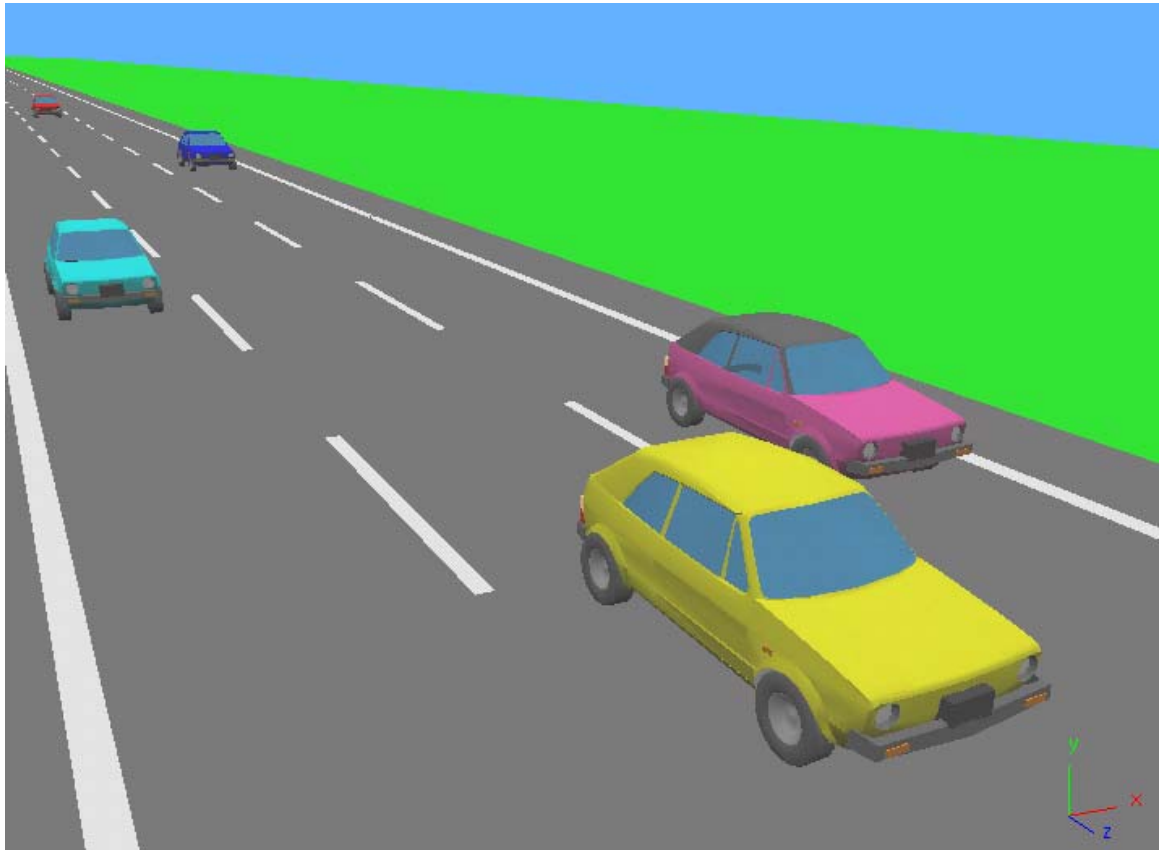


Towards Evolution of Collective Sensory Systems for Intelligent Vehicles

Final Report for the Project Period 2005 to June 30, 2006

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Overview

This METRANS intermediate report covers recent research conducted on sensor-based collision avoidance during freeway lane changing. This work builds on previous METRANS work in 2004. The report is divided into two parts:

Part I:

Theoretical work on the modeling of Collision Avoidance Systems (CAS), including past research in the field, key issues in CAS, and existing algorithms for simulation. This section compares these models in depth and proposes modifications appropriate for the proposed problem. This work also outlines several potential scenarios for CAS and discusses how these new modifications may improve existing models.

Part II:

Validation of the theory using a test vehicle outfitted with sensors. This test vehicle will eventually be driven on Southern California freeways to collect preliminary data on neighboring vehicle density and proximity. This section includes a detailed analysis of possible sensor alternatives, criteria for sensor selection, and recommendations on which sensors to use.

Additional analysis for the theoretical work and evaluation using the test vehicle will be conducted for the final report that will be submitted at the end of the performance period on June 30, 2006 (includes a no-cost extension).

PART 1: Theory

2 Introduction

Collision avoidance system (CAS) is an emerging automotive safety technology that assists drivers in avoiding potential collisions. The information sources of the collision avoidance system come from multiple on-board sensors. The bearing, range, and range rate information of other vehicles and/or objects around the host vehicle can be measured by radar, laser range scanner, and/or cameras in real time. Other regular on-board sensors measure host vehicle speed, acceleration, steering angle, yaw rate, etc. The collision avoidance system processes all the information in real time to keep track of the most current vehicle-to-vehicle kinematic conditions. When a potential collision is identified by the system, appropriate warnings are issued to the driver to facilitate collision avoidance. If the driver fails to react in time to the warnings to avoid the imminent collision, an overriding system takes over control to avoid or mitigate the collision in an emergency situation. Therefore a collision avoidance system could assist drivers in two ways, warning

and/or overriding, according to the dynamic situation.

In developing a collision warning system (CWS), two important parameters involving driver behavior have to be considered. One parameter is the time it takes for the driver to respond to the crash alert and begin braking, i.e., driver reaction time (RT), and the second parameter is the driver deceleration (or braking) behavior in response to this alert across a wide variety of initial vehicle-to-vehicle kinematic conditions. An overriding system has the advantage of being less sensitive to human factors, hence it is more promising in terms of achieving better and robust system performance. In addition, both warning and overriding systems are subject to some objective hardware limits and environmental factors, such as the maximum traction available from the ground-tire contact and brake efficiency, etc. A traction sensor could be used to obtain a better estimate of the current road traction conditions.

3 Previous Work

A lot of research has been done on the collision warning system, which is the first resort in assisting drivers in collision avoidance. The key is to ensure that warnings are issued to drivers at the appropriate time, i.e., just in time for the driver to react and avoid the collision while not too early or too frequent to become a nuisance or distraction to the driver. Different measures were defined to characterize the emergency of various dynamic situations, and different levels of human-vehicle experiments were carried out to calibrate these measures to human performances and reactions, based on which different warning criteria were developed to assist the human drivers.

3.1 Measures Defined

First, as mentioned above, quantitative measures need to be defined to characterize the emergency of various dynamic situations. The measures defined in the literature include time-based, distance-based and deceleration-based measures.

One frequently used time-based measure is the time-to-collision (TTC), which refers to the time it would take for a collision to occur at the prevailing speeds, distances, and trajectories associated with the host vehicle and the closest lead vehicle [van der Horst 1990]. In particular, the minimum TTC value (TTC_{min}) indicates how imminent a potential or actual collision has been during the process of approaching. More specifically, three different TTC measures were further investigated in [Kiefer et al. 2003]. The TTC1 measure was defined the same as the TTC above, which is mathematically defined as the range R (i.e., the bumper to bumper distance between the two vehicles) divided by the closing speed between these two vehicles, or $-R/RR$, where RR is the range rate. Note that the vehicle speeds are assumed to remain constant here, and that the current acceleration of either vehicle is irrelevant to the TTC1 calculation. The inverse TTC1 measure was

simply defined as the inverse of TTC_1 , or $-RR/R$. The TTC_2 measure was defined as the time it would take the host and lead vehicles to collide assuming the prevailing vehicle speeds and acceleration/deceleration values (i.e., at the current “constant” rate of speeding/slowing), and if either vehicle comes to a stop, it would remain stopped thereafter.

Another related time-based measure is the time headway (th), which is the time interval between the lead vehicle and the host vehicle, and calculated as the range between the two vehicles divided by the following host vehicle speed, or R/V_H [Fuller 1981]. Time headway is important because it specifies how much time the following driver has to react in case the lead vehicle suddenly brakes at maximum deceleration level.

One important deceleration-based measure is the required deceleration (a_{req}) measure, which is defined as the constant deceleration level required for the host vehicle to avoid the crash at the current time point [Kiefer et al. 1999]. This measure was calculated under the same assumptions as the TTC_2 measure above. In comparison, the actual deceleration (a_{act}) measure is defined as the constant deceleration level required to yield the observed stopping distance. The difference between the two measures is due to the safety margins adopted by individual drivers in avoiding the crashes during the experiments.

One distance-based measure is the projected minimum distance (D_{min}) between the host and lead vehicles during the approaching/avoiding process [Brunson et al. 2002]. It was calculated using the prevailing range and vehicle speeds, and the assumption that both vehicles would keep the current acceleration levels for a period equal to the assumed driver reaction time, after which the host vehicle starts to brake at a constant maximum deceleration value, and if either vehicle comes to a stop during the process, it would remain stopped thereafter. An alert is issued when the projected D_{min} is within the target minimum distance threshold D_{thresh} in two of the last three time intervals. Based on this warning criterion, another distance-based measure, the corresponding warning range (R_w), can be calculated, and a warning is issued if the actual range is within the warning range [Burgett et al. 1998]. Another related measure is the projected time to D_{min} (TT_{DM}), which measures the imminence or urgency of the situation [Polychronopoulos et al. 2004].

3.2 Driver Reaction Time

Driver reaction time is a very important parameter and plays a major role in the success of the collision warning systems. In this thesis the driver reaction time includes the human mental processing time in response to a signal or stimulus, the movement time for the driver’s foot to switch from gas to brake pedal, and the brake device delay.

A lot of research experiments have been done to measure human driver reaction times to different stimuli under various situations. [Olson 1989, Sens et al. 1989, Green 2000] give comprehensive reviews on driver reaction times reported in the past literature. It was noticed that the

driver reaction time data reported were almost always skewed toward longer values, as shown in Figure 6.1. Hence the lognormal probability distribution was used as an approximate statistical distribution model for driver reaction times t_r with parameters μ and σ^2 [Taoka 1989, Brunson et al. 2002], i.e., the logarithm of the driver reaction time $\ln t_r$ is distributed normal with the same parameters μ and σ^2 .

Of the various experiments conducted on driver reaction times, two kinds of situations are given particular attentions in this thesis. One is normal driver reaction times toward unexpected natural driving scenarios, such as the onset of the brake lights of the lead vehicle or the yellow traffic lights within certain range. The other is the driver reactions in response to some unexpected artificial signals, such as a red icon appearing in front of the driver or specific auditory signals, which could be considered potential warning signals.

From the results reported in various literature, the best estimate for natural driver brake reaction time to common but uncertain signals (e.g. lead vehicle brake light or yellow traffic light) lies between 1.14 and 1.38 seconds [Gazis et al. 1960, Sivak et al. 1982, Chang et al. 1985, Sivak et al. 1981]. Standard deviations of results vary widely across studies, but 0.6 seems a good estimate. Hence the lognormal distribution model with parameters $\mu = 1.13$ and $\sigma = 0.46$ would approximately represent the natural human driver reaction time t_r with mean 1.25 and standard deviation 0.6 seconds.

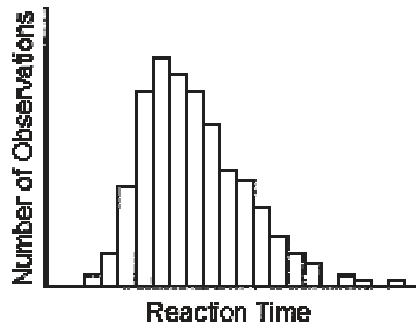


Figure 6.1: Hypothetical Reaction Time Distribution [Green 2000]

On the other hand, the experiments on driver reaction times in response to the sudden appearance of a red square reported mean values of 0.96 second on easy straight roads and 1.3 seconds on curvy routes, resulting approximately 1.13 seconds on average for all driving conditions [Alm and Nilsson 1994]. The driver brake reaction time in response to some completely unexpected auditory signals was estimated to be 0.9 second or longer in 50% of all sudden accident situations, and about 1.2 seconds on the 75th percentile [Johansson and Rumar 1971]. Finally, driver reaction times under different types of dual-modality (i.e., both visual and auditory) crash alerts were extensively investigated in a series of experiments on potential Forward Collision Warning Systems [Kiefer et al. 1999], where the shortest reaction times with the least variance were recorded under surprise, unexpected conditions. It was further verified that brake

reaction times were faster (0.90 versus 1.15 seconds on average) with FCW alerts [Kiefer et al. 2005a].

