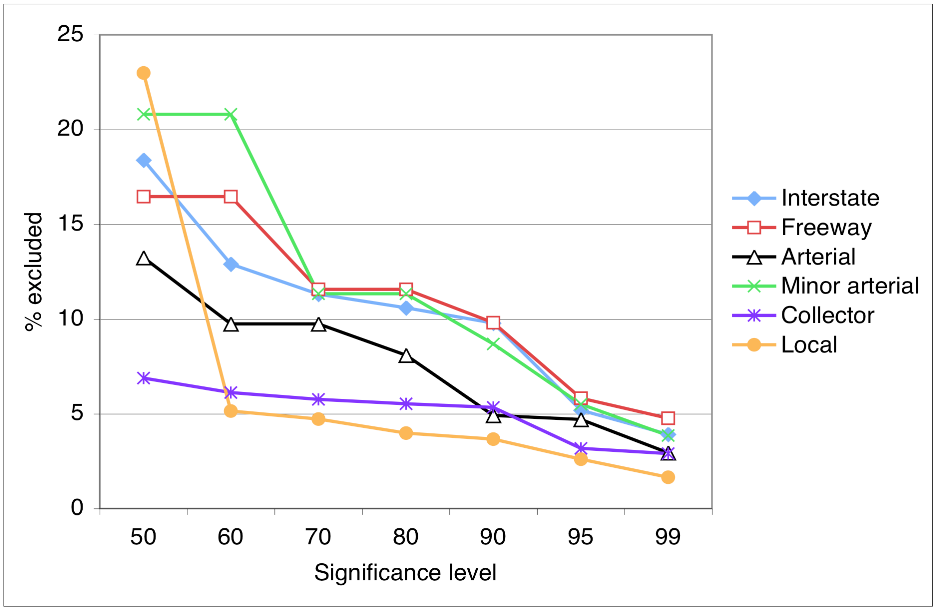

Figure 70. Percent-Excluded for Steering Rate vs. Throttle Rate

Figure 71 shows how the percent exclude varies with the significance level and road type. The effect of road type is reduced for significance levels in excess of 80%.

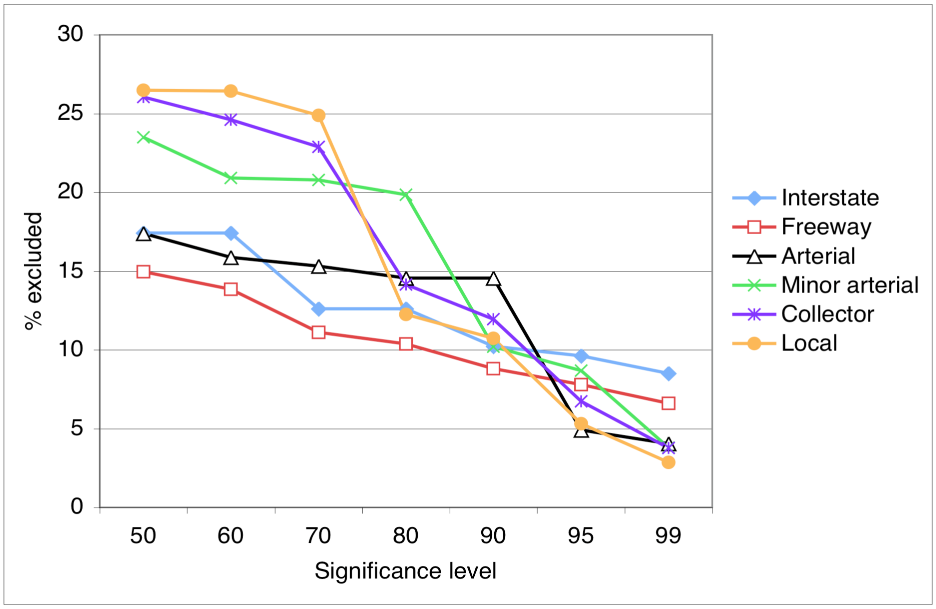

Figure 71. Percent-Excluded for Heading Rate vs. Acceleration

What percentage of the data is excluded when multiple pairs of measures are used?

In the previous section, four groups of bivariate normal ellipses were used to distinguish between normal and abnormal driving. Although the data was not distributed bivariate normal, it was assumed to be so for computational ease. The predictions were somewhat accurate around the 95th percentile, a region of interest. Going one step further, detection of abnormal driving was explored when two pairs of bivariate normal ellipses were considered. An initial question to be considered is classification performance as a function of the classification rule (and, or) used to combine the two ellipses (Table 42).

Table 42. Classification Rules

Rule	Case	Ellipse 1	Ellipse 2	Result
AND	1	In	In	Normal
	2	In	Out	
	3	Out	In	
	4	Out	Out	Maneuver
OR	1	In	In	Normal
	2	In	Out	Maneuver
	3	Out	In	
	4	Out	Out	

Appendix E (page 109) contains the values used to calculate the percent-excluded using various combinations of steer and throttle, heading, and speed. Values were determined for the 0, 90th, 95th, and 99th percentiles. The 0 percentile corresponds to using a single variable for the “and” combinations and the 100th percentile for the “or” combinations.

Figure 72 shows the percent-excluded plot by road type using the steer vs. throttle ellipse and the heading vs. speed ellipse with the “and” rule. For local roads, all combinations, except for the combination with 0 percentile, showed very similar values with between 1% and 2% being excluded. The effect of increasing a threshold for a particular variable, say from 90% to 95%, depended upon the road and variable combination examined. There was no consistent pattern.

Figure 73 shows the percent-excluded plot by road type using the steer vs. throttle ellipse and the heading vs. speed ellipse as the input variables with the “or” rule. These graphs showed systematic changes as percent values changed. The percent-excluded by the “or” rule decreased with the road class. For example, 90th percentile cuts for both variables led to exclusion values just under 20%. For local roads, the same rule led to the exclusion of just over 12% of the data. Thus, for these variables, the amount of data excluded depends very much on the type of road.

Figure 74 shows the percent-excluded plot by road type using the steer rate vs. throttle rate ellipse (Ellipse 1) and the heading rate vs. acceleration ellipse (Ellipse 2) with the "and" rule. Here, for all road types, using variable pairs of 90th percentile or greater only excluded about 1% of the data. Lower road classes again had smaller exclusion values.

Figure 75 presents the percent-excluded plot by road type using the steer rate vs. throttle rate ellipse (Ellipse 1) and the heading rate vs. accelerate ellipse (Ellipse 2) with the "or" rule. The plots are similar to Figure 73, the other instance of the "or" rule, with steady decreases in exclusions as the percentile rule used increased. Again, the trend was that as the road class decreased, the percent-excluded decreased.

