Tuning Collision Warning Algorithms to Individual Drivers for Design of Active Safety Systems

Ali Rakhshan
and Hossein Pishro-Nik
School of Electrical and
Computer Engineering
University of Massachusetts
Amherst, Massachusetts
Emails: {arakhshan, pishro}@ecs.umass.edu

Donald L. Fisher
School of Mechanical and
Industrial Engineering
University of Massachusetts
Amherst, Massachusetts
Email: fisher@ecs.umass.edu

Mohammad Nekoui
Olympus Communication Technology
of America
San Diego, California
mohammad.nekoui@olympus.com

***Abstract*—Every year, many people are killed and injured in highway traffic accidents. In order to reduce such casualties, collisions warning systems has been studied extensively. These systems are built by taking the driver reaction times into account. However, most of the existing literature focuses on characterizing how driver reaction times vary across an entire population. Therefore, many of the warnings that are given turn out to be false alarms. A false alarm occurs whenever a warning is sent, but it is not needed. This would nagate any safety benefit of the system, and could even reduce the overall safety if warnings become a distraction. In this paper, we propose our solution to address the described problem; First, we briefly describe our method for estimating the distribution of brake response times for a particular driver using data from a Vehicular Ad-Hoc Network (VANET) system. Then, we investigate how brake response times of individual drivers can be used in collision warning algorithms to reduce false alarm rates while still maintaining a high level of safety. This will yield a system that is overall more reliable and trustworthy for drivers, which could lead to wider adoption and applicability for V2V/V2I communication systems. Moreover, we show how false alarm rate varies with respect to probability of accident. Our simulation results show that by individualizing collision warnings the number of false alarms can be reduced more than 50%. Then, we conclude safety applications could potentially take full advantage of being customized to an individual's characteristics.**

I. Introduction[1]

Despite the increases in safety introduced into the automobile, at latest count (2010) the number of deaths is over 30,000, the number of injuries is over two million, and the number of crashes is over five million. As a way to address this problem, collision warning systems hold great promise, especially as distractions inside and outside the vehicle increase almost exponentially year by year [1]. Rear end collision warning systems have been studied extensively. They do reduce the behaviors that lead to crashes. However, radical changes in the effectiveness of collision warning systems are now possible due to the progress that is being made in Vehicular Ad Hoc Networks. Vehicular ad hoc networks potentially allow all vehicles to communicate with each other (V2V or vehicle to vehicle communication) and with technologies embedded in the infrastructure that transmit crash relevant information (V2I or vehicle to infrastructure communication).

[1]This work was supported by the NSF under CCF 0844725.

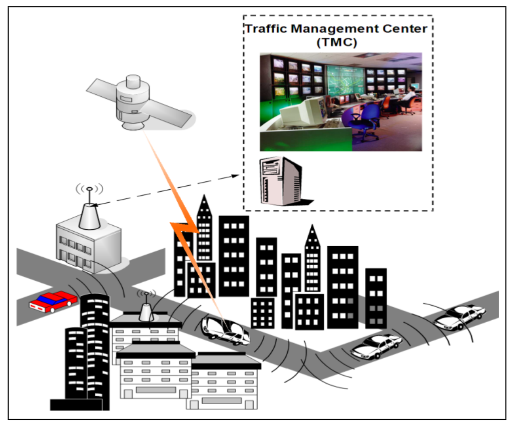

Fig. 1: A typical VANET deployment in urban areas

Effectiveness of warnings depends on how much time the driver needs to react. Reaction times have long been studied in cognitive science [3]–[5]. When the latent cognitive processes are arranged in series and the task is a simple one (e.g., decide whether a particular stimulus has or has not been presented), transportation engineers will often decompose the time it takes an individual to complete a task into the driver perception time and driver reaction time [6]. Specifically, the driver perception time (or just perception time) is defined as the amount of time it takes an individual to recognize that an event has occurred (stimulus has been presented) and, assuming several events are possible, which of these several events has occurred. The driver reaction time (or just reaction time) is defined as the amount of time it takes an individual to prepare a motor response and then complete the response (e.g., take the foot off the accelerator, move the foot to the brake, turn the wheel). The driver perception-reaction time (PRT) is defined as the sum of the driver perception and reaction times. In this paper, we use "perception reaction time" and "brake response time" interchangeably, but in general, BRTs are just a special case of PRTs.