Table 6.1 gives a summary of driver reaction times in response to different types of unexpected stimuli, characterized by the lognormal probability density model with parameters μ and σ . Note that the parameter μ is also the median, i.e., the 50th percentile value, and the parameter σ is the dispersion parameter. The mean and standard deviation (std) values as well as the 75th, 85th, and 90th percentile values are also listed in the table.

Types	mean	std	median(μ)	σ	75%	85%	90%
Natural (no alerts)	1.25	0.6	1.13	0.46	1.53	1.81	2.02
Visual alert	1.13	0.52	1.03	0.44	1.38	1.62	1.80
Auditory alert	0.99	0.44	0.9	0.43	1.2	1.40	1.55
Visual + Auditory alert	0.90	0.34	0.84	0.37	1.08	1.23	1.35

Table 6.1: Estimates of Unexpected Driver Reaction Time in Seconds

Table 6.1 Estimates of Unexpected Driver Reaction Time in Seconds

3.3 Collision Warning Systems

The Crash Avoidance Metrics Partnership (CAMP) was established to accelerate the research in advanced automotive collision avoidance systems to improve traffic safety. In [Kiefer et al. 1999], CAMP developed basic elements of Forward Collision Warning (FCW) systems, which provide alerts intended to assist drivers in avoiding or mitigating rear-end crashes. Crash alert timing and crash alert modality (auditory, visual and/or haptic) requirements as well as driver reaction time and braking behavior were studied by conducting a series of closed-course human factors studies using a “surrogate target” methodology, where drivers were asked to perform last second braking maneuvers while approaching a slowing or stopped vehicle (surrogate target). Drivers were instructed to use either “normal” or “hard” braking to avoid a crash. It was discovered that the 95th percentile required deceleration values for last-second “normal” braking judgments correspond very closely to the 50th percentile required deceleration values for last-second “hard” braking judgments (i.e., 95th “normal” $\approx$ 50th “hard”), as shown in Figure 6.2.

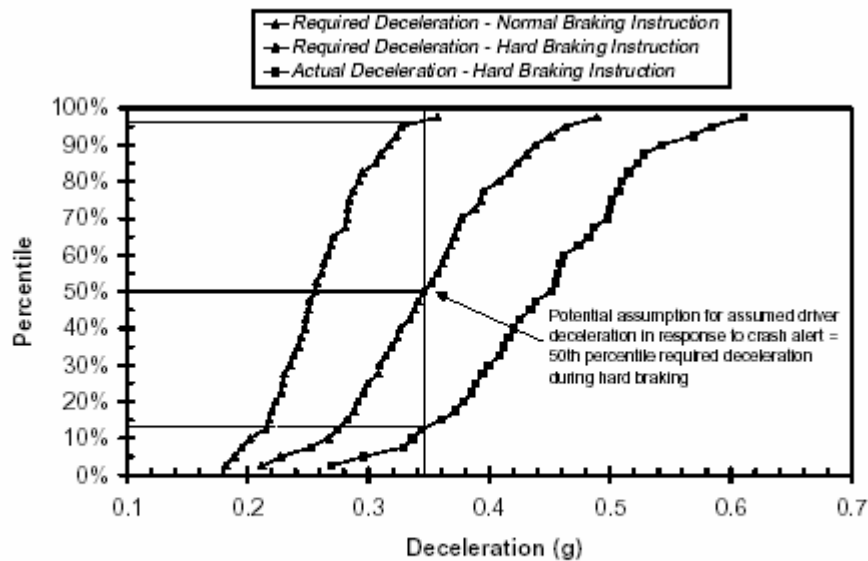


Figure 6.2: Percentile Values for the Required and Actual Deceleration Measures During the Lead Vehicle Decelerating (at -0.28g) Scenario with Initial Speed 45mph [Kiefer et al. 1999]

Figure 6.2 Percentile Values for the Required and Actual Deceleration Measures During the Lead Vehicle Decelerating (at -0.28g) Scenario with Initial Speed 45mph [Kiefer et al. 1999]

Drivers' reaction times to a variety of interfaces under surprise and alerted conditions were also evaluated and combined with knowledge of driver's braking behavior to develop the FCW alert model. This timing criterion intends to provide an alert after most attentive drivers would have started a "normal" last-second braking maneuver, yet soon enough for most inattentive drivers to still avoid a crash using last-second "hard" braking. This approach tries to minimize the number of nuisance alerts while maintaining high FCW effectiveness under tested conditions. Based on the required deceleration measure, this model is significantly different from models that are based on time-headway or time-to-collision. The difference was attributed to the surrogate target methodology, which was believed to present a more realistic crash threat than previously available.

In [Kiefer et al. 2003], a follow-on study extended the previous CAMP human factors work addressing FCW timing requirements by gathering not only "last-second" braking maneuver data, but also data from "last-second" steering (or lane-change) maneuvers. Drivers performed "normal" or "hard" last-second braking and steering maneuvers under a wide variety of vehicle-to-vehicle kinematic scenarios. Differences were observed between last-second braking and last-second steering onsets, depending on the kinematic conditions. When the difference in speed between the lead and following vehicles (or range rate) increased, mean last-second steering onsets tended to occur later (i.e., were more aggressive) than mean last-second hard braking onsets. (This difference was not observed under small range rate conditions examined.)

Two last-second braking onset timing models, the Required Deceleration Model and the 3-Tiered Inverse Time-To-Collision Model, were developed using the last-second maneuver database established from both CAMP studies. Using linear regression approach, the Required Deceleration Model predicts a continuous dependent variable, which is then used to decide if the driver is in a hard braking onset scenario. In contrast, the logistic regression statistical modeling technique was used in the 3-Tiered Inverse TTC model to predict the probability the driver was in hard braking scenario (and not a normal braking scenario). The latter model assumes the driver deceleration response (to the crash alert) is based on an inverse TTC threshold that decreases linearly with speed [Kiefer et al. 2005b]. One advantage of this model is that it requires only coarse (rather than accurate) knowledge of lead vehicle deceleration levels.

In both CAMP studies, the Braking Onset Range, estimated based on the above models, along with the assumed Delay Time Range, is used to calculate (total) Warning Range as the crash alert warning criterion [Kiefer et al. 1999]. The Delay Time Range is calculated based on the projected change in range to the vehicle ahead during the Total Delay Time interval given prevailing kinematic conditions (i.e., the speed and deceleration levels of the lead and following vehicles). This interval is a composite sum of various system delay times, including the interface delay, driver brake reaction time, and brake system delay.

The effectiveness of the CAMP FCW timing approach described above was further tested under a wide range of factors such as driver characteristics, environmental factors, interface design, distraction activity, kinematic conditions, and training/false alarms [Kiefer et al. 2005a]. The Surprise Trial Methodology and Vision Occlusion techniques are used here intended to simulate a “surprised” distracted driver, who has been intentionally distracted by look-down tasks or vision occlusion until the onset of an FCW alert presentation, immediately following which he/she must quickly decide upon and execute a crash avoidance maneuver. Results indicate that under CAMP FCW alert timing conditions, drivers were able to execute an unassisted, successful braking maneuver for over 85 percent of the trials across the approach conditions examined, while the unsuccessful trial rates almost doubled when no alert was presented for the look-down trials. It appears that the underlying cause for unsuccessful look-down trials with alerts was due to long alert onset-look up delays 1 (the average time between when the alert was presented and when the eyes “landed” on the forward view) for some drivers. The average alert onset-look up delay time was 1,505 milliseconds (ms) for unsuccessful trials, while the corresponding average alert onset-look up delay time was 566 ms for successful trials, and the total average was 685 ms. In addition, there is generally a lack of both age and gender effects under FCW alert conditions observed across all various experimental approaches, suggesting that a “one size fits all” FCW alert timing approach may be feasible.

In a related research [Curry et al. 2005], a subset of the previous closed-course experiments

with a surrogate target was replicated in the National Advanced Driving Simulator (NADS) facility for comparison and validation purposes. It was concluded that the test scenarios should emphasize high lead vehicle decelerations and high closing speeds (particularly when the lead vehicle is stationary), and attention should be focused on the interpretation of last-second hard braking or hard steering onset behavior. It was observed that the NADS data showed generally better agreement with the closed-course values under these conditions. When there was disagreement, it was usually the case that the NADS drivers reacted more cautiously, initiating braking or steering earlier than their closed-course counterparts.

As part of its ongoing research activities supporting the development, testing and evaluation of collision warning systems, the National Highway Traffic Safety Administration (NHTSA) developed an experimentally-based rear-end collision warning algorithm and sponsored analysis of its performance [Brunson et al. 2002]. Integrated along with a General Motor (GM)-developed algorithm, this warning algorithm processes data received from a vehicle-mounted radar and other vehicle sub- systems to alert drivers to potentially dangerous situations and the need to take evasive action. The decision to issue an alert is based on the projected minimum distance (D_{min}) calculated at each time interval, assuming constant lead vehicle deceleration, a driver reaction time estimate, the maximum host vehicle deceleration level, and measured estimates of the parameters characterizing the current host vehicle and vehicle-to-vehicle dynamic situations.

1 Note that this is the additional delay time besides the assumed driver brake reaction time when the driver was looking down during the distraction.

Two sets of theoretical analyses were performed on the NHTSA Alert Algorithm. The first examined the performance of the alert algorithm under the assumption of perfect input data. The second analysis examined the effects of measurement noise and driver variability on the performance of the alert algorithm in terms of Probability of False Alarm (PF A) versus Probability of a Miss (Pmiss). The results indicated that the error in estimating the driver response (braking level and reaction time) had a much greater impact on algorithm performance than the error in measuring the vehicle dynamics.

Verification testing was also conducted with the alert algorithm installed in a test vehicle equipped with a prototype collision warning system. It was noted that the performance of the algorithm was dependent on the ability of the radar system to report valid targets on curves and at longer ranges. Algorithm performance was most affected when the host vehicle was traveling at higher speeds. For instance, sometimes the radar detect range is even shorter than the imminent warning range. In addition, data quality and resolution also affect the algorithm performance, especially the resolution of relative acceleration (a_R) was the principal source of error in the slower lead vehicle test scenarios.

Finally, a simulation was performed to estimate the proportion of rear-end collisions that

could be avoided with the alert algorithm for an example scenario. It was shown that the probability of collision was closely related to the probability distribution of the driver reaction time t_r .

A similar distance-based collision warning algorithm was investigated especially for the situation where two vehicles were initially traveling at the same speed V_0 in the same direction when the lead vehicle began to brake [Burgett et al. 1998]. Following the same warning logic as above, a warning range R_w could be computed assuming constant lead vehicle deceleration level a_L , driver reaction time t_r , measured values of initial speed V_0 and time headway t_h , and assumed maximum host vehicle deceleration a_{Hmax} . Furthermore, a family of warning criteria plots can be generated by computing and storing the warning range R_w and its corresponding warning range rate RR_w pairs that are parametric in lead vehicle deceleration a_L for each combination of initial conditions V_0 and t_h , as shown in Figure 6.3. It was claimed that the warning curve for each (V_0, t_h) pair on the range/range rate plot can be used as an efficient warning criterion without the estimation of a_L . While it is desirable to eliminate the estimation of a_L for the warning criteria, these warning curves would not work under common conditions. An example is shown in Figure 6.3, where the warning curves for $V_0 = 48$ mph and several t_h values are plotted. A sample time trajectory for the case $t_h = 2$ s and $a_L = -3$ m/s² is also plotted with dash dot lines. It can be observed that the sample time trajectory is very close to the warning curve of $t_h = 2$ s between the lead vehicle brake point and the warning point, hence it is not clear when to issue the warning, let alone the sensor noise in measuring range and range rate. As the example shown in the paper [Burgett et al. 1998], these warning criteria would work when t_h is rather long ($t_h = 5$ s in the example), which is, however, not the main focus of collision warning systems.