Thus, the data shows that the rule ("and" or "or") leads to a roughly 10-fold difference in the number of points excluded, depending on the road situation. Lower class roads are more likely to have more points excluded for dual-pair ellipses. Keep in mind that all of the relationships are based on assumptions of normality of the underlying data, which is not true. However, as shown for pairs of variables in the previous section, the estimates of exclusion are somewhat reasonable for the region of interest (90th percentile and up).

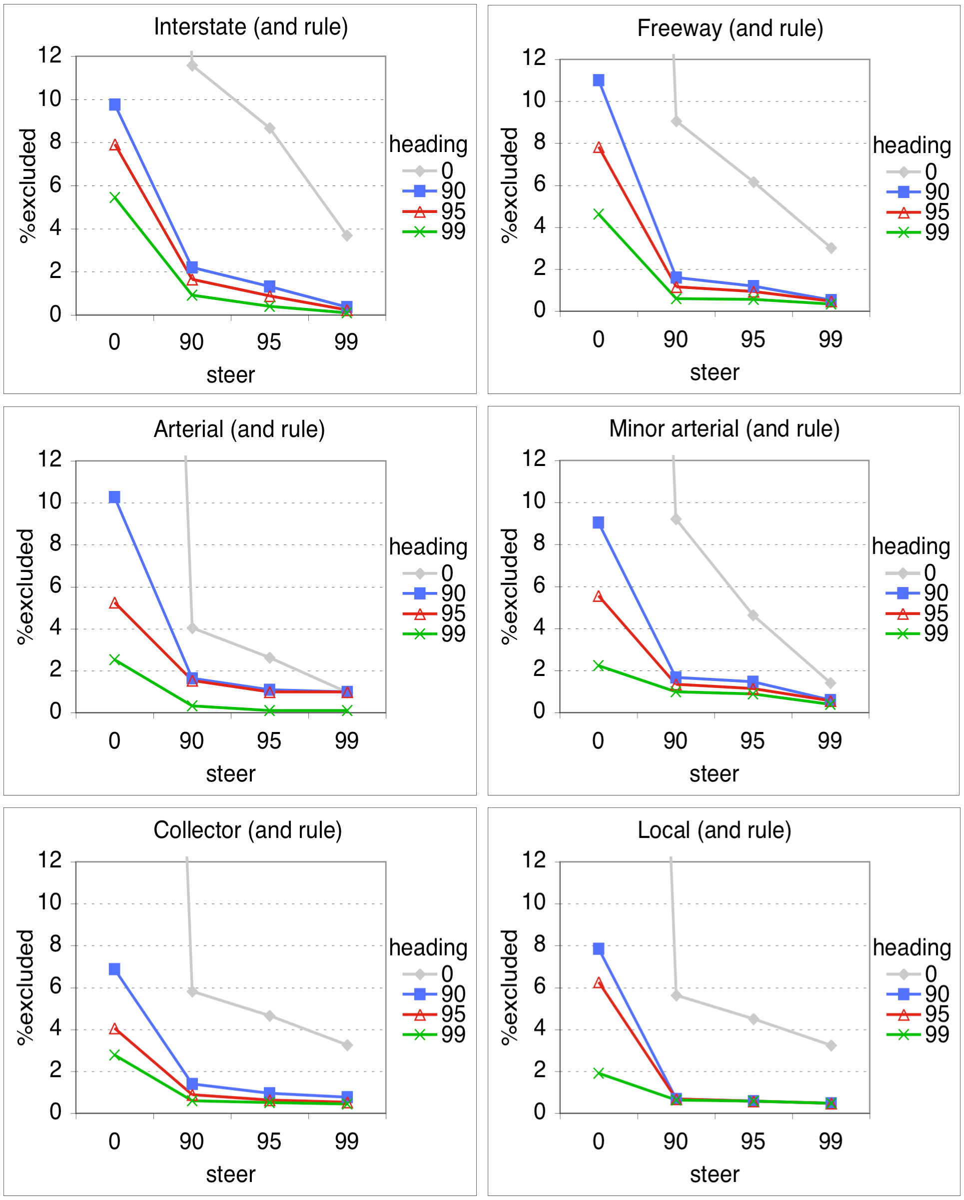

Figure 72. % Excluded Using Steer vs. Throttle and Heading vs. Speed Ellipses

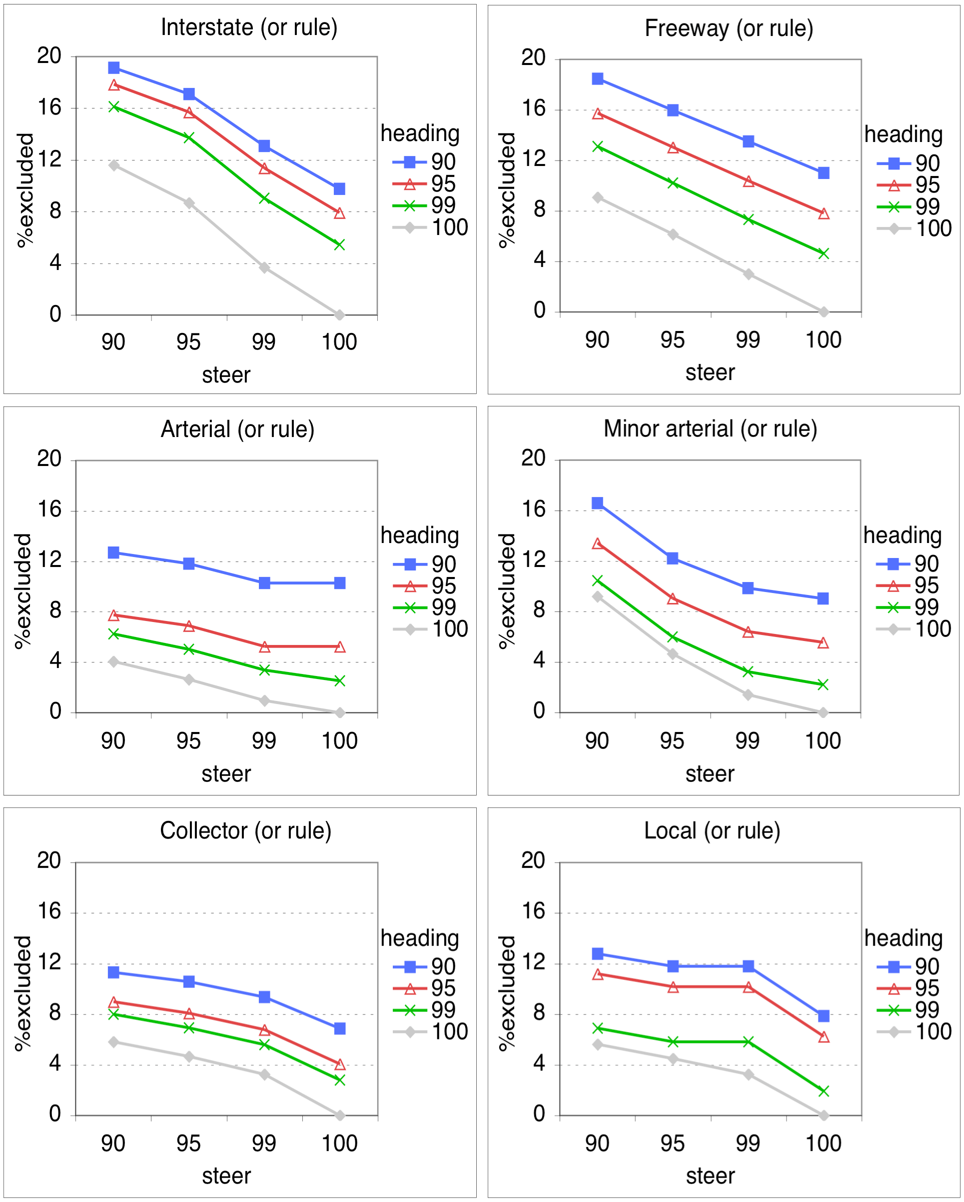

Figure 73. % Excluded Using Steer vs. Throttle or Heading vs. Speed Ellipses

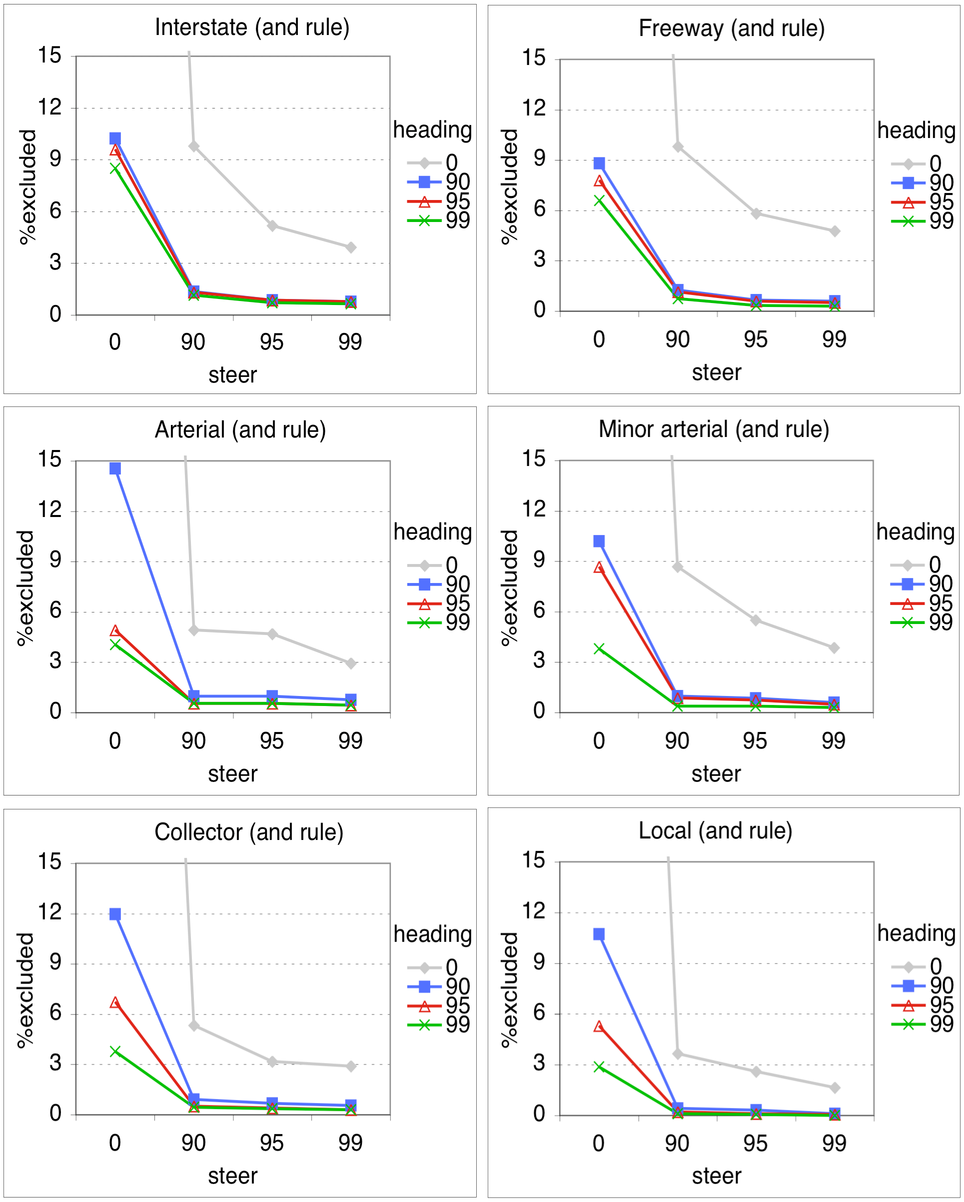

Figure 74. % Excluded Using Steering Rate vs. Throttle Rate
and Heading Rate vs. Acceleration Ellipses