Our main contribution in this paper is to show how different safety applications could potentially benefit from being personalized to an individual driver brake reaction time. Our work shows that by individualizing collision warnings the number of false alarms can be reduced more than 50%. The rest of paper is organized as follows. In section II, we review the relevant literature formally defining the PRT. Section III describes the problem of false alarms and its relationship to probability of accident. In section IV, we briefly propose our method [17] that can be used to estimate the brake reaction times of individual drivers which can then be entered into rear end collision warning algorithms. Then, we can use the information available from vehicular Ad Hoc Networks to tune collision warning algorithms to individual drivers. Section V presents the mathematical assumptions for testing our claim. Our simulation results are discussed in section VI. We show how false alarm rates vary when the warning system uses either population or individual PRT distribution. The paper is finally concluded in section VII.

II. Related Work

The problem with estimating brake reaction times in real world scenarios is that the PRTs will be a function of how soon the driver needs to respond after the onset of a signal. In the field, the signal that is used is often the change from green to amber. [2] has shown that the PRT will be delayed if the driver is relatively far from a signal when the signal changes as above. In this study, among those drivers who stopped, the PRT is relatively short when the projected time to the stop line (TTSL) at amber onset is 2 or 3 seconds (computed from vehicle velocity and distance to stop line at amber onset), but is much longer on average when the projected TTSL is on the order of 7 to 8 seconds. Clearly, the estimate of the PRT will be too large if all observations are considered. Drivers with a large projected TTSL do not need to respond immediately and therefore using their PRTs in the computation may not be ideal.

Interestingly, [2] have been able to resolve the above dilemma. They argue that only a subset of the brake reaction times should be analyzed if one is interested in estimating the brake reaction times for situations in which the driver must quickly come to a stop, as is the case in rear end collisions. They confined their analysis to those observations which occurred in what they define as the transition zone, a zone where the driver needs to make a go/no go decision after the signal has turned from green to amber. They provide persuasive evidence that this transition zone is well defined by all TTSLs that are 4 seconds or less. Note when the TTSL is 4 seconds or less, the PRTs are all 1.8 seconds or less. Drivers do not have an option here of putting off the decision of whether to brake or not. We can do much the same thing when analyzing vehicle response times inside the vehicle for individual drivers (confine the analysis to the transition zone).

The question at this point is how we model drivers' response times within the transition zone. Virtually every study to examine the perception-reaction times of samples of drivers has found that the population distribution of reaction times is skewed right. In the transportation literature, the perception-reaction time distribution is often approximated by a lognormal distribution ([9] [2] [7] [6] [10] [11] [12]). In section V, we exploit this distribution to characterize the probability density function for the PR times of people across the sample population.