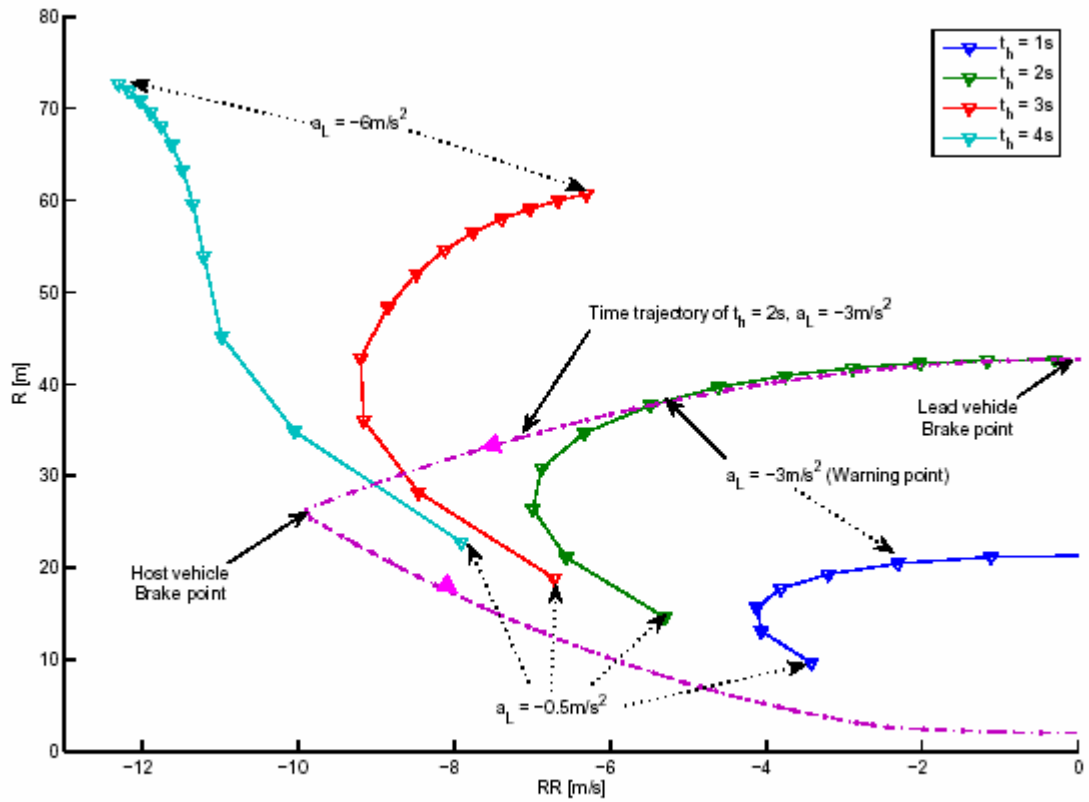


Figure 6.3: Warning Curves (Solid Lines) Parametric in a_L ($V_0 = 48 \text{ mph}$, $t_r = 1.5 \text{ s}$, $a_{H_{max}} = -5 \text{ m/s}^2$) with a Sample Time Trajectory (Dash Dot Lines) of $t_h = 2 \text{ s}$ and $a_L = -3 \text{ m/s}^2$

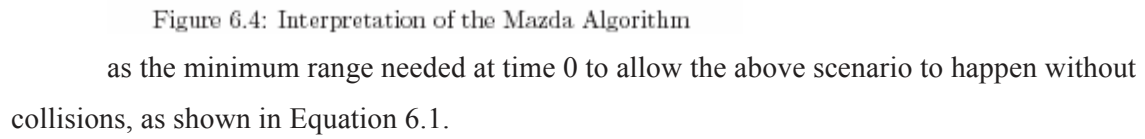
Figure 6.3: Warning Curves (Solid Lines) Parametric in a_L ($V_0 = 48 \text{ mph}$, $t_r = 1.5 \text{ s}$, $a_{H_{max}} = .5 \text{ m/s}^2$) with a Sample Time Trajectory (Dash Dot Lines) of $t_h = 2 \text{ s}$ and $a_L = .3 \text{ m/s}^2$

4 Warning and Overriding Algorithms

Various warning and overriding algorithms have been developed and investigated in the literature [Lee and Peng 2005]. Most of them compute a warning range (R_w) based on the current kinematic information, and a warning is issued if the current range R is less than R_w . Some of them also calculate an overriding range (R_o), and automatic brake (overriding) is applied if R is within R_o .

4.1 Mazda Algorithm

The Mazda overriding algorithm [Doi et al. 1994] considers a hypothetical worst case, as shown in Fig- ure 6.4. First, it assumes that initially both the host vehicle and the lead vehicle maintain constant speeds V_H and V_L respectively. Then the lead vehicle starts to brake after time τ_2 at deceleration level $-\alpha_2$, while the host vehicle starts to brake after an additional time τ_1 at deceleration level $-\alpha_1$, which continues until both vehicles come to a full stop. The overriding range R_o is computed



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where RR is the range rate, i.e., the relative velocity between the two vehicles ($RR \equiv V_L - V_H$), and R_{min} is a constant headway offset. The shaded area in Figure 6.4 is the required safety range buffer between the two vehicles should the hypothetical scenario described above happen. The following parameters were used: $\alpha_1 = 6 \text{ m/s}^2$, $\alpha_2 = 8 \text{ m/s}^2$, $\tau_1 = 0.1 \text{ s}$, $\tau_2 = 0.6 \text{ s}$, $R_{min} = 5 \text{ m}$. The system provides a warning when the actual range R approaches R_o , i.e., $R_w = R_o + \epsilon$, where ϵ is a system parameter. The system applies automatic brake to try to avoid collisions if R is within R_o .

4.2 Honda Algorithm

The Honda algorithm [Fujita et al. 1995] uses the following warning criterion:

$$R_w = -2.2 \cdot RR + 6.2 \quad (6.2)$$

which is based on the TTC_1 measure, as defined in Section 6.1.1, with a constant headway offset of 6.2 m. Warning is issued when the TTC_1 , after offset adjustment, is below 2.2 s.

The Honda overriding algorithm also considers a hypothetical scenario, as shown in Figure 6.5. It consists of two parts, depending on whether the lead vehicle is expected to stop within the considered time range τ_2 . It is assumed that the lead vehicle brakes constantly at deceleration level $-\alpha_2$ (if the estimated lead vehicle stopping time $t_{LS} \equiv V_L/\alpha_2 < \tau_2$) or $-\alpha_1$ (if $t_{LS} \geq \tau_2$), while the host vehicle starts to brake after reaction time τ_1 at deceleration level $-\alpha_1$. Then the safety range R_o is estimated as the minimum range buffer needed to avoid collisions until τ_2 at both situations, which

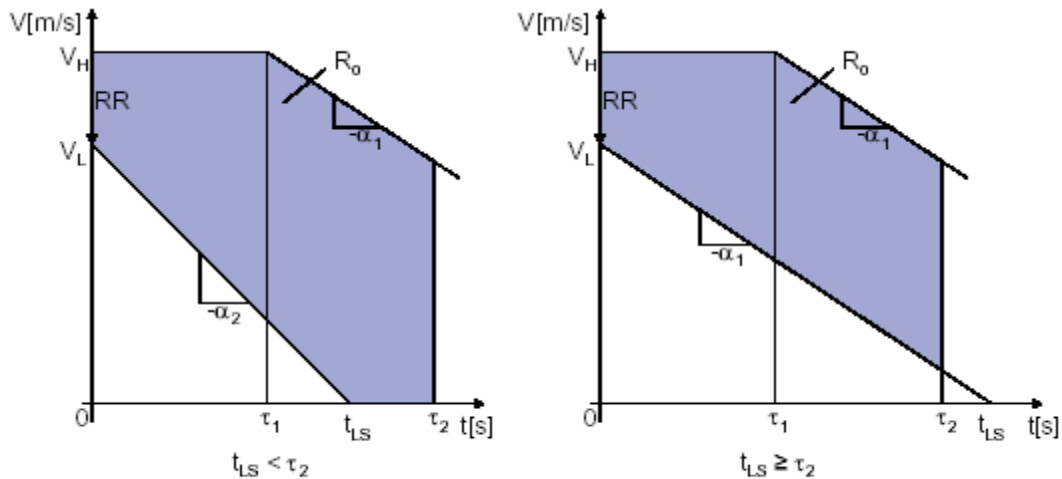


Figure 6.5: Interpretation of the Honda Overriding Algorithm

Figure 6.5: Interpretation of the Honda Overriding Algorithm

is represented by the shaded areas in Figure 6.5 and computed by Equation 6.3.

$$R_o = \begin{cases} V_H \cdot \tau_2 - \frac{1}{2}\alpha_1(\tau_2 - \tau_1)^2 - \frac{V_L^2}{2\alpha_2} & t_{LS} < \tau_2 \\ -RR \cdot \tau_2 + \alpha_1\tau_1\tau_2 - \frac{1}{2}\alpha_1\tau_1^2 & t_{LS} \geq \tau_2 \end{cases}$$

The following parameters were used: $\alpha_1 = 7.8 \text{ m/s}^2$, $\alpha_2 = 7.8 \text{ m/s}^2$, $\tau_1 = 0.5 \text{ s}$, $\tau_2 = 1.5 \text{ s}$.
s. Auto- matic brake is applied to assist collision avoidance if the current range R is within R_o .

4.3 Berkeley Algorithm

The Berkeley algorithm [Seiler et al. 1998] proposes a conservative R_w to provide a wide range of visual feedbacks (cautionary warnings) to the driver, and a non-conservative R_o to reduce undesirable effects of overriding to normal driving operations. As shown in Figure 6.6, it is assumed that the lead vehicle brakes at the maximum constant deceleration level $-\alpha$, while the host vehicle starts to brake after reaction time τ at the same deceleration level. Note that the reaction time τ here accounts for both driver reaction time and system delay time. The warning range R_w is estimated as the minimum range buffer needed to avoid collisions until both vehicles come to a full stop in the above scenario, while the overriding range R_o only considers the range buffer needed from time 0 to τ .

$$R_w = \frac{V_H^2 - V_L^2}{2\alpha} + V_H\tau + R_{min}$$

$$R_o = -RR \cdot \tau + \frac{1}{2}\alpha\tau^2$$

The following parameters were used: $\alpha = 6 \text{ m/s}^2$, $\tau = 1.2 \text{ s}$, $R_{min} = 5 \text{ m}$.

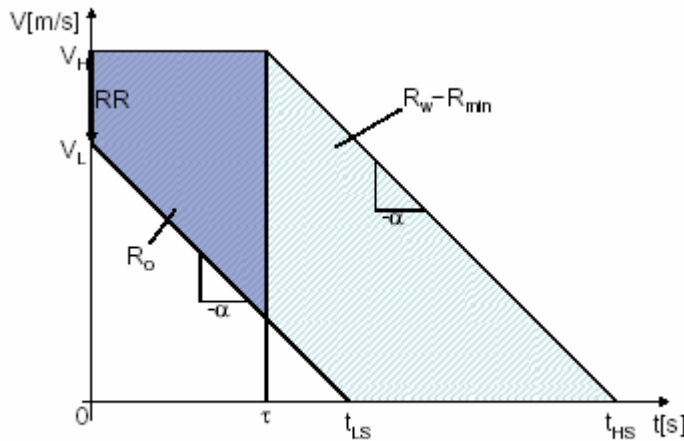


Figure 6.6: Interpretation of the Berkeley Algorithm

Figure 6.6: Interpretation of the Berkeley Algorithm

4.4 NHTSA Alert Algorithm

The NHTSA Alert Algorithm [Brunson et al. 2002] considers slightly more complicated

scenarios, as shown in Figure 6.7. It assumes that the lead vehicle brakes constantly at current deceleration level a_L , while the host vehicle, with a current constant acceleration level a_H , starts to brake constantly at the maximum deceleration level a_{Hmax} ($a_{Hmax} \leq a_L < 0$) after reaction time t_r . Two different situations are considered, depending on whether the lead vehicle stops first or the host vehicle stops first under the above assumptions. The lead vehicle stopping time t_{LS} and host vehicle stopping time t_{HS} are estimated by:

$$t_{LS} = -\frac{V_L}{a_L}$$

$$t_{HS} = \begin{cases} t_r - \frac{V_H + a_H t_r}{a_{Hmax}} & V_H + a_H t_r > 0 \\ -\frac{V_H}{a_H} & \text{otherwise} \end{cases}$$

Usually it is assumed that $V_H + a_H t_r > 0$, in which case a warning system might be helpful. The shaded areas in Figure 6.7 represent the range buffer needed to avoid collisions under both situations, as computed by Equation 6.8.