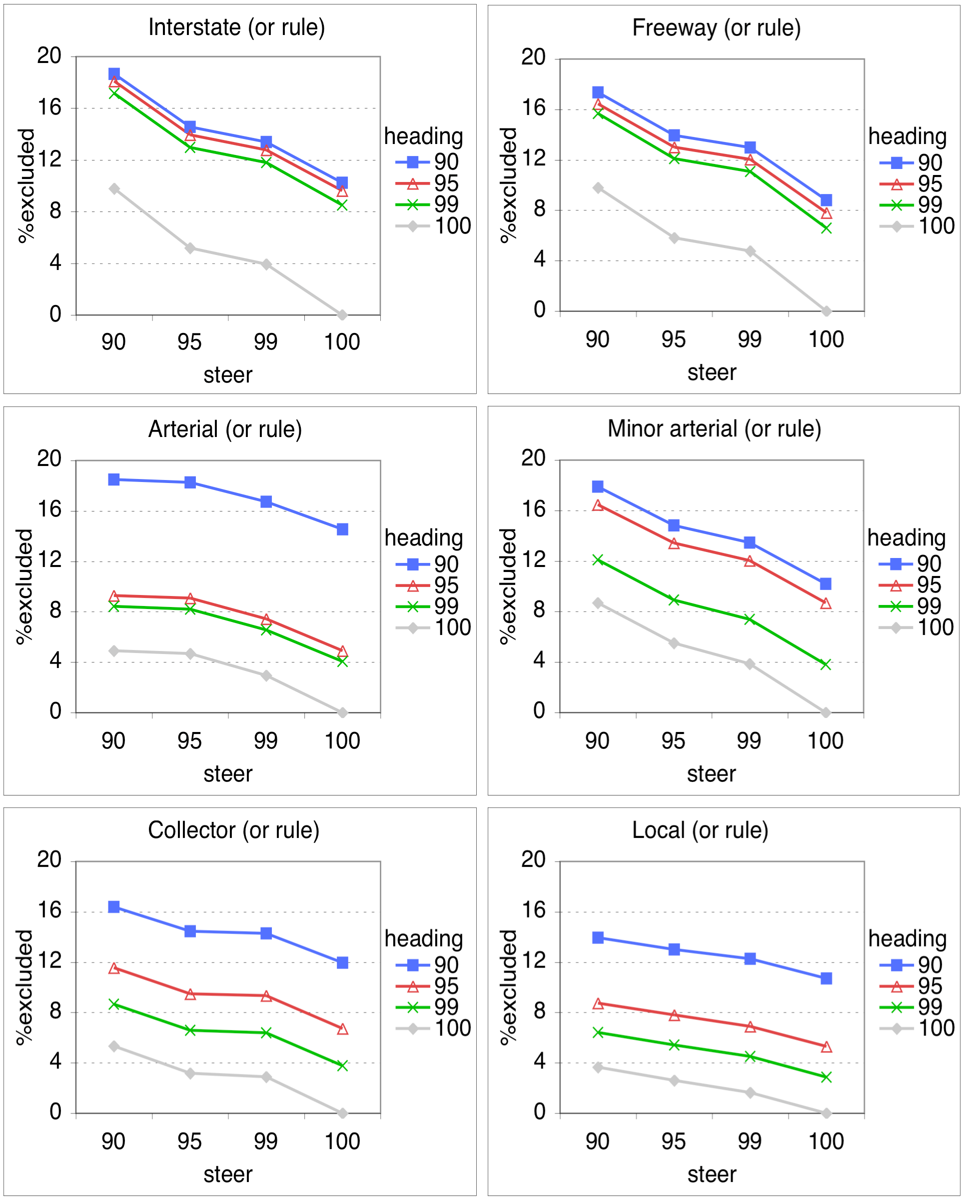

Figure 75. % Excluded Using Steering Rate vs. Throttle Rate Ellipse or Heading Rate vs. Acceleration Ellipse

APPENDIX B – NONPARAMETRIC DENSITY ESTIMATION USING KERNEL DENSITY ESTIMATION

aebaron 9/20/06 3:45 PM
Comment: Needs to be revised

The kernel density estimation method is usually used to eliminate noises and sharp edges in photo images. The main idea and procedure of kernel density estimation are represented in Figure 76.

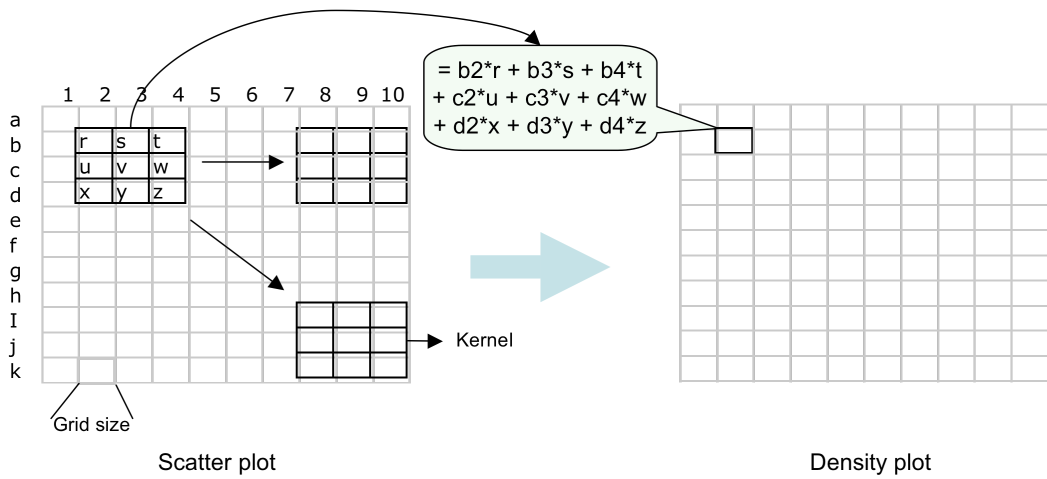

Figure 76. Conceptual Diagram of Kernel Density Estimation

Kernel density estimation is defined as the following equation:

$$\hat{f}(x) = \frac{1}{hn}\sum_{i=1}^{n} K\left(\frac{x - X_i}{h}\right)$$

where,

$\hat{f}(x)$ = density estimation of the variable x

n = number of observations

h = bandwidth

$K(\bullet)$ = a smooth, symmetric kernel function integrating to one.

The shape of the estimated density differs by different kernel functions. Table 43 shows some commonly used kernels.

Table 43. Kernel Functions

$K(\bullet)$	Kernel
$K(u) = \frac{1}{2}\boldsymbol{I}(\lvert u\rvert \le 1)$	Uniform
$K(u) = (1 - \lvert u\rvert)\boldsymbol{I}(\lvert u\rvert \le 1)$	Triangle
$K(u) = \frac{3}{4}(1 - u^2)\boldsymbol{I}(\lvert u\rvert \le 1)$	Epanechnikov
$K(u) = \frac{15}{16}(1 - u^2)^2\boldsymbol{I}(\lvert u\rvert \le 1)$	Quartic (Biweight)
$K(u) = \frac{1}{\sqrt{2\pi}}\exp(-\frac{u^2}{2}) = \varphi(u)$	Gaussian

In this study, a Gaussian kernel function was adopted. The smoothness of density estimation can be controlled by kernel standard deviation. Figure 77 represents smoothness change by kernel standard deviation