III. Problem Description

Current efforts in the realm of intelligent transportation systems (ITS) typically consider drivers that can show a wide variety of behaviors during a driving session. Yet we all know that a specific driver has specific driving behaviors. He or she could be vigilant or distracted; could perceive and react soon to an event or might have a longer perception-reaction time; could be aggressive in acceleration/deceleration or could be smoother in those. Since existing collision warning algorithms don't use the PRT distribution of individuals, drivers with different PRT in the same scenario receive the same warnings. Clearly, this approach isn't optimal for design of safety systems. To best explain our idea of this paper, let us consider a safety application of a simple VANET. Here, a vehicle is following another vehicle on a one lane roadway when the lead vehicle suddenly begins to decelerate to avoid an unexpected obstacle, or due to a mechanical failure. Then, the following vehicle must also brake to avoid a collision. However, the driver of the following vehicle will take a certain amount of time to first perceive that he or she must brake (perception time), and then another length of time to actually apply the brake (reaction time). Perception-reaction time has undergone much scrutiny within the human factors literature. This time could increase as a result of various factors such as whether the driver is distracted or expecting a hazard. If the driver does not have sufficient time to react, a collision could occur, resulting in damage to the vehicles, or even injury or loss of life for the drivers or any passengers. Thus, any system that could help the driver of the following vehicle to react more quickly would be greatly beneficial. One such system is a simple warning. This could consist of both visual and auditory cues such as a warning light flashing, and an alarm being sounded. After receiving the warning, the driver could react more quickly, since the driver would understand that the warning indicates that they must brake immediately, and no thought will be required to assess the situation and decide on the best course of action. Such a system must be used carefully. With time, drivers may come to trust and rely on the warning system. Then, the system failing to provide a warning when one is needed could prove disastrous, as the driver may not react in time and collide with the leading vehicle. On the other hand, if the warnings that are given turn out to be false alarms too frequently, drivers may begin to ignore them. This would negate any safety benefit of the system, and could even reduce overall safety if the warnings become a distraction. This means that the system must attempt to minimize the frequency of false alarms while still maintaining a high level of safety.

To minimize false alarms, the system must only send warnings when the driver would not otherwise have time to react. In other words, by adapting the collision warning algorithm for different drivers' varying needs, safety of driving will be improved. Clearly, to do so will require an accurate model of the driver's reaction time. Different drivers may tend to react more quickly or slowly, so the system must be able to model the reaction times of each individual driver. However, most of the existing literature focuses on characterizing how driver reaction times vary across an entire population, rather than how the reaction times of an individual driver vary. In this paper, we will attempt to consider the behaviors of individual drivers, and investigate why this model is reasonable.

IV. Proposed Solution

Our proposed solution to address the described problem consists of two steps:

- Real-Time estimation of the distribution of brake response times for an individual driver.
- Using the estimated distribution to customize warnings in order to minimize false alarms.

Our team has successfully completed a project [17] to find a method for estimating the distribution of PRTs for a particular driver using data from a Vehicular Ad-Hoc Network (VANET) system which has information about the positions, velocities, accelerations of cars on the roads, road configurations, and the status and position of traffic signals. In this project, we proposed methods that can be used to estimate what the distribution of a driver's PRTs would be if he or she did not intentionally delay braking for a particular braking event. This method draws from the fundamental ideas presented by [9] and [2] , viewing PRT as a function of variables such as travel speed, distance, and time headway. However, we improved on their analysis by using regression methods that allow us to use all of the data to help determine the distribution of PRT, rather than discarding data points with a long time headway, low speed, or large distance from the intersection. Our approach also does not rely on the assumption that the distribution of response times is the same whenever the time headway from the intersection is less than 4 seconds. Further, in addition to estimating the center point of the distribution of PRTs, we also estimated the distribution's spread. This is essential for our intended application in an accident warning system, where we will use percentiles of this distribution. We also extended the analysis to incorporate measurements of reaction times in other settings than a traffic signal change, and focus the analysis on estimating the distribution of PRTs for an individual driver, rather than for a population of drivers. A limitation of this approach lies in the question of whether it is valid to extend results about response times from driving simulations to real life. These criticisms can be addressed to a certain extent by ensuring that the circumstances in which reaction times are measured in the simulator are similar to those encountered by real drivers, including subjects with a range of demographic characteristics and a variety of levels of expectancy in the braking stimuli. We have also suggested an admittedly ad-hoc method of adjusting the distribution of reaction times obtained from the driving simulator to account for the differences observed by [18]. It is also reassuring that as we gather more data for a driver in real car driving situations, the information obtained from the driving simulations contributes less to our estimated PRT distribution for that driver. That said, if an accident warning system based on these methods for estimating the PRT distribution is implemented on a wide scale in the future, it would be worth considering obtaining a sample of data from real drivers to use in training the model.