$$R_w = \begin{cases} V_H t_r + \frac{1}{2} a_H t_r^2 - \frac{(V_H + a_H t_r)^2}{2 a_{Hmax}} + \frac{V_L^2}{2 a_L} + D_{thresh} & t_{LS} \leq t_{HS} \\ -RR \cdot t_r - \frac{1}{2} a_R t_r^2 + \frac{(RR + a_R t_r)^2}{2(a_L - a_{Hmax})} + D_{thresh} & t_{LS} > t_{HS} \text{ or } a_L \geq -1 \end{cases}$$

where

$$D_{thresh} = 0.1 V_H + 2$$

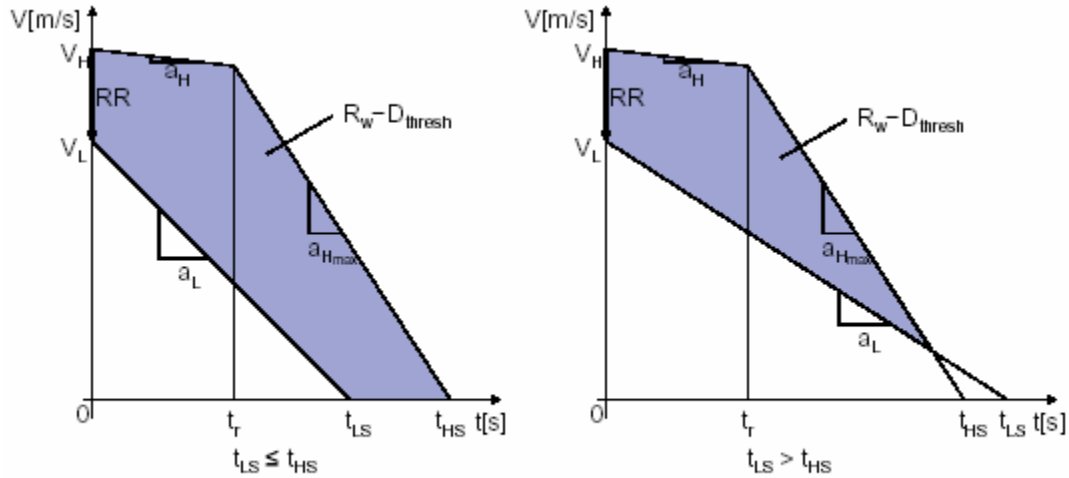


Figure 6.7: Interpretation of the NHTSA Alert Algorithm

Figure 6.7: Interpretation of the NHTSA Alert Algorithm

Here the system tries to estimate the relative acceleration ($a_R \equiv a_L - a_H$) in real time from the time derivative of range rate (RR) data measured by radar sensors, then the lead vehicle

deceleration level a_L is computed from a_R estimation and a_H measurement, in contrast to previous algorithms where a_L is a pre-selected parameter. The driver reaction time t_r , which includes both the driver and system delays, is normally set to 1.5 s, and is reduced to 0.5 s when brake is applied. The assumed host vehicle maximum braking capability a_{Hmax} is set to $-0.55 \text{ g} \approx -5.4 \text{ m/s}^2$ for imminent alerts, and lower levels for cautionary alerts.

4.5 CAMP Alert Algorithm

The CAMP Alert Algorithm [Kiefer et al. 1999] considers essentially the same scenarios with the same assumptions as the NHTSA algorithm. The only differences are that D_{thresh} is set to zero and that a_{Hmax} is replaced by *required deceleration* a_{Hreq} , which is modeled by:

$$a_{Hreq} = \begin{cases} 0.685a_L - 0.086(V_H + a_H t_r) - 1.617 & t_{LS} \leq t_r \\ 0.685a_L + 0.086(RR + a_R t_r) - 0.833 & t_{LS} > t_r \end{cases}$$

Note that the accelerations are expressed in m/s^2 , velocities and range rate in m/s , distances and ranges in m , and times in s . Hence a_{Hreq} varies according to the different underlying dynamic scenarios, and is not a pre-fixed parameter as the a_{Hmax} .

4.6 Other Alert Algorithms

There are some other alert algorithms developed for use in automotive collision warning and avoidance system, as summarized in [Yang et al. 2003]. For example, if the current host vehicle acceleration a_H is set to zero in the NHTSA alert algorithm, then the first case of Equation 6.8 simplifies to:

$$R_w = V_H t_r - \frac{V_H^2}{2a_{Hmax}} + \frac{V_L^2}{2a_L} + R_{min} \quad t_{LS} \leq t_{HS}$$

In addition, if the lead vehicle keeps a constant speed slower than the host vehicle, i.e., $a_L = a_H = 0$, then the second part of Equation 6.8 simplifies to:

$$R_w = -RR \cdot t_r - \frac{RR^2}{2a_{Hmax}} + R_{min} \quad a_L = a_H = 0, V_L < V_H$$

Furthermore, if the lead vehicle is stopped or stationary, i.e., $V_L = 0$, then the above Equation can be rewritten as:

$$R_w = V_H \cdot t_r - \frac{V_H^2}{2a_{Hmax}} + R_{min} \quad a_L = a_H = 0, V_L = 0 < V_H$$

There are still some other alert algorithms that are based on TTC 1 (R/RR), th (R/V_H), or a linear combination of the two:

$$R_w = -RR \cdot \tau_1 + V_H \cdot \tau_2 + R_{min}$$

where τ_1 and τ_2 are predefined parameters as before.

5 New Criterion Proposal

As summarized in last section, most warning and overriding criteria used in automotive collision avoidance systems are expressed in terms of range, i.e., a warning and/or overriding range (R_w / R_o) is computed according to current state measurements and the appropriate warning/overriding algorithm selected, then the control system decides whether to issue an alert or apply automatic brake based on the comparison result of the current range R and the appropriate range criteria. It is still difficult to clearly quantify the level of danger or threat from the comparison result since the range criteria vary nonlinearly under different dynamic conditions. For instance, the Berkeley algorithm [Seiler et al. 1998] proposed a non-dimensional warning level w that varies linearly between warning range R_w and overriding range R_o :

$$w = \frac{R - R_o}{R_w - R_o}$$

This is not very appropriate since it is known that the danger level does not have a linear relationship with the range criteria. Therefore it is desirable to have a new criterion that has a direct relationship to human drivers' sense of danger/threat level and the urgency level of the situation for the required action, e.g. braking.

5.1 Tlsb Measure

Time-to-last-second-brake (Tlsb), is a new time-based measure proposed for rear-end collision threat assessment. It is defined as the time left for the driver or the control system at the current situation to take the last evasive action, e.g. braking at the maximum level, to avoid a rear-end collision. It is calculated based on the assumptions that the lead vehicle would keep current deceleration or acceleration level a_L constantly until it comes to a full stop if $a_L < 0$ and in this case it would remain stopped thereafter, and that the host vehicle also keeps current acceleration level a_H until the last moment when it will be able to decelerate at maximum deceleration level a_{Hmax} to avoid collisions if necessary. Therefore Tlsb tries to estimate how long the host vehicle could still keep the current state until it has to brake at maximum level to just avoid a potential rear-end collision with the lead vehicle. It can be estimated from the following six state variables:

$$T_{lsb} = f(v_H, a_H, R, RR, a_R, a_{Hmax})$$

where the current host vehicle speed v_H and acceleration a_H can be measured by vehicle state sensors, the current range R and range rate RR between the host vehicle and the lead vehicle can be measured by on-board radar or laser sensors, the current relative acceleration a_R

between the two vehicles can be estimated from the RR history, and the current available maximum deceleration level a_{Hmax} can be estimated from tire-road friction coefficient monitor, as reviewed in [Li et al. 2006].

5.2 Scenario 1: Lead Vehicle Stopped or Moving Slowly ($a_L = 0$)

First, let's consider a simple scenario where the lead vehicle is initially stopped or traveling at a constantly slower speed than the host vehicle (i.e., $a_L = 0, RR < 0$). This is an important type of scenario where a collision avoidance system might be helpful. For instance, an inattentive driver might overlook a stopped or slowly moving vehicle ahead or underestimate its threat level until it is too late. The characteristic of this type of scenario is that the closing speed (RR) is usually high and often an evasive action is necessary even when the range is still rather large. Hence the requirement for the driver or the sensor system to detect an object and estimate the relative R & RR at a rather far range (up to 150 m $\square$ 200 m) is high in this case.

For simplicity, let's further assume that the host vehicle currently keeps a constant speed v_H (i.e., $a_H = 0$). Then the time-to-last-second-brake T_{lsb} for this scenario only depends on R , RR , and a_{Hmax} , as computed by Equation 6.17.

$$T_{lsb} = -\frac{R - R_{min} + \frac{RR^2}{2a_{Hmax}}}{RR}$$

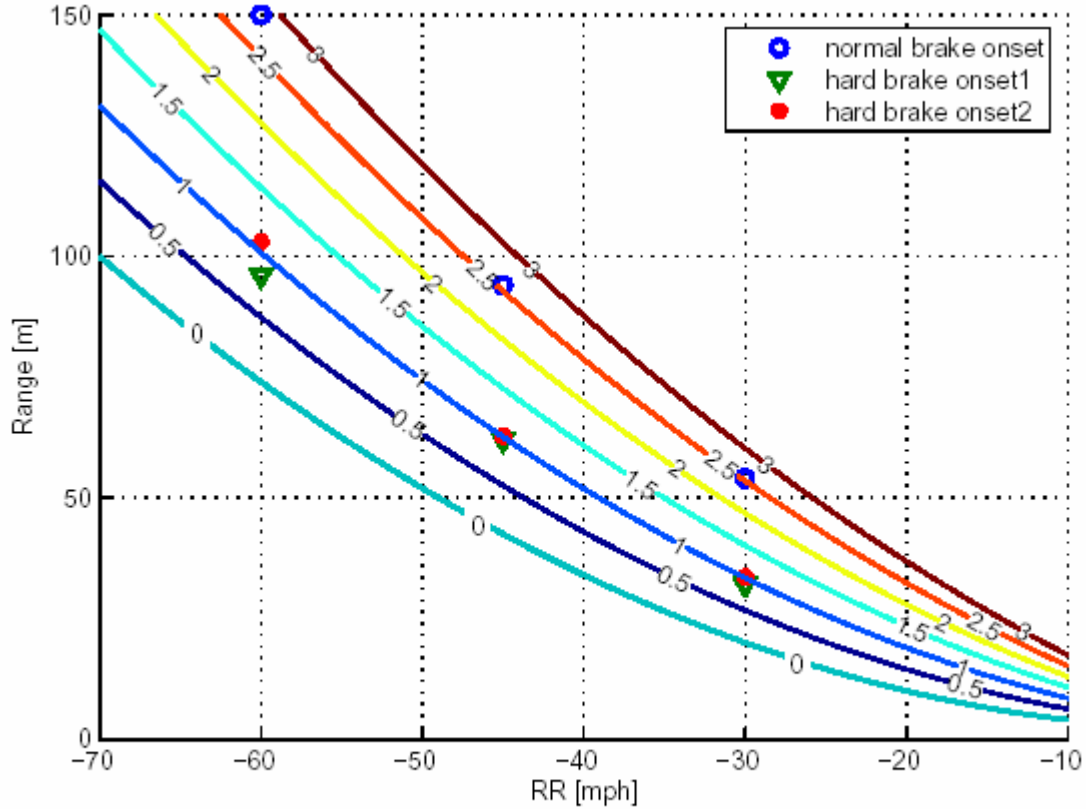


Figure 6.8: T_{lsb} Contours in Seconds with CAMP Data under Scenario 1: Host Vehicle Approaches Stopped or Slow Lead Vehicle ($a_L = a_H = 0$, $a_{H_{max}} = -5 \text{ m/s}^2$)

Figure 6.8: T_{lsb} Contours in Seconds with CAMP Data under Scenario 1: Host Vehicle Approaches Stopped or Slow Lead Vehicle ($a_L = a_H = 0$, $a_H = -5 \text{ m/s}^2$)

which can be obtained just by solving t_r from Equation 6.12. For a given road-tire friction condition, e.g. $\mu = 0.5$, and take $R_{min} = 2 \text{ m}$, then the contours of T_{lsb} can be plotted as parabolic curves on a range/range-rate plot, as shown in Figure 6.8.