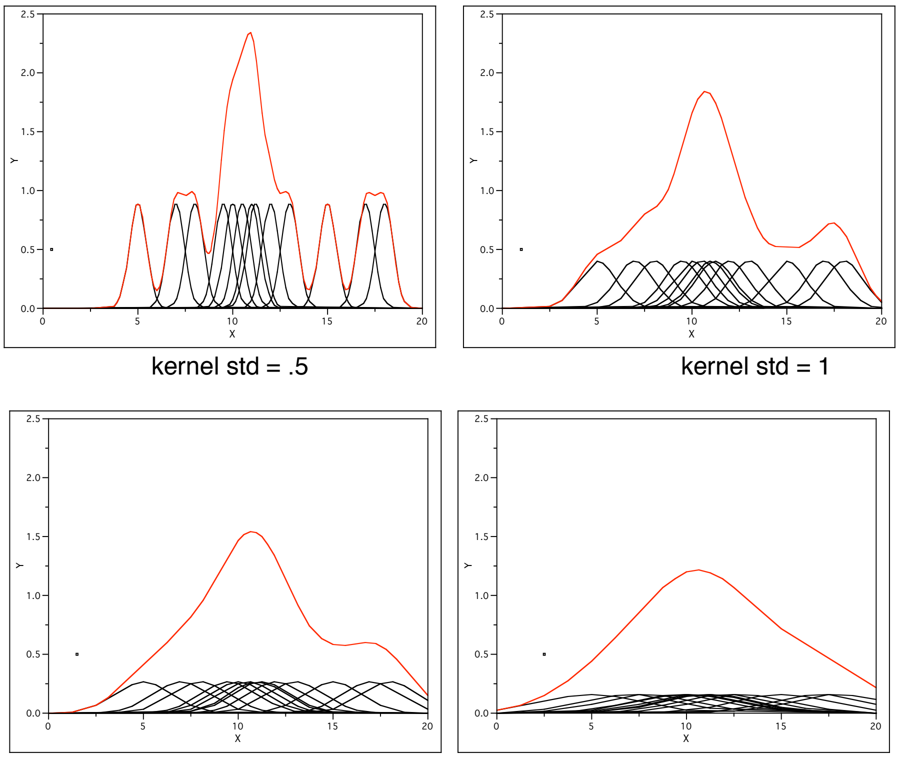

Figure 77. Gaussian Kernel Density Function with Different Kernel Standard Deviation

Figures 78 – 82 are examples from the study. They all show the bivariate relationship between heading angle and transmission speed on interstate roads with differently-smoothed, nonparametric density distribution.

The kernel standard deviation can be adjusted for each variable. Figure 78 is the most strict adjustment. The initial kernel standard deviation was obtained by following equation:

$$\text{Initial Kernel Std} = \frac{0.5 \times (\text{Standard Deviation of the Variable})}{(\text{Sample\_size})^{(1/6)}}$$

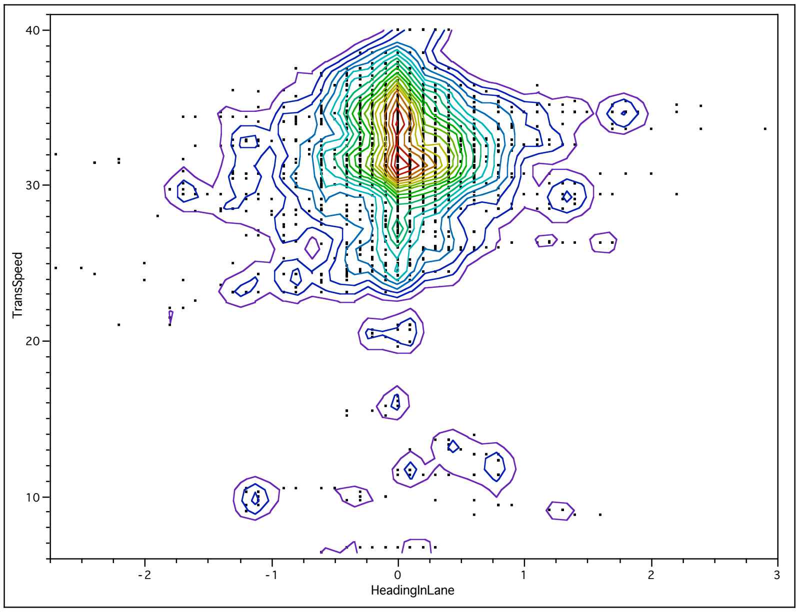

Figure 78. Kernel std: HeadingInLane (0.07), TransSpeed (0.68)

Figure 79 was drawn with approximately 4 times larger standard deviation for the x variable (HeadingInLane). It shows the horizontal smoothing effect. Figure 80 was drawn with approximately 4 times larger standard deviation for the y variable (TransSpeed). The vertical smoothing effect can be observed in Figure 80. Figure 81 adopted 2.5 times larger standard deviation for both x and y variables. Figure 82 adopted 4 times larger standard deviation for both variables. The smoothing effect for both variables can be observed in Figures 81 and 82.

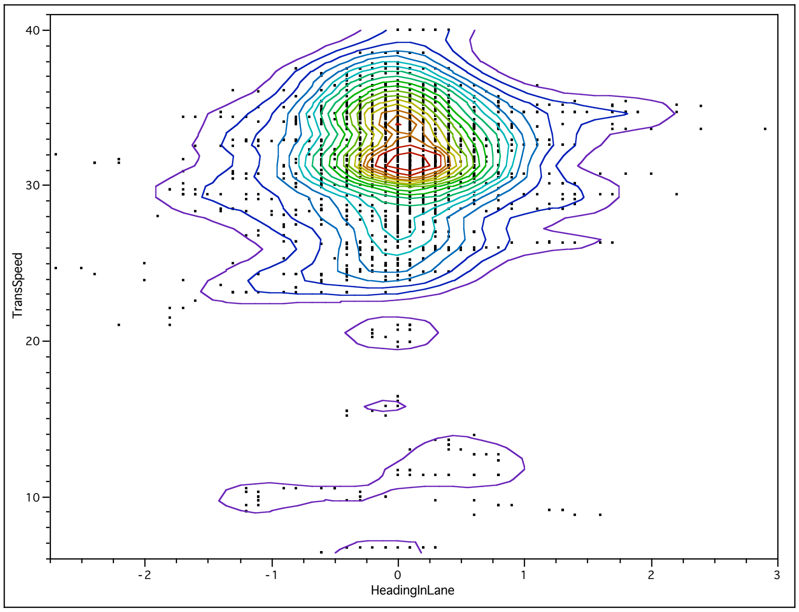

Figure 79. Kernel std: HeadingInLane (0.28), TransSpeed (0.68)

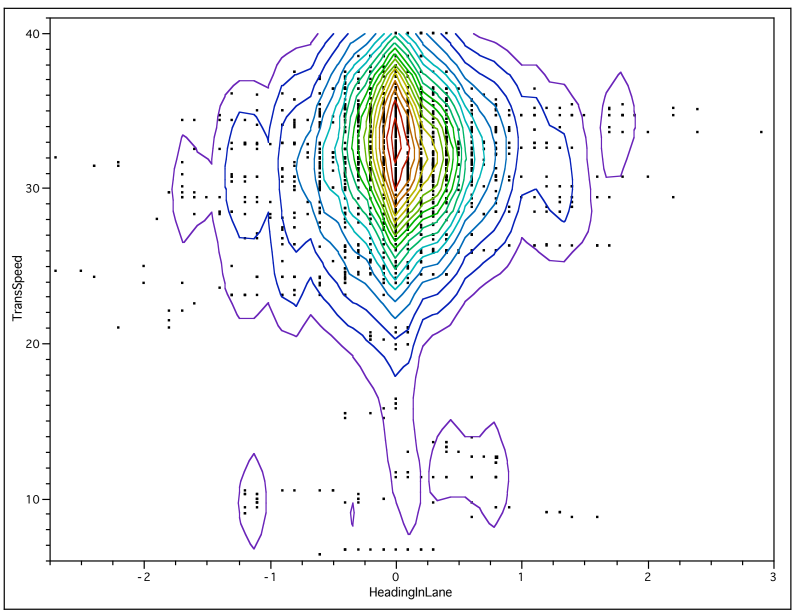

Figure 80. Kernel std: HeadingInLane (0.28), TransSpeed (0.68)