In summary, we developed new models for estimating the brake reaction times for individual drivers with data available from Vehicular Ad Hoc Networks that will be used to individualized collision warnings. Also, we in [17] have expanded slightly on this analysis, showing in Figures 2 and 3 how the estimated brake reaction time distribution changes with the sample size and the allocation of the sample among two

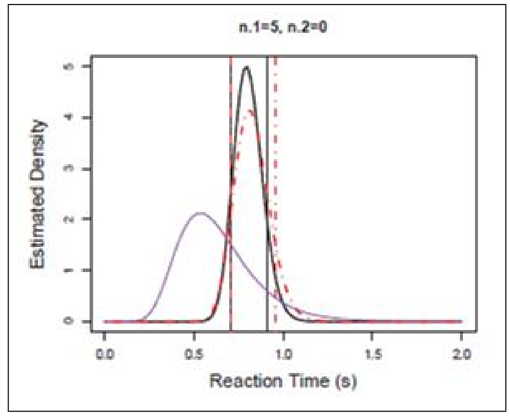

Fig. 2: Estimate of the distribution of PRTs for an individual obtained in a simulation with sample size=5. (The black - symmetric – curve represents the individual's "true" response time distribution. The purple - asymmetric – curve represents the distribution of reaction times in the population, which is used as an estimate when the sample size is 0. The dashed red curve is the estimated distribution. The vertical lines are at the 10^{th} and 90^{th} percentiles. TTSL = 1.5 s)

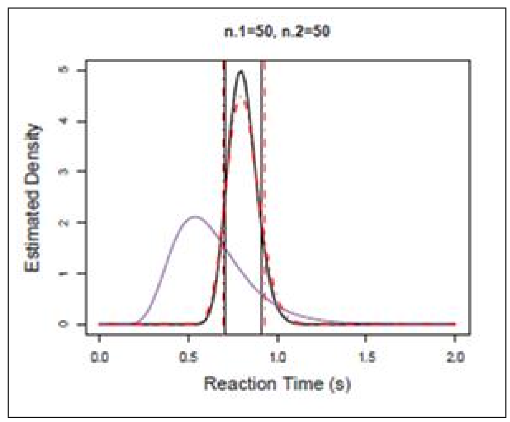

Fig. 3: Estimate of the distribution of PRTs for an individual obtained in a simulation with sample size=50.

different scenario types. The number of observations in the first scenario, n.1, in each plot is displayed at the top on the left; the number of observations in the second scenario, n.2, is displayed opposite it. These results are dependent upon the parameter values used in the simulation (TTSL = 1.5 s), but they illustrate that a very good estimate of the distribution of brake response times for an individual in a given scenario can be obtained with only five observations from that scenario (Figure 2) and that near perfect estimates can be obtained with only 50 observations (Figure 3). Note that we didn't need to estimate the PRT distribution at each of an infinite number of time headways since they could either bin the results or assume, reasonably, the mean and variance of the PRT distribution change in a smooth way as TTSL varies.

V. PRT Distributions

Currently in the existing literature about this subject, there are many studies that find a probability density function for the PRTs of people across the sample population. These distributions describe the probability that a random PRT for a random driver will fall within a certain range. For our simulations, we used the results from [6]. In this study, the author finds the "surprise" PRT probability density function to follow a log-normal distribution where its parameters to be $\mu = 0.17$ and $\sigma = 0.44$. In this scenario, the driver does not know when or even if the stimulus for braking will occur, i.e., he or she is surprised, something like a real-world occurrence on the highway. Next, we want to relate this distribution to the distribution of PRTs for an individual driver. In probability theory, the Central Limit Theorem states, under certain conditions, the sum of a large number of random variables is approximately normal. Therefore, we begin with the assumption that the probability density function for the PRTs of an individual driver will follow a truncated normal distribution. PRTs cannot ever be negative, so we use a truncated normal distribution.