As mentioned in Section 6.1.3, the human drivers' last-second "normal" and "hard" braking onset data were recorded in CAMP experiments [Kiefer et al. 1999, Kiefer et al. 2003], and especially the data for the lead vehicle stationary trials were also plotted here in Figure 6.8 using different markers. These data points represent the average range at host vehicle braking onsets under different conditions, i.e., last-second normal or hard braking condition, and $v_H = 30 \text{ mph}$, 45 mph , or 60 mph , respectively. It can be seen from the figure that the last-second normal braking data align nicely with the $T_{lsb} = 2.5 \text{ s}$ curve, which implies that alert drivers normally brake 2.5 seconds before the last moment when maximum brake is needed. Furthermore, two sets of CAMP last-second hard braking data both align well with the $T_{lsb} = 1 \text{ s}$ curve, which means that an attentive driver would perform a last-second hard brake action about 1 second before maximum (the

hardest) brake is needed to avoid a rear-end collision. These observations are especially true when host vehicle speed is not too high (e.g. $v_H = 30$ mph or 45 mph) and within a range of 100 m or so, which implies that human drivers have a fairly good sense of urgency about when to take a last-second evasive action under an attentive condition and medium threat level, for instance, the host vehicle approaches a red light or a car stopped at an intersection, and their action timings appeared to be rather consistent under the above conditions. Therefore the proposed T_{lsb} measure appears to be an excellent measure that aligns nicely with human drivers' sense of urgency to take the last evasive action, and hence a good candidate for threat assessment analysis.

5.3 Scenario 2: Lead Vehicle Decelerating ($a_L < 0$)

In Scenario 2, the lead vehicle and the host vehicle initially travel at the same speed level ($RR = 0$) with a certain initial time headway ($t_h = R/v_H$) between them, then the lead vehicle suddenly starts to brake at deceleration level a_L constantly. This type of scenario is also very important in the study of collision avoidance systems, since the sudden brake of lead vehicles on freeways is also a major cause of traffic accidents. The characteristic of this scenario is that usually the initial range R is not too large ($R < 50$ m) and the requirement on the driver or the sensor system to detect an abrupt negative change in relative acceleration a_R is high.

For simplicity, it is still assumed that the host vehicle currently keeps a constant speed v_H ($a_H = 0$) in this case. As the NHTSA alert algorithm described in Section 6.2.4, two different cases are considered in this scenario 2 to estimate the time to last second brake T_{lsb} , depending on whether the lead vehicle is expected to stop first or not. The lead vehicle stopping time t_{LS} is still estimated by Equation 6.6, while the estimation of the host vehicle stopping time t_{HS} is slightly changed, since it depends on the T_{lsb} instead of t_r now:

$$t_{HS} = T_{lsb} - \frac{V_H}{a_{Hmax}}$$

Accordingly, Equation 6.8 also changes to the following:

$$R = \begin{cases} V_H T_{lsb} - \frac{V_H^2}{2} \left(\frac{1}{a_{Hmax}} - \frac{1}{a_L} \right) + R_{min} & t_{LS} \leq t_{HS} \\ -\frac{1}{2} a_L T_{lsb}^2 + \frac{(a_L T_{lsb})^2}{2(a_L - a_{Hmax})} + R_{min} & t_{LS} > t_{HS} \end{cases}$$

More generally, if $RR = 0$, the above equation has the following form:

$$R = \begin{cases} V_H T_{lsb} - \frac{V_H^2}{2a_{Hmax}} + \frac{V_L^2}{2a_L} + R_{min} & t_{LS} \leq t_{HS} \\ -RR \cdot T_{lsb} - \frac{1}{2} a_L T_{lsb}^2 + \frac{(RR + a_L T_{lsb})^2}{2(a_L - a_{Hmax})} + R_{min} & t_{LS} > t_{HS} \end{cases}$$

Then, T_{lsb} can be solved from Equation 6.19 or 6.20 depending on the current conditions. In

practice, first it is assumed that the lead vehicle stops first ($t_{LS} \leq t_{HS}$), then T_{lsb} can be solved from the first

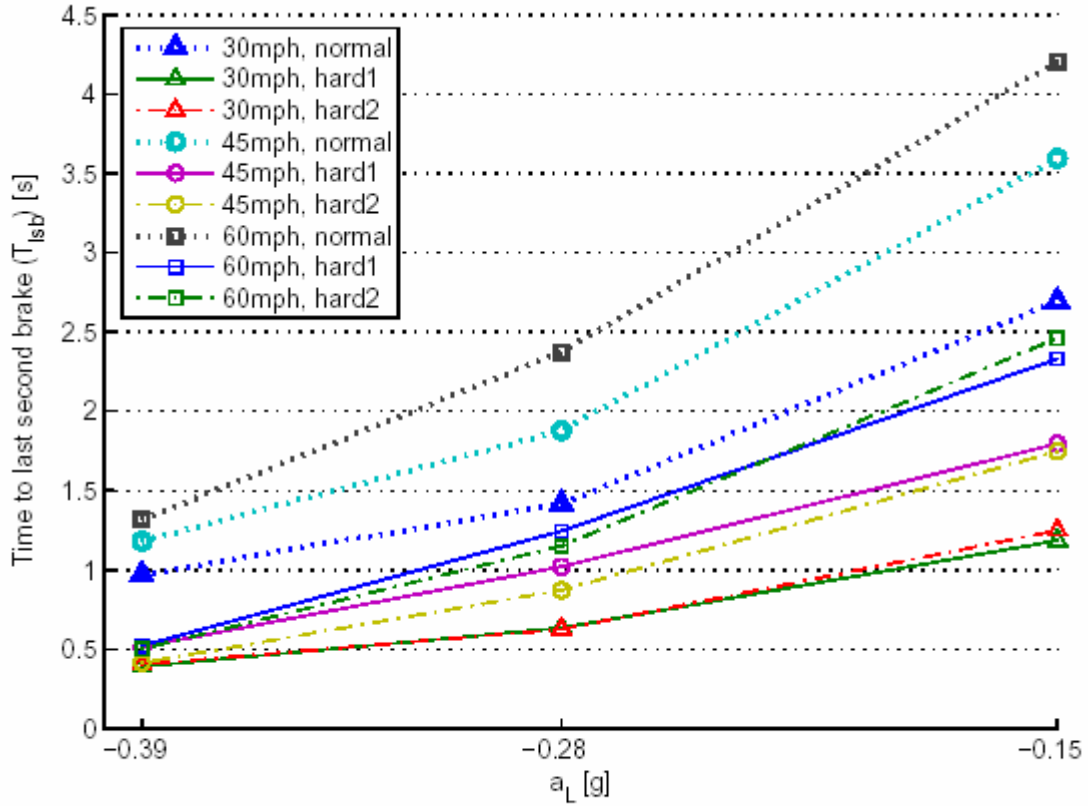


Figure 6.9: CAMP Data Represented in T_{lsb} Measure under Scenario 2: Lead Vehicle Decelerating ($a_{H_{max}} = -5 \text{ m/s}^2$)

Figure 6.9: CAMP Data Represented in T_{lsb} Measure under Scenario 2: Lead Vehicle Decelerating ($a_H = -5 \text{ m/s}^2$)

part of the Equations, then T_{HS} can be computed from Equation 6.18 and whether the condition $t_{LS} \leq t_{HS}$ holds or not can be verified. If $t_{LS} \leq t_{HS}$ holds, then the computation for T_{lsb} is completed. Otherwise T_{lsb} is solved from the second part of Equation 6.19 or 6.20 where the more positive solution is taken and the other solution discarded.

The human drivers' last-second "normal" and "hard" braking onset data recorded during the lead vehicle decelerating trials in CAMP experiments [Kiefer et al. 1999, Kiefer et al. 2003] can be plugged in the above equations to compute the T_{lsb} measure, as shown in Figure 6.9. The CAMP data include average range R and range rate RR at host vehicle braking onset under different conditions, i.e., last-second normal or hard braking condition, different initial host vehicle speeds ($v_H = 30 \text{ mph}$, 45 mph , or 60 mph), and different lead vehicle deceleration levels ($a_L = -0.15 \text{ g}$, -0.28 g , or -0.39 g), respectively. It can be noted from the figure that the T_{lsb} measure for

all the last-second hard braking data under heavy lead vehicle braking scenario ($a_L = -0.39 \text{ g}$) converged to about 0.5 second while the T_{lsb} for the corresponding last-second normal braking data were between 1 and 1.5 seconds, implying the urgency of this kind of scenario. In addition, the time buffer left until last-second brake seems to increase as the lead vehicle deceleration level decreases and/or the host vehicle speed increases.

5.4 General Scenario

In general, as the NHTSA alert algorithm described in Section 6.2.4, two different cases are considered to estimate the time to last second brake T_{lsb} , depending on whether the lead vehicle is expected to stop first or not. The lead vehicle stopping time t_{LS} is still estimated by Equation 6.6, while the estimation of the host vehicle stopping time t_{HS} is computed as follows:

$$t_{HS} = T_{lsb} - \frac{V_H + a_H T_{lsb}}{a_{H_{max}}} \quad V_H + a_H T_{lsb} > 0$$

Generally it is assumed that the condition $V_H + a_H T_{lsb} > 0$ holds² and the T_{lsb} measure can be solved from the following equations, using the same strategy as described in Section 6.3.3:

$$R = \begin{cases} V_H T_{lsb} + \frac{1}{2} a_H T_{lsb}^2 - \frac{(V_H + a_H T_{lsb})^2}{2 a_{H_{max}}} + \frac{V_L^2}{2 a_L} + R_{min} & t_{LS} \leq t_{HS} \\ -R_R \cdot T_{lsb} - \frac{1}{2} a_R T_{lsb}^2 + \frac{(R_R + a_R T_{lsb})^2}{2(a_L - a_{H_{max}})} + R_{min} & t_{LS} > t_{HS} \end{cases}$$

5.5 Error Estimation of the T_{lsb} Measure

From the above calculation process of the T_{lsb} measure, it follows that the error of the estimated T_{lsb} depends on the error or measurement noise of the six underlying state variables as specified in Equation 6.16. For simplicity, it is assumed that the input measurement noise is generated as independent random variables with the distributions given in Table 6.2 [Brunson et al. 2002]. Here, $U[a, b]$ represents the uniform distribution in the interval from a to b , while $G(\mu, \sigma)$ represents the Gaussian distribution with mean μ and standard deviation σ . All units are metric (m, m/s, and m/s²). These noise distributions were derived from a noise analysis of data collected from the prototype collision warning system in the Engineering Development Vehicle (EDV) developed under the ACAS FOT.

Parameter	Noise Distribution
v_H	$U[-0.15, 0.15]$
a_H	$G(-0.07, 0.17)$
R	$G(0.4, 0.025)$
RR	$U[-0.0625, 0.0625]$
a_R	$G(-0.6, 0.1)$

Table 6.2: Input Noise Distributions

Table 6.2: Input Noise Distributions

In order to estimate the error of Tlsb measure, the true input measurements are drawn using the distributions specified in Table 6.3, where $L(\mu, \sigma)$ represents the Laplacian distribution with mean

2 Otherwise the host vehicle is already decelerating hard enough, hence not an emergent scenario.

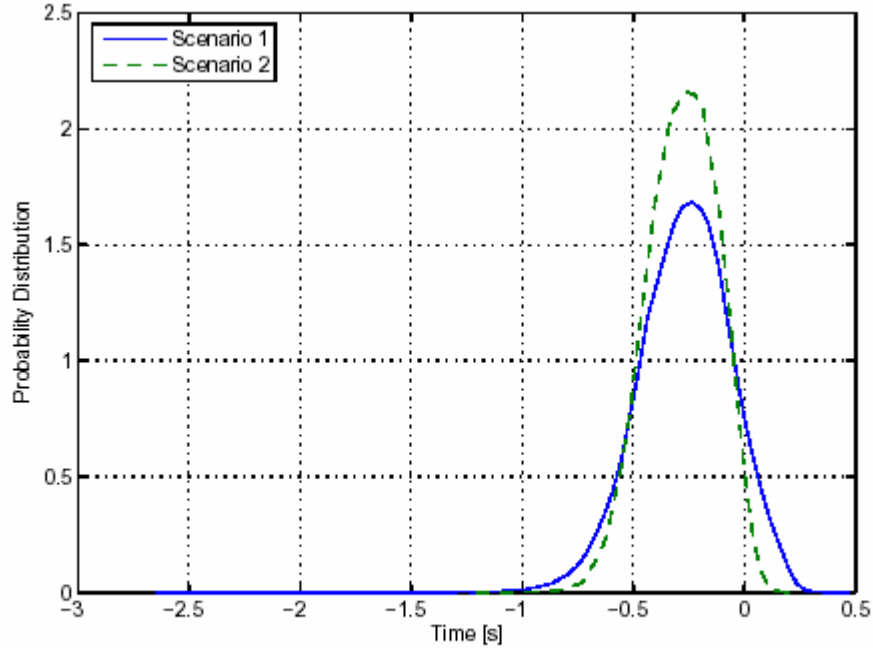


Figure 6.10: Error Distributions of Estimated T_{lsb} ($T_{lsb,est} - T_{lsb,true}$) due to Sensor Noise under Scenario 1 and Scenario 2

Figure 6.10: Error Distributions of Estimated Tlsb ($T_{lsb,est} - T_{lsb,true}$) due to Sensor Noise under Scenario 1 and Scenario 2

μ and standard deviation σ . The details of Scenario 1 (lead vehicle stopped or moving slowly) and Scenario 2 (lead vehicle decelerating) are described in Section 6.3.2 and Section 6.3.3 respectively. Again all units are metric (m, m/s, and m/s²).