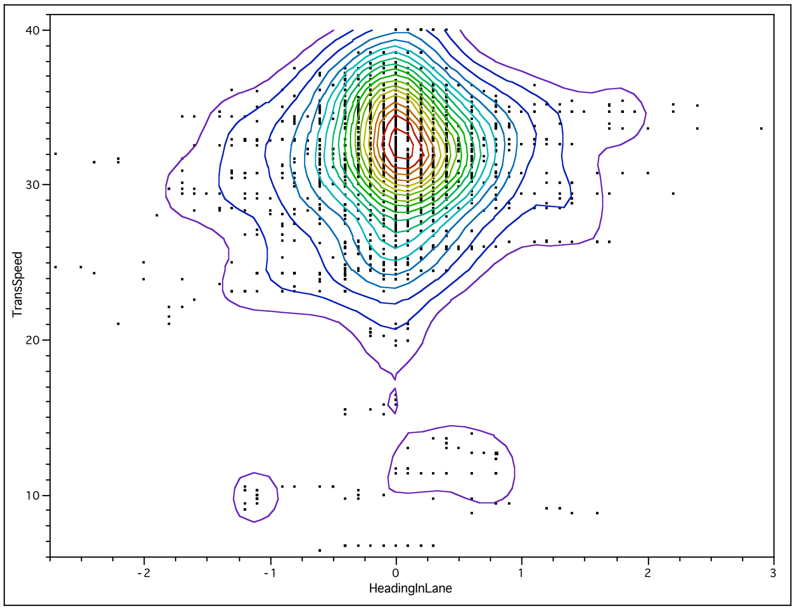

Figure 81. Kernel std: HeadingInLane (0.17), TransSpeed (1.66)

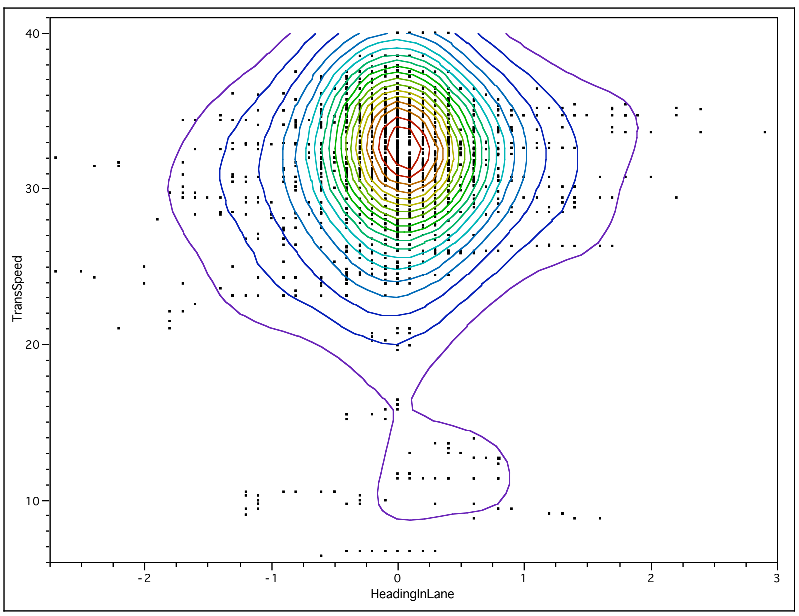

Figure 82. Kernel std: HeadingInLane (0.28), TransSpeed (2.73)

APPENDIX C – SAMPLE TABLE USED TO CREATE DENSITY PLOTS

In Table 44, the values in the columns Steer and Throttle were the coordinates used in each figure in this document. Equivalent quantile density points are connected with a contour line.

The density plots are represented in Figures 2 - 29 of this report and density grids are saved in Excel files (each density grid has 2,601 lines).

Table 44. Density Grid for Interstate (part of 2,601 rows table)

	Steer	Throttle	Density	Quantile density
1	-18	0	0	0
2	-18	0.94	6.37E-09	0
3	-18	1.88	1.82E-07	0.00000772
4	-18	2.82	0.0000014	0.00006701
5	-18	3.76	0.00000307	0.00016330
6	-18	4.7	0.00000213	0.00012154
7	-18	5.64	8.99E-07	0.00003952
8	-18	6.58	0.00000866	0.00050666
9	-18	7.52	0.00007676	0.00873522
10	-18	8.46	0.00026895	0.03624713
11	-18	9.4	0.00047677	0.07262792
12	-18	10.34	0.00050142	0.07614776
13	-18	11.28	0.00035514	0.05294117
14	-18	12.22	0.00018237	0.02342673
15	-18	13.16	0.0000541	0.00531817
16	-18	14.1	0.00000604	0.00034157
17	-18	15.04	1.01E-07	0.00000338
18	-18	15.98	0	0
19	-18	16.92	9.00E-20	0
20	-18	17.86	9.00E-20	0

APPENDIX D – ELLIPSE PARAMETERS

Table 45. 'A' and 'B' Values of 50-99% Ellipses for Steering Angle vs. Throttle

	50		60		70		80		90		99	
Road type	a	b	a	b	a	b	a	b	a	b	a	b
Interstate	5.35	7.28	6.14	8.36	7.06	9.61	8.15	11.1	9.74	13.3	13.8	18.7
Freeway	5.16	6.75	5.92	7.75	6.81	8.91	7.86	10.3	9.39	12.3	13.3	17.4
Arterial	8.83	6.75	10.1	7.75	11.6	8.91	13.4	10.3	16.1	12.3	22.7	17.4
Minor arterial	8.34	5.88	9.58	6.75	11.0	7.76	12.7	8.96	15.2	10.7	21.5	15.1
Collector	18.9	6.75	21.7	7.75	24.9	8.91	28.8	10.3	34.4	12.3	48.6	17.4
Local road	25.2	6.08	28.9	6.97	33.2	8.02	38.3	9.25	45.8	11.1	64.8	15.6