$$f(x|\mu) = \frac{\alpha}{\sigma\sqrt{2\pi}} e^{-\frac{(x-\mu)^2}{2\sigma^2}} \qquad \text{for} \qquad x \geq 0 \tag{1}$$

Equation (1) represents the standard equation for the probability density function of a normal variable, with the added constant multiplier α to compensate for the distribution being truncated. Then, we must find a way to relate the distribution for an individual to the overall distribution for the population. To do this, we will let the mean of the distribution for an individual driver, denoted by μ , be a random variable. This assumption will represent the fact that different drivers in the population have different PRT means, and that more drivers have means within certain ranges than others. To analyze the situation, we will let X be a random variable representing the PRT for an individual driver, and let M be a random variable representing the different means of the distributions for individual drivers. Then, because μ is also a random variable, we can let the probability density function of μ be $f_M(\mu)$. We then combine these to find their joint distribution. Then, for our model of driver PRTs to be reasonable, the marginal distribution $f_X(x)$should closely match the log-normal distribution for the overall population found in the literature.

VI. Simulation Results

Once a distribution for a driver's reaction time has been established, we would like to use this information to improve safety and minimize the rate of false alarms. One simple method for doing this would be to give the driver a warning when they are approaching an obstacle, and there will not be enough time for them to react otherwise. As we mentioned, [6] established that the distribution of PRTs of drivers reacting to surprise events follows a log-normal curve with parameters $\mu = 0.17$ and $\sigma = 0.44$. Since failing to give a warning when one is needed could be very dangerous, we will assume that the percentage of possible collisions that the system fails to provide warning for is fixed at a small number (e.g. at 1%), and then try to minimize the frequency of false alarms that the system gives subject to this constraint. If the system detects that the driver has less than his or her PRT to react to an obstacle, it should give the driver a warning. We can only state the probability that any PRT is above or below a certain value. Thus, the constraint states that we must calculate some threshold T_t that there is only a 1% chance that a PRT will be above, and send a warning whenever a driver has less than this amount of time to react. Therefore, we can calculate the threshold to send the warnings using the distribution for the entire population:

$$P(X \leq T_t) = \phi\left(\frac{\ln(T_t) - 0.17}{0.44}\right) = 1 - \text{prob. of accident} \tag{2}$$

$$\text{If probability of accident=1\%} \quad \Rightarrow T_t = e^{1.9} \approx 3.3 \tag{3}$$

Also, we can calculate warning threshold using the distribution for an individual driver (assuming that the standard deviation of an individual driver =0.2):

$$P(X \leq T_t) = \phi\left(\frac{T_t - \mu}{0.2}\right) = 1 - \text{prob. of accident} \tag{4}$$

As we can see, T_t for an individual driver depends on μ. Thus,

$$\text{If probability of accident=1\%} \quad \Rightarrow T_t \approx 0.4652 + \mu \tag{5}$$

Now that we have established the thresholds for sending collision warnings, we can calculate the false alarm rates that will result from using the different systems. A false alarm occurs whenever a warning is sent, but it is not needed. Then, suppose that the system has calculated that a driver has t seconds to react, and that t is less than T_t, so a warning has been sent. Then, the false alarm rate is the probability that the driver's reaction time, X, will be less than t. Let $F_X(x)$ denote the cumulative distribution function for this distribution then $F_X(t)$ is the total false alarm rate.

$$P(X \leq T) = \int_0^{T_t} \int_0^t \frac{\alpha}{\sigma\sqrt{2\pi}} e^{-\frac{(x-\mu)^2}{2\sigma^2}} \frac{1}{T_t} dx dt \tag{6}$$

In equation (6), for example, using the distribution for the entire population ($\mu = 0.17$ and $\sigma = 0.44$) means that over 60% of the warnings will be false alarms. However, if we use the distribution for a individual driver with standard deviation 0.2 and mean μ, the false alarm rate reduces to 29.5%, a large improvement over the rate obtained by using the distribution for the overall population.