True Parameter	Scenario 1	Scenario 2
v_H	$U[20, 30]$	$U[20, 30]$
a_H	$L(0, 0.3)$	$L(0, 0.3)$
R	$U[60, 80]$	$U[20, 40]$
RR	$U[-v_H, -v_H + 5]$	$U[-v_H + 20, -v_H + 30]$
a_R	$L(-a_H, 0.3)$	$L(-5 - a_H, 0.3)$

Table 6.3: True Input Measurement Distributions

Table 6.3: True Input Measurement Distributions

In addition, the true maximum available host vehicle deceleration $a_{Hmax,true}$ is drawn from a truncated Gaussian distribution with mean -0.6 g, standard deviation of 0.1 g, minimum of -0.8 g, and maximum of -0.3 g. Also it is assumed that a_{Hmax} can be estimated within $\pm 10\%$ white noise. Then the relative frequency distribution of the error of the T_{lsb} measure (i.e., $T_{lsb,est} - T_{lsb,true}$) can be estimated, as shown in Figure 6.10. The various percentile values and statistical measures of the T_{lsb} estimation error are summarized in Table 6.4. It can be observed from the figure and the numbers in the table that 99% of the T_{lsb} estimation error range is within 1 s, and that the estimated value of T_{lsb} will not exceed the true value by more than 0.25 s with a probability of over 99.9%.

Percentile	0.1%	1%	50%	99%	99.9%	mean	std
Scenario 1	-1.0567	-0.7966	-0.2587	0.1640	0.2433	-0.2672	0.2067
Scenario 2	-0.8133	-0.6631	-0.2714	0.0330	0.1015	-0.2784	0.1577

Table 6.4: Error of T_{lsb} Estimation Due to Sensor Noise in Seconds

Table 6.4: Error of T_{lsb} Estimation Due to Sensor Noise in Seconds

5.6 Warning/Overriding Criterion on T_{lsb}

The T_{lsb} measure provides a straightforward and quantitative assessment of the current situation. From its definition it follows that potential collisions would be avoided if the driver or the control system could react within T_{lsb} with a sufficient level of deceleration.

From previous work on driver reaction times as described in Section 6.1.2, human drivers usually do not have a consistently fast reaction time on the road, it may take up to 2 s to account for 90% drivers' reaction time under a natural driving scenario without any warning signals. The situation is slightly better in that 90% drivers can react within 1.8 s if a visual warning signal is used, 1.55 s if an auditory warning signal is issued, and 1.35 s if visual plus auditory warning signals are applied. However, on the other hand, the interference level of the warning signals also increases (from none, visual, auditory, to visual + auditory signal) as the driver reaction time decreases. The higher the interference level, the more probable drivers would experience the pre-warning signals as a nuisance. Hence it is desirable to set the warning timing not too early to reduce the interference level, and at the same time not too late to give most drivers sufficient time to react. As a result of this trade-off it is

difficult to achieve a satisfactory performance if the collision avoidance system solely relies on human drivers to take action in an emergency, due to the great driver behavior variation.

On the other hand, an overriding system can be used at critical moments to automatically apply brakes at maximum level to avoid collisions. The advantages are that it is not subject to the influence of driver reaction time and braking level variability, and that the T_{lsb} measure can give a relatively accurate estimate of how much time is left for the overriding system to react.

Based on the above discussions and observations, the following warning and overriding criterion based on T_{lsb} measure is proposed:

- $1.5 \text{ s} \leq T_{lsb} < 2.5 \text{ s}$: Cautionary warning (visual signal)
- $0.5 \text{ s} \leq T_{lsb} < 1.5 \text{ s}$: Imminent warning (visual + auditory signal)
- $T_{lsb} < 0.5 \text{ s}$: Overriding (automatic brake)

The overriding threshold (0.5 second) is chosen to avoid collisions with a probability of 99.9%, according to the T_{lsb} error distribution described in Section 6.3.5 and assuming the system delay of automatic brake to be 250 milliseconds. Besides, the CAMP data shown in Sections 6.3.2 and 6.3.3 also imply that alert drivers would have taken a normal or hard brake action before the 0.5 s threshold in most situations. Then the two one-second warning stages are defined according to general human driver reaction times and the error distribution of T_{lsb} estimation. The warning thresholds can be further adjusted according to individual driver's sensitivity level to warnings. For instance, a responsive driver might desire shorter warning time ranges than a slow driver.

The proposed T_{lsb} warning and overriding criterion has several advantages over the previous warning and overriding criteria as described in Section 6.2. First, it is defined in time domain instead of distance domain, which is in agreement with natural human sense and judgment of urgency. Besides, it gives a concrete time measure in terms of how much time is left for the driver or the control system to react to avoid a potential rear-end collision ahead, which serves as an excellent direct measure of the severity and urgency of threats under current situations.

Second, the estimation process of the T_{lsb} measure takes into account all possible current dynamic information (i.e., v_H , a_H , R , RR , a_R , a_{Hmax}) while most previous algorithms only used partial updated information and assumed the rest of the state variables to be constants. It follows that the estimation of T_{lsb} will be more sensitive to real time sensor noise and that the accuracy of T_{lsb} estimates can be improved by increasing the reliability and precision of sensor measurements. However, even when the sensor data is noisy, it is still better than a constant assumption in most cases.

Third, as mentioned before, the T_{lsb} criterion is less sensitive to human driver variability. In contrast to previous algorithms, the computation of the T_{lsb} measure does not depend on assumed human driver reaction time t_r any more, even though the warning criterion is still

defined with reference to the human driver reaction times. The overriding criterion depends on neither human driver reaction time nor braking level, which are two very important human factors in other collision avoidance systems.

Fourth, the overriding system can avoid collisions more effectively at the last moment based on the Tlsb measure. According to the error distribution analysis of the estimated Tlsb measure described in Section 6.3.5, and assuming that the automatic brake systems have a constant time delay of 250 milliseconds, the overriding system is able to avoid rear-end collisions with a probability of over 99.9%.

At last, the Tlsb measure can be combined with TTC information to take into account of last-second steering possibilities, please see more detailed discussions in section 6.4.4.

PART II: Development of Sensor Testbed

6 Definitions:

- **Proximity:** A distance signaled by an ON/OFF output; part presence and absence
- **Position:** The location (coordinates) of an object with respect to a defined reference datum
- **Displacement:** Movement from one position to another over a specific distance or angle
- **Dimensional:** Part-specific geometric attributes; determined via part inspection
- **Vibration:** A displacement that repeats at a particular frequency or set of frequencies and has an average displacement of zero

7 Introduction

The automobile industry has been using sensors on cars for the past couple of decades. Sensors are used for all sorts of reasons. To be used with complicated engine management systems, braking systems, and even warning you when you are backing up of any obstructions in your way. Still to this day though there are no sensors to warn you while you are driving of a danger either due to a car coming close to you or your car coming close to a barrier. There may be many reasons for not having these features on any cars. Maybe it is too intrusive of a system to put into a car and it would not be marketable. There is no reason though why it is not capable of being built. If people can build and race off-road vehicles with no driver and no remote control that drives by itself and can be aware of obstructions, than why can't it be implemented on passenger cars of tomorrow.

The main point of this project is a basic derivation of what was talked about above. Sensors will be used to count the number of vehicles that pass by you in either lane on your right or left hand side while you are driving. Therefore you will need at least four sensors on a test vehicle, one at each corner of the car to be able to sense when a vehicle has come within a lanes range of the test car. A data acquisition box will be needed to collect this data which then will be interpreted as to how many vehicles have passed by the test vehicle. This is the basics the project, understanding how to create a sensory system that will detect when a vehicle has come in a dangerous range to you while you are on the road. The difficult part of this project is finding sensors that will do this. There are many sensors available on the market today but what kind of sensor can work in such a harsh environment. You have the wind which is a very important factor in overcoming, also the constant up and down motion of the vehicle, and any other vibrations such as the engine and road conditions. Most sensors are very sensitive to different types of environments and choosing a proper sensor is the key to making this

project successful.

8 Choosing a Sensor

After defining the points to consider when selecting a position sensor, you can then rank them from greatest to least importance.

- Type of motion and degrees of freedom to be measured (e.g., linear or rotational, single- or multidimensional)
- Measurement range of interest and type of output (e.g., switched, nonlinear, or linear position output)
- Installation issues, limitations on mounting and physical size for both the sensor and the driver; also, sensor-to-driver interconnecting cable length
- Output (e.g., voltage, current, digital, switch points, visual indications, communication bus)
- Life expectancy and/or duty cycle required (i.e., short, medium, extended term)
- Environmental conditions for sensor, cable, and driver (e.g., temperature, humidity, moisture, corrosive fluids and oils, fluid pressure, vibration or shock, mechanical wear, EMI)
- Measurement performance (e.g., precision, accuracy, linearity error, resolution, bandwidth, repeatability, hysteresis, sensor and driver temperature stability/coefficients)
- Measuring range and performance indicators, transducer self-diagnostics, IEEE 1451.4 capability, TEDS

9 Proximity Switch or Position Transducer

The second question to ask is whether we need to know only if a target is present or absent, or whether we need information about target location throughout a range of motion. If all we need is a discrete ON/OFF signal indicating target presence or absence relative to a fixed location, then a proximity switch might be adequate. If the application calls for a continuously varying signal representative of the location of the target throughout a range of motion, we should specify a position transducer.

Proximity switches are typically used:

- To determine if a part or component (target) is installed on or in an assembly (e.g., a pressed-in mounting boss on a PCB assembly)
- To determine if or when a target arrives at or moves from a predetermined location relative to the switch (e.g., forming a metal part in a bending/stamping operation)

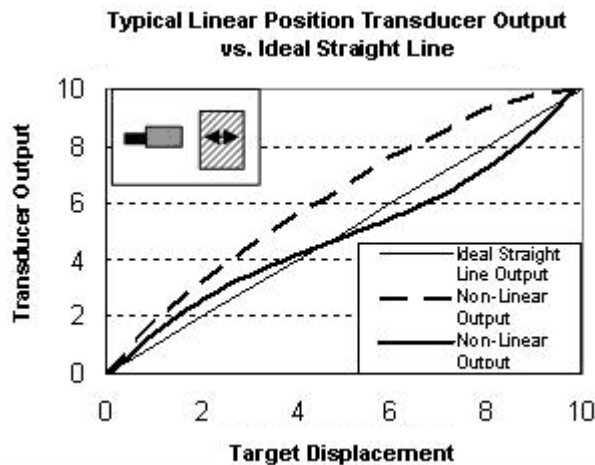


Figure 1. Position transducers provide a continuously changing output relative to target position throughout a range of motion. Linear devices typically have a nonlinearity error of 1% or less, but high-performance, nonlinear transducers can provide precise, cost-effective measurement for many applications.

9.1 Nonlinear and Linear.

High-quality nonlinear position transducers can provide a repeatable output signal vs. target position that we can characterize and develop a look-up table or algorithm for machine control. Linear transducers provide a linear output signal vs. target position that can simplify transducer implementation. Other selection considerations include measurement resolution and bandwidth, system or sensor robustness within the application environment, output signal types, size, and power requirements.