Table 46. 'A' and 'B' Values of 50-99% Ellipses for Heading vs. Speed

	50		60		70		80		90		99	
Road type	a	b	a	b	a	b	a	b	a	b	a	b
Interstate	0.63	6.13	0.72	7.03	0.83	8.08	0.95	9.33	1.14	11.1	1.61	15.8
Freeway	0.58	5.02	0.66	5.76	0.76	6.62	0.88	7.64	1.05	9.13	1.49	12.9
Arterial	1.06	7.19	1.22	8.25	1.40	9.48	1.62	10.9	1.93	13.1	2.73	18.5
Minor	1.01	6.27	1.16	7.20	1.34	8.27	1.54	9.55	1.84	11.4	2.61	16.1
arterial	1.25	6.27	1.44	7.20	1.65	8.27	1.91	9.55	2.28	11.4	3.23	16.1
Collector	1.54	5.93	1.77	6.81	2.04	7.83	2.35	9.03	2.81	10.8	3.97	15.3
Local road												

Table 47. Percent-Excluded for Steer vs. Throttle

Level of inclusion	Interstate	Freeway	Arterial	Minor arterial	Collector	Local
50	39.16	40.52	27.68	31.13	18.72	24.04
60	31.50	31.04	18.27	23.36	14.51	18.68
70	20.33	23.69	14.66	16.35	11.07	13.80
80	15.99	15.00	7.44	13.43	8.19	10.72
90	11.59	9.07	4.05	9.21	5.82	5.63
95	8.67	6.16	2.63	4.65	4.66	4.51
99	3.69	3.02	0.98	1.41	3.26	3.24

Table 48. Included/Excluded Ratio for Steering vs. Throttle Angle

Level of inclusion	Interstate	Freeway	Arterial	Minor arterial	Collector	Local
50	1.55	1.47	2.61	2.21	4.34	3.16
60	2.17	2.22	4.47	3.28	5.89	4.35
70	3.92	3.22	5.82	5.12	8.03	6.25
80	5.25	5.67	12.44	6.44	11.21	8.33
90	7.63	10.03	23.70	9.86	16.19	16.77
95	10.53	15.24	37.08	20.49	20.46	21.16
99	26.08	32.09	100.56	69.98	29.64	29.89

Table 49. Percent-Excluded for Heading vs. Speed

Level of inclusion	Interstate	Freeway	Arterial	Minor arterial	Collector	Local
50	28.56	32.31	29.87	39.29	37.80	37.95
60	21.10	23.54	21.88	33.58	30.09	28.50
70	16.02	19.07	16.41	25.10	22.02	20.28
80	12.57	14.25	12.69	19.17	14.75	12.79
90	9.76	11.01	10.28	9.04	6.88	7.86
95	7.93	7.84	5.25	5.57	4.07	6.26
99	5.45	4.63	2.52	2.23	2.79	1.91

Table 50. Included/Excluded Ratio for Heading vs. Speed

Level of inclusion	Interstate	Freeway	Arterial	Minor arterial	Collector	Local
50	2.50	2.09	2.35	1.55	1.65	1.63
60	3.74	3.25	3.57	1.98	2.32	2.51
70	5.24	4.24	5.09	2.98	3.54	3.93
80	6.96	6.02	6.88	4.22	5.78	6.82
90	9.25	8.08	8.72	10.06	13.53	11.73
95	11.62	11.76	18.04	16.95	23.60	14.97
99	17.34	20.61	38.74	43.88	34.85	51.33

Table 51. ‘A’ and ‘B’ Values of 50-99% Ellipses for Steering Rate vs. Throttle Rate

	50		60		70		80		90		99	
Road type	a	b	a	b	a	b	a	b	a	b	a	b
Interstate	1.01	1.74	1.16	1.99	1.34	2.29	1.54	2.64	1.84	3.16	2.61	4.47
Freeway	1.06	1.11	1.22	1.27	1.40	1.46	1.62	1.69	1.93	2.02	2.73	2.85
Arterial	1.83	1.25	2.1	1.44	2.42	1.65	2.79	1.91	3.34	2.28	4.71	3.23
Minor arterial	1.69	1.01	1.94	1.16	2.23	1.34	2.57	1.54	3.07	1.84	4.34	2.61
Collector	12.2	1.06	14.0	1.22	16.1	1.40	18.6	1.62	22.2	1.93	31.4	2.73
Local road	16.5	0.96	19.0	1.11	21.8	1.27	25.2	1.47	30.1	1.76	42.6	2.48

Table 52. ‘A’ and ‘B’ Values of 50-99% Ellipses for Heading Rate vs. Acceleration

	50		60		70		80		90		99	
Road type	a	b	a	b	a	b	a	b	a	b	a	b
Interstate	0.23	0.11	0.27	0.12	0.31	0.14	0.35	0.16	0.42	0.19	0.60	0.27
Freeway	0.27	0.09	0.30	0.10	0.35	0.11	0.40	0.13	0.48	0.16	0.68	0.22
Arterial	0.48	0.15	0.55	0.18	0.64	0.20	0.73	0.24	0.88	0.28	1.24	0.40
Minor arterial	0.37	0.18	0.43	0.21	0.49	0.24	0.57	0.28	0.68	0.33	0.96	0.47
Collector	0.40	0.21	0.45	0.24	0.52	0.28	0.60	0.32	0.72	0.39	1.02	0.55
Local road	0.51	0.22	0.58	0.25	0.67	0.29	0.77	0.33	0.92	0.39	1.30	0.56

Table 53. Percent-Excluded for Steering Rate vs. Throttle Rate

Level of inclusion	Interstate	Freeway	Arterial	Minor arterial	Collector	Local
50	18.39	16.46	13.24	20.81	6.88	22.98
60	12.91	16.46	9.74	20.81	6.11	5.15
70	11.31	11.57	9.74	11.34	5.76	4.72
80	10.60	11.57	8.10	11.34	5.52	3.98
90	9.79	9.81	4.92	8.68	5.34	3.66
95	5.18	5.82	4.70	5.50	3.18	2.60
99	3.93	4.78	2.95	3.87	2.91	1.65

Table 54. Included/Excluded Ratio for Steering Rate vs. Throttle Rate

Level of inclusion	Interstate	Freeway	Arterial	Minor arterial	Collector	Local
50	4.44	5.08	6.55	3.81	13.53	3.35
60	6.75	5.08	9.27	3.81	15.36	18.42
70	7.84	7.65	9.27	7.82	16.37	20.17
80	8.43	7.65	11.35	7.82	17.12	24.12
90	9.21	9.19	19.31	10.52	17.72	26.30
95	18.29	16.18	20.26	17.17	30.50	37.45
99	24.45	19.94	32.85	24.86	33.39	59.77