Using the distribution for the overall population, not only is there a higher overall false alarm rate, these false alarms are not evenly distributed across the population. Drivers with fast reaction times will have very high false alarm rates, but drivers with slow reaction times will have lower rates.

Finally, and most importantly, we want to know how much the false alarm rate can be reduced versus Probability of Accident when the individual brake reaction times are used rather than the population brake reaction times. It is clear from Figure 4 that when we use the population brake reaction the false alarm rate is higher by almost a factor of two than when we use the individual driver's brake reaction time. In addition, as the standard deviation of a driver's brake reaction time increases, the difference between two models shrinks. In other words, increasing the standard deviation results in losing the benefit from using the individual distribution. Therefore, safety applications could potentially take full advantage of being customized to an individual's characteristics. Regardless, there is an observable tradeoff between the false alarm rate and

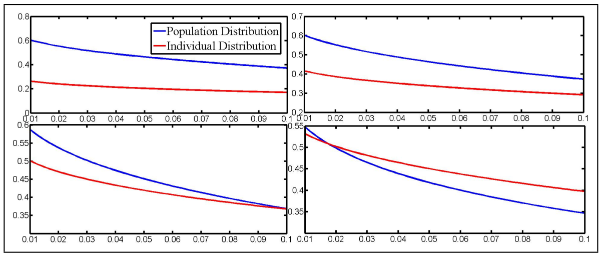

Fig. 4: False Alarm Rate (y axis) versus Probability of Accident (x axis). (Standard deviations of the individual distribution, clockwise, beginning in the upper left: 0.2, 0.4, 0.6, 0.8), Mean of the individual distribution=1.31, based on results from [6].

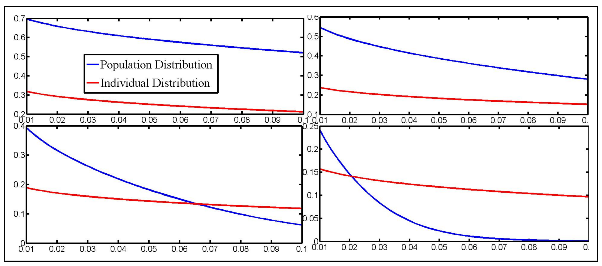

Fig. 5: False Alarm Rate (y axis) versus Probability of Accident (x axis). (Means of the individual distribution, clockwise, beginning in the upper left: 1, 1.5, 2, 2.5)- Standard Deviation of individual distribution=0.2.

probability of accident, one that cannot be remediated by obtaining estimates of an individual's brake reaction time. Also, Figure 5 shows that false alarms are not evenly distributed across the population. Drivers with fast reaction times will have very high false alarm rates, but drivers with slow reaction times will have lower rates; eventually even lower than the rate for individual distribution, as shown where the curves intersect. However, at this point, both false alarm rate and probability of accident will be low. Therefore, it is even more desirable to use individual distributions for novice drivers with fast reaction but the analysis applies to all drivers. As we mentioned in section III , if the warnings that are given turn out to be false alarms too frequently, drivers may begin to ignore them and since novice drivers receive the most false alarms the danger to ignore the safety system is higher for them. On the other hand, if it were simply the case that novice drivers were careless, warnings might be of little use. But, the existing research suggests that many novice drivers are clueless, not careless, e.g. in [13]. Thus, it is of vital importance to minimize false alarms so that the system only sends warnings when it is needed. As we discussed, VANET can be used to derive individual brake response times; Therefore, we will be able to adapt collision warning algorithms to driver's PRT.