10 Fundamentals of Electro-Acoustics

10.1 History

Acoustics is the study of sound. Until the 19th century, acoustics primarily consisted of the physics of sound propagation related to human hearing. During the early 1800's, electromagnetism was discovered and one of the first non-musical instrument sound generators, the telegraph, was developed. The invention of the telephone in 1876 resulted in the creation of microphones and loudspeakers, followed by the phonograph at the end of the 19th century. Radio was developed during the early 1900's.

During the early part of the 20th century, a small group of researchers began applying engineering principles, such as equivalent circuits, to the science of acoustics in order to improve the design and construction of microphones and loudspeakers. This was the birth of the applied science of electro-acoustics. The work was carried out in several universities and in the research laboratories of

companies such as Bell Laboratories and Victor Talking Machine, which became RCA Victor.

To better communicate and share their discoveries, they formed the Acoustical Society of America in 1929, and the first text book on electro-acoustics, *Applied Acoustics*, was authored by Frank Massa and Harry Olson in 1934. Many of the fundamental principles developed by these pioneers is still used today in the design of electro-acoustic transducers and systems.

10.1.1.1.1 ACOUSTIC TRANSMISSION MEDIA

Electro-acoustic transducers operate as transmitters or receivers. When operating as transmitters, they transform electrical energy into acoustic energy that propagates through a medium, which is usually air or water. When operating as receivers, they transform the acoustical energy into electrical energy.

The fundamental equations for defining sound transmission are the same for all transmission media. However, because many of the fundamental acoustical properties are vastly different between fluid media such as water and gaseous media such as air, there are many fundamental differences between transducers and systems that are designed to operate in them. Some comparative acoustic properties of air and water are contained in the chart below:

TABLE I				
	Temp. (°C)	Density (kg/m³)	Velocity (m/sec.)	Acoustic Impedance (MKS Rayls)
Fresh Water	20	1000	1480	1.48×10^6
Sea Water (35 ppt salinity)	13	1026	1500	1.54×10^6
Air	0	1.29	332	428
Air	20	1.21	343	415

10.2 GENERAL PROPERTIES

10.2.1 Wavelength of Sound as a Function of Sound Speed and Frequency

The wavelength of sound changes as a function of both speed of sound and frequency, as shown by the expression:

$$\lambda = \frac{c}{f}$$

10.2.1.1.1 (1)

where: λ is the wavelength
 c is the speed of sound
 f is the frequency

Figure 2 shows a plot of the wavelength of sound from Equation (1) in air and water at room temperature as a function of frequency.

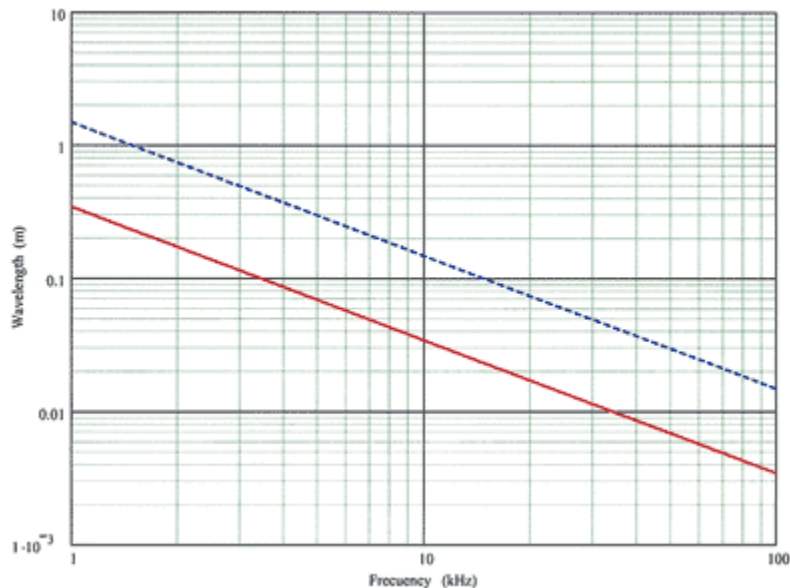


Figure 2: Plot of the Wavelength as a Function of Frequency for Sound in Air and Water at Room Temperature

10.3 Transducer Beam Patterns

The acoustic radiation pattern, or beam pattern, is the relative sensitivity of a transducer as a function of spatial angle. This pattern is determined by factors such as the frequency of operation and the size, shape and acoustic phase characteristics of the vibrating surface. The beam patterns of transducers are reciprocal, which means that the beam will be the same whether the transducer is used as a transmitter or as a receiver. It is important to note that the system beam pattern is not the same as the transmitting or receiving beam pattern of the transducers, as will be explained in a later section.

Transducers can be designed to radiate sound in many different types of patterns, from omni-

directional to very narrow beams. For a transducer with a circular radiating surface vibrating in phase, as is most commonly used in ultrasonic sensor applications, the narrowness of the beam pattern is a function of the ratio of the diameter of the radiating surface to the wavelength of sound at the operating frequency. The larger the diameter of the transducer as compared to a wavelength of sound, the narrower the sound beam.

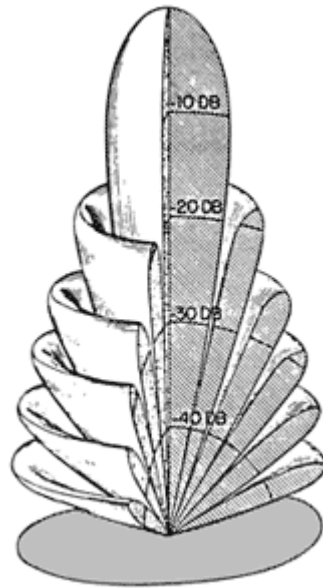


Figure 3: Three-Dimensional Representation of the Beam Pattern Produced by a Transducer With a Diameter Large Compared to a Wavelength

As can be seen, it produces a narrow conical beam and a number of secondary lobes of reduced amplitude separated by nulls. Even though the beam is called conical, it does not have straight sides and a flat top as the word "conical" may imply. The beam angle is usually defined as the measurement of the total angle where the sound pressure level of the main beam has been reduced by 3 dB on both sides of the on-axis peak. However, the transducer still has the sensitivity at greater angles, both in the main beam and in the secondary lobes.

When using transducers, it is important to be aware that nearby unwanted targets that are beyond the beam angle can inadvertently be detected, because the transducers are still sensitive at angles greater than the beam angle. Some transducers used in sensing applications are specially designed to minimize or eliminate the secondary lobes to avoid detecting unwanted targets.

10.3.1 ULTRASONIC TRANSDUCERS AND SYSTEMS OPERATING IN A GASEOUS MEDIUM

Ultrasonic sound is a vibration at a frequency above the range of human hearing, usually greater than 20 kHz. The microphones and loudspeakers used to receive and transmit ultrasonic sound are called transducers. Most ultrasonic sensors are echo ranging systems that use a single transducer to both

transmit the sound pulse and receive the reflected echo, typically operating at frequencies between 40 kHz and 250 kHz. A variety of different types of transducers can be used in these systems.

10.3.2 Speed of Sound in Air as a Function of Temperature

The speed of sound in air varies as a function of temperature by the relationship:

$$c(T) = 13,044 \sqrt{1 + \frac{T}{273}} \quad 10.3.2.1.1 \quad (2)$$

where: $c(T)$ is the speed of sound in air as a function of temperature in inches/sec.

T is the temperature of air in °C

10.3.3 Attenuation of Ultrasonic Sound in Air as a Function of Frequency and Humidity

As the sound travels, the amplitude of the sound pressure is reduced due to friction losses in the transmission medium. The attenuation of sound in air increases as the frequency increases, and at any given frequency the attenuation varies as a function of humidity. The value of humidity that produces the maximum attenuation is not the same for all frequencies. For example, above 125 kHz the maximum attenuation occurs at 100% relative humidity; however, at 40 kHz the maximum attenuation occurs at 50% relative humidity.

Since an ultrasonic sensor usually is required to operate at all possible humidities, target range calculations should use the largest value of attenuation. A good estimate for the maximum attenuation in air at room temperature over all humidities for frequencies up to 50 kHz is given by:

Noncontact position measurement devices offer several advantages over contact-type sensors. They provide higher dynamic response with higher measurement resolution, have lower (or no) hysteresis, and can measure small, fragile parts. There is no risk of a probe's damaging delicate structures, and they can do their work in highly dynamic processes and environments.

Noncontact measurement devices are based on various technologies, including electric field, electromagnetic field, and light/laser. In this article we will discuss two complementary displacement transducer technologies in detail: capacitive and inductive (eddy current), which operate on electric and electromagnetic fields, respectively.

11 The Basics of Capacitive Position Measurement

Consider two parallel steel plates with a gap between them. When a voltage is applied to one of the plates, the difference between the charges stored on the surfaces of the plates will cause an electric field to exist between them. This is a parallel-plate capacitor. Capacitance describes how the space

between the two conductors affects an electric field between them, and refers to the capacity of the two plates to hold this charge. A large capacitance can hold more charge than a small one. The amount of existing charge determines the amount of current required to change the voltage on the plate.

Capacitance is measured in farads, after Michael Faraday (1791–1867), an English physicist and chemist who did pioneering work in electricity and magnetism. One farad is a large unit; a typical capacitor used in electronic circuitry is measured in microfarads.

The capacitance changes sensed in a typical capacitive sensor are ~ 1 fF.

The basic operation of a capacitive position measurement sensor can be deduced from the familiar equation for a parallel-plate capacitor:

$$C = \epsilon_0 \epsilon_r A / d \quad (1)$$

where:

- ϵ_0 = absolute permittivity of free space (8.85×10^{-12})
- ϵ_r = relative permittivity (dielectric constant) of medium in gap between plates
- A = plate common surface area
- d = plate separation (displacement)

There are three ways to change the capacitance of the parallel-plate system:

- Variation of the distance between the plates (d)
- Variation of the shared area of the plates (A)
- Variation of the dielectric constant (ϵ_r)

The first two methods are shown in Figure 4. The effects of the third method on noncontact position measurement are discussed later in this article.

In a capacitive position sensor, the electrified plate is the sensor surface and the second plate is the target. The electronics continuously change the voltage on the sensor surface. This is the excitation voltage. The amount of current required to change the voltage is detected by the electronics and indicates the amount of capacitance between sensor and target. An AC bridge circuit or other active electronic circuit is typically used to convert the capacity change into a current or voltage signal and output.

In ordinary capacitance-based position measurement, the size of the sensor and the target, and the dielectric material (usually air) remain constant. The only variable is the gap. All changes in

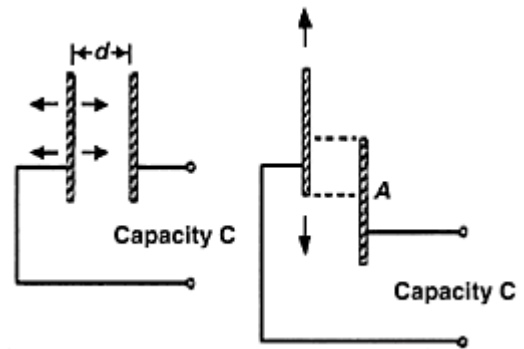


Figure 4. Assuming unvarying dielectric constant between the sensor and target, changes in capacitance result from changing the distance between sensor and target or the common area between the sensor and target. Changing the dielectric material between two plates fixed at a constant gap also changes the capacitance of the system.

capacitance are therefore the result of a change in the position of the target relative to the sensor. The driver is calibrated and the output scaled to provide a specific voltage for a corresponding change in capacitance (i.e., gap or displacement).

11.1 Target Size and Surface Condition

Capacitive transducers measure the average position of the target surface within the spot size (viewing area) of the sensor. A sensor with a circular shape will project a cylindrical electric field. In standard sensors, the field is focused by sensor design and construction. By the time the field reaches the target, however, it can spread as much as 30%, resulting in a field spot size on the target that is larger than the active sensor size. For ideal operation, we need a target at least 30% larger than the active sensor size. Using a smaller target introduces variables, such as

Figure 5.