Table 55. Percent-Excluded for Heading Rate vs. Acceleration

Level of inclusion	Interstate	Freeway	Arterial	Minor arterial	Collector	Local
50	17.41	14.96	17.40	23.49	26.05	26.49
60	17.41	13.84	15.86	20.90	24.60	26.43
70	12.60	11.12	15.32	20.77	22.88	24.89
80	12.60	10.37	14.55	19.86	14.15	12.26
90	10.23	8.81	14.55	10.19	11.96	10.72
95	9.62	7.80	4.92	8.68	6.74	5.31
99	8.50	6.60	4.05	3.80	3.77	2.87

Table 56. Included/Excluded Ratio for Heading Rate vs. Acceleration

Significance level	Interstate	Freeway	Arterial	Minor arterial	Collector	Local
50	4.74	5.68	4.75	3.26	2.84	2.78
60	4.74	6.22	5.30	3.78	3.07	2.78
70	6.94	7.99	5.53	3.81	3.37	3.02
80	6.94	8.64	5.87	4.04	6.06	7.16
90	8.77	10.36	5.87	8.81	7.36	8.33
95	9.39	11.82	19.31	10.52	13.85	17.84
99	10.76	14.14	23.70	25.31	25.54	33.89

APPENDIX E – PERCENTILES EXCLUDED

Table 57. Percent-Excluded Values using the Steer vs. Throttle and Heading vs. Speed Ellipses with the "And" Rule

Road type	Head / steer	0	90	95	99
Interstate	0	100	9.76	7.93	5.45
	90	11.59	2.20	1.66	0.91
	95	8.67	1.32	0.88	0.41
	99	3.69	0.37	0.24	0.10
Freeway	0	100	11.01	7.84	4.63
	90	9.07	1.60	1.16	0.60
	95	6.16	1.19	0.93	0.56
	99	3.02	0.52	0.49	0.34
Arterial	0	100	10.28	5.25	2.52
	90	4.05	1.64	1.53	0.33
	95	2.63	1.09	0.98	0.11
	99	0.98	0.98	0.98	0.11
Minor arterial	0	100	9.04	5.57	2.23
	90	9.21	1.67	1.34	0.98
	95	4.65	1.47	1.15	0.88
	99	1.41	0.59	0.56	0.39
Collector	0	100	6.88	4.07	2.79
	90	5.82	1.39	0.89	0.59
	95	4.66	0.95	0.62	0.50
	99	3.26	0.77	0.53	0.45
Local	0	100	7.86	6.26	1.91
	90	5.63	0.69	0.69	0.64
	95	4.51	0.58	0.58	0.58
	99	3.24	0.48	0.48	0.48

Table 58. Percent Excluded Values using the Steer vs. Throttle and Heading vs. Speed Ellipses with the "Or" Rule

Road type	Head / steer	90	95	99	100
Interstate	90	19.14	17.85	16.12	11.59
	95	17.11	15.72	13.72	8.67
	99	13.08	11.38	9.04	3.69
	100	9.76	7.93	5.45	0.00
Freeway	Head / steer	90	95	99	100
	90	18.47	15.75	13.10	9.07
	95	15.97	13.06	10.22	6.16
	99	13.51	10.37	7.31	3.02
	100	11.01	7.84	4.63	0.00
Arterial	Head / steer	90	95	99	100
	90	12.69	7.77	6.24	4.05
	95	11.82	6.89	5.03	2.63
	99	10.28	5.25	3.39	0.98
	100	10.28	5.25	2.52	0.00
Minor arterial	Head / steer	90	95	99	100
	90	16.58	13.43	10.45	9.21
	95	12.22	9.08	6.00	4.65
	99	9.86	6.42	3.24	1.41
	100	9.04	5.57	2.23	0.00
Collector	Head / steer	90	95	99	100
	90	11.31	8.99	8.01	5.82
	95	10.59	8.10	6.94	4.66
	99	9.38	6.80	5.61	3.26
	100	6.88	4.07	2.79	0.00
Local	Head / steer	90	95	99	100
	90	12.79	11.20	6.90	5.63
	95	11.78	10.19	5.84	4.51
	99	11.78	10.19	5.84	3.24
	100	7.86	6.26	1.91	0.00

Table 59. Percent-Excluded Values using the Steer Rate vs. Throttle Rate and Heading Rate vs. Accelerate Ellipse with the "And" Rule

Road type	steer_R \ Head_R	0	90	95	99
Interstate	0	100	10.23	9.62	8.5
	90	9.79	1.36	1.32	1.15
	95	5.18	0.85	0.85	0.71
	99	3.93	0.78	0.78	0.64
Freeway	0	100	8.81	7.8	6.6
	90	9.81	1.27	1.16	0.75
	95	5.82	0.67	0.60	0.34
	99	4.78	0.60	0.52	0.30
Arterial	0	100	14.55	4.92	4.05
	90	4.92	0.98	0.55	0.55
	95	4.7	0.98	0.55	0.55
	99	2.95	0.77	0.44	0.44
Minor arterial	0	100	10.19	8.68	3.8
	90	8.68	0.98	0.88	0.39
	95	5.5	0.85	0.75	0.39
	99	3.87	0.59	0.49	0.29
Collector	0	100	11.96	6.74	3.77
	90	5.34	0.92	0.50	0.45
	95	3.18	0.68	0.42	0.36
	99	2.91	0.56	0.30	0.30
Local	0	100	10.72	5.31	2.87
	90	3.66	0.42	0.21	0.11
	95	2.6	0.32	0.11	0.05
	99	1.65	0.11	0.05	0.00

Table 60. Percent-Excluded Values using the Steer Rate vs. Throttle Rate and Heading Rate vs. Accelerate Ellipses with the “Or” Rule

Road type	Head_R / steer_R	90	95	99	100
Interstate	90	18.67	18.09	17.14	9.79
	95	14.57	13.96	12.97	5.18
	99	13.38	12.77	11.79	3.93
	100	10.23	9.62	8.5	0.00
Freeway	90	17.35	16.46	15.67	9.81
	95	13.96	13.02	12.09	5.82
	99	12.99	12.05	11.08	4.78
	100	8.81	7.8	6.6	0.00
Arterial	90	18.49	9.30	8.42	4.92
	95	18.27	9.08	8.21	4.7
	99	16.74	7.44	6.56	2.95
	100	14.55	4.92	4.05	0.00
Minor arterial	90	17.89	16.48	12.09	8.68
	95	14.84	13.43	8.91	5.5
	99	13.47	12.06	7.37	3.87
	100	10.19	8.68	3.8	0.00
Collector	90	16.38	11.57	8.66	5.34
	95	14.45	9.50	6.59	3.18
	99	14.30	9.35	6.38	2.91
	100	11.96	6.74	3.77	0.00
Local	90	13.96	8.76	6.42	3.66
	95	13.00	7.80	5.41	2.6
	99	12.26	6.90	4.51	1.65
	100	10.72	5.31	2.87	0.00