VII. Conclusion

This paper deals with the development of safety systems for Vehicular Ad hoc Networks. In recent years, collision warning systems have been developed to help mitigate rear-end collisions. However, these types of systems generally rely solely on the distribution of the entire population of drivers, thereby ignoring the distinct characteristics of individual drivers. Collision warning systems that are currently used may cause drivers to become frustrated with the overly high numbers of false alarms, causing them to ignore warnings or even disable the system. If drivers are distracted by overly frequent warnings, the safety benefits of the system are compromised or even lost. In this paper, we have demonstrated how the rates of false alarms vary with respect to probability of accidents and the various distributions of individual drivers. We recommend that an improved collision warning system be developed in the near future. Such a system will use real time estimated individual PRT distribution as the main factor. This innovative system will surely reduce the rate of rear-end traffic collisions, thereby dramatically improving the safety benefits for all drivers.

References

[1] National Highway Traffic Safety Administration (2012a), *2010 Motor Vehicle Crashes: Overview. Traffic Safety Factors (Revised February 2012* Washington D.C.: Accessed 11/12/12.

[2] P. Goh and Y. D. Wong, *Driver perception response time during the signal change interval* Appl Health Econ Health Policy, 2004.

[3] F.C. Donders, *On the speed of mental processes*, In W. G. Koster (Ed.), Attention and Performance Acta Psychologica , 1869.

[4] J.T. Townsend and Y.G. Ashby, *The Stochastic Modeling of Elementary Psychological Processes*. Cambridge: Cambridge University Press, 1983.

[5] R. Ratcliff, *Response time distributions*, (Chapter 22). In H. Cooper (Ed.), APA Handbook of Research Methods in Psychology, 2012.

[6] R.J. Koppa, *Human Factors*, In Nathan H. Gartner, Carroll J. Messer, and Ajay K. Rathi (Eds.), Revised Monograph on Traffic Flow Theory (Ch.3), ¡http://www.fhwa.dot.gov/publications/, 2005.

[7] M. Green, *How long does it take to stop?*, Methodological analysis of driver perception-brake times, Transportation Human Factors,2(3), 195-216, 2000.

[8] R.D. Luce, *Response times: Their Role in inferring elementary mental organization*, Oxford: Oxford Univ Press, 1986.

[9] M.S. Chang and A.J. Santiago, *Timing traffic signal changes based on driver behavior*, Transportation Research Record, 1027, 20-30, 1985.

[10] A. Maxwell and K. Wood, *Review of Traffic Signals on High Speed Road. Paper presented at the Europian Transport Conference*, http://www.etcproceedings.org/paper/review-of-traffic-signals-on-high-speed-roads, Accessed 12/2/12.

[11] R.H. Wortman and J.S. Matthias, *An Evaluation of Driver Behavior at Signalized Intersections*, Phoenix: Arizona Department of Transportation, 1983.

[12] X. Zhang and G.H. Bham, *Estimation of driver reaction time from detailed vehicle trajectory data.*, Proceedings of the 18th IASTED International Conference: modeling and simulation,574-579, 2007.

[13] A. Pollatsek, D. Fisher and A.K. Pradhan, *Identifying and Remediating Failures of Selective Attention in Younger Drivers*, Current Directions in Psychological Science, 15,255-259, 2006.

[14] C.E. McCulloch, S.R. Searle and J.M. Neuhaus, *Generalized, Linear, and Mixed Models.*, Hoboken: 2nd ed ,Wiley, 2008.

[15] N. Ravishanker, D.K. Dey, *A First Course in Linear Model Theory*, Boca Raton: Chapman and Hall/CRC , 2002.

[16] S.R. Searle, G. Casella and C.E. McCulloch, *Variance Components.*, New York: Wiley, 1992.

[17] *Real-Time Estimation of the Distribution of Brake Response Times for an Individual Driver*, http://www.ecs.umass.edu/~nekoui/Evan_PR_estimation.pdf, 2012.

[18] D.V. McGehee , E.N. Mazzae and G.H.S. Baldwin, *Driver Reaction Time in Crash Avoidance Research: Validation of a Driving Simulator Study on a Test Track.*, Proceedings of the International Ergonomics Association 2000 Conference, 320-323, 2000.