Error-Correction Multipliers		
Target Diameter	Spherical Shape	Cylindrical Shape
1 in.	0.93	0.97
1/2 in.	0.77	0.94

target shape and whether it is axially centered on the sensor, all of which result in a corresponding change in capacitance. In special cases, the transducer can be calibrated to a particular geometric configuration. Figure 5 gives examples of error correction multipliers for a 3/8 in. diameter sensor operating on non-flat targets [3]. Because capacitive transducers sense the target surface, its consistence in terms of orientation, surface finish, dirt, oil, and contamination figures prominently in measurement accuracy.

11.2 Target Material and Thickness

The sensor's electric field seeks a conductive *surface*, meaning that these transducers are not affected by target material (magnetic, nonmagnetic) provided that it is a conductor. Because the electric field resides at the surface of the conductor, target thickness is not important.

Capacitive transducers are often used to measure a change in position or in a conductive target's mechanical characteristics. In addition, the devices are effective in measuring presence, density, thickness, location, and other characteristics of nonconductors as well. Nonconducting materials, such as plastic, have a dielectric constant (ϵ) different from that of air (ϵ for air $\sim 1.0005364 \pm 0.0000003$ at 20 C; $\epsilon_{\text{vacuum}} = 1.0$; $\epsilon_{\text{polyethylene}} \sim 2.3$; $\epsilon_{\text{range of water}} \sim 48$ to 88; $\epsilon_{\text{water}} = 78$ at 1 MHz and 25°C) [4]. Inserting a nonconductive material between the sensor and a conductive reference material will change the capacitance relative to the thickness, density, location, etc., of the material.

It is often not feasible because of application or installation constraints to provide a reference target behind the nonconductive target material. With proper calibration and setup, these measurements can still be made by a technique called *fringing*, in which the electric field from the sensor wraps back onto the sensor itself. When a nonconductive material is brought into this field, the material's dielectric

will alter that of the air medium around the sensor, allowing it to measure properties and characteristics of the nonconductive target material.

11.3 Environment

Although capacitive transducers are not affected by material magnetic properties, they are sensitive to the medium in the gap between the sensor and the target.

Maintaining a steady dielectric constant in the gap is therefore important—and humidity affects the dielectric constant of air. The dielectric constant of air increases with humidity and will change the capacitance between sensor and target. Furthermore, moisture and other fluids can migrate into the sensor and negatively interact with its construction. Experimental results show that RH changes from 50%–80% can cause errors up to 0.5%. Capacitive transducers are therefore not recommended for applications characterized by excessive dirt, dust, water, machining fluids, or oils. On the other hand, inductive transducers are unaffected by these contaminants, as will be discussed later.

Temperature-induced error, another area of concern, calls for temperature compensation of the system. But this technique does not solve the problem of temperature-induced expansion and contraction of system components. This can manifest itself as differential thermal expansion and result in measurement errors >0.0005 in. While not significant when measuring and controlling to 0.01 in., it is very much so when the tolerance is 0.001 in. or less. There is simply no substitute for careful fixture design and system installation.

12 The Basics of Inductive (Eddy Current) Position Measurement

Consider a coil of wire wound in a helical shape with an air core. Copper or some other nonferrous material is typically used in inductive sensor coils to avoid magnetic hysteresis effects and nonlinearity errors caused by ferrous materials. This wire coil is an inductor.

In 1824, Hans Christian Oersted (1777-1851), the Danish physicist, chemist, and electromagnetist, discovered that passing a time-varying current through a coil creates a magnetic field around the coil capable of shifting a compass needle. Faraday and the American physicist Joseph Henry (1797-1878) discovered the complementary effect: a moving magnetic field induces a voltage in an electrical conductor proportional to the rate of change of current (see Figure 6).

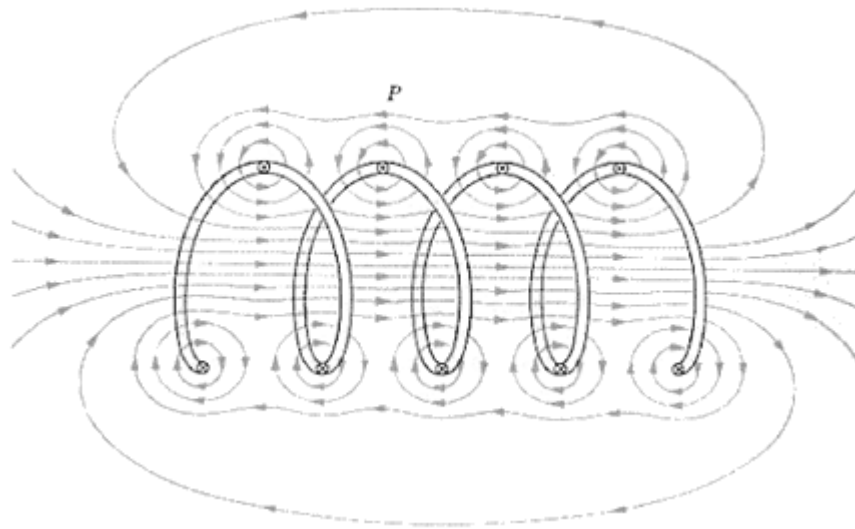


Figure 6. Self-inductance is the inducing of a voltage in a current-carrying wire when the current is changing. The magnetic field created by the AC induces the voltage. The magnetic field lies in concentric circles around the wire and expands and contracts across the conductor as the current changes.

Once again consider the coil, but with the turns wound around a permeable material (e.g., an iron core). When the current increases in one loop, the magnetic field expands perpendicular to the direction of current flow and intersects neighboring loops of wire. This induces a voltage in the loops, producing an inductance in the coil dependent upon the location of the permeable core. Sliding the core to a new position relative to the coil produces a different inductance. The magnetic flux in the coil can be related to the current through the coil as well as the currents in the iron core, or within another nearby conductive object such as a target.

Now consider the air-core coil again (the iron core having been removed), positioned near the conductive target. The flux field's effect on the target is similar to that on the core. The magnetic field at a given location in the target can be defined as the sum of two parts, one proportional to the current through the coil (induced) and the other due to self-induced currents in the conductive target. The coil and target constitute the primary and secondary windings, respectively, of an air-core transformer, which is an approximate model for eddy current transducers coupled with the target through inductive effects (see Figure 7).

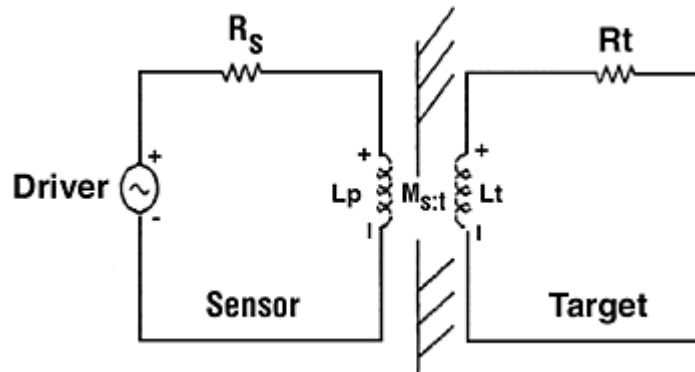


Figure 7. An air-core transformer is an appropriate model for an eddy current sensor. The magnetic field between the sensor and the target consists of two parts: one is caused by the current flowing through the sensor coil, and the second is a result of the currents generated in the target. Field intensity is proportional to current strength. The flux in the target consists of the target's self-inductance, L_t , and the mutual inductance between the sensor and the target, $M_{s:t}$. In a similar fashion, the flux in the sensor consists of the self-inductance of the sensor, L_s , and the mutual inductance between the sensor and the target, $M_{t:s}$. The mutual inductance depends on the geometry of the sensor and target, and, in general, $M_{t:s} = M_{s:t}$.

The coil's *self*-inductance depends only on its geometry; the *mutual* inductance between the coil and target, $M_{p:t}$, depends on the geometry of both coil and target and on target material properties. If the coil and target are far apart, the flux through the target due to the current in the coil will be small, and so will the mutual inductance.

12.1 Target Size and Surface Condition.

Target size is a primary consideration when selecting an eddy current sensor. The coil projects a toroidal field around the sensor face. Two sensor styles are typically available: shielded and unshielded. The shield loads the coil field, reducing the diameter and distance it extends from the sensor. Shielded sensors have the advantage of reducing the effect that conductive materials (other than the target) near the sensor or target can have on the measurement. The field diameter for shielded sensors is $\sim 1.5 \times$ the coil diameter; for unshielded types it is $\sim 3 \times$ the coil diameter. For standard operating conditions, the target size should be at least the size of the sensor field, but with special calibration and application, smaller targets can be used effectively. Target diameter becomes crucial when the target has a curved surface, as when measuring the X,Y axis runout on a rotating shaft.

Because the inductive field penetrates the target, the field provides a position measurement that averages target surface roughness, so surface finish is not important for most applications. However, where high accuracy and resolution in microinches or better are required, surface finish can affect measurements. For these applications, a surface roughness of $<32 \mu\text{in.}$ is recommended.

12.2 Target Material and Thickness

As we have seen, the quality of eddy current sensor-to-target field coupling depends on target electrical resistivity and magnetic permeability. This coupling determines the magnitude of coil impedance change vs. displacement. The ideal target materials are nonferrous with low electrical resistivity; among the best are aluminum, brass, and copper. Even though austenitic stainless steels have a higher resistivity than aluminum and reduce the signal by ~30% compared to aluminum, they are adequate for many applications. The exceptions are those that require extremely high measurement resolution and precision, such as many semiconductor- or optics-based applications where low thermal distortion of the target might be desirable.

A comparative measure of a material's thermal-mechanical stability is *thermal distortion*, the ratio of the coefficient of thermal expansion, α , (min./in./°F) and thermal conductivity, k , (Btu/hr./ft²./°F/ft.). As an example, for 6061 aluminum, $\alpha/k \sim 0.12$; for 303 stainless steel, $\alpha/k \sim 1.02$.

Ferrous materials vary widely in their magnetic permeability and electrical resistivity. Ferromagnetic materials have a high magnetic permeability that distinguishes them from nonferromagnetic materials and strongly influences eddy current fields. Moreover, ferromagnetic materials produce a stronger magnetic flux density, β , ($= \mu_r H$). Please note that an overarching quantification of system performance is beyond the scope of this article. Each particular system must be tested against the material under consideration (see Figure 8).

Important issues are:

- Exponential change in signal vs. displacement shows why inductive transducers are most efficient over a measuring range equivalent to 1/3 the coil diameter.
- Ferrous material exhibits inductance change and therefore a weaker system signal as compared to a nonferrous material. This often is reflected in a reduced measuring range and/or compromised performance against ferrous target materials, and is the reason nonferrous materials with low electrical resistivity are recommended in applications requiring high resolution and measurement precision.
- The effect of coil oscillation frequency. In this case, a higher δL is achieved against magnetic steel when operating at a lower frequency.

Figure 8.

Electrical Properties for Selected Materials [9,10]		
Material	Electrical Resistivity $\mu\Omega\text{-cm @ } 25^\circ\text{C}$	Magnetic Permeability μ_r
Aluminum	2.65	1
Copper	1.673	1
Gold	2.19	1
304 Stainless Steel	6.8	1
Lead	20.65	1
Nickel	6.84	100
1040 alloy (72 Ni, 14 Cu, 11 Fe, 3 Mo)	56	20,000-100,000
416 Stainless Steel	57	200
Mumetal (77 Ni, 5 Cu, 1.5 Cr)	60	20,000-100,000

12.3 Environment.

Inductive position sensors, while sensitive to target material properties, are not affected by nonconductive materials in the sensor-to-target gap. This feature offers distinct advantages in dirty environments (e.g., dirt, dust, water, and machining fluids and oils), assuming that the sensor is designed and built to withstand these fluids.

Temperature-induced error is another area that requires attention. The wire coil, in addition to providing the means to the measurement, is a temperature-sensitive resistor (Cu has a temperature coefficient of resistance of $0.00393 \, \Omega/\Omega/^\circ\text{C}$ at 20°C). For best performance, you must account for temperature errors over the environmental temperature operating range. The manufacturer can often provide temperature compensation to reduce the magnitude of this error, but even so, the problem remains of temperature-induced expansion and contraction of the components of the installation/application and should be handled as previously discussed.

13 Summary

Selecting a non-contact position measurement sensor requires defining the application requirements and then identifying and prioritizing the performance and device selection criteria. Many nonlinear transducers are capable of highly precise, high-performance measurements, yet are cost effective in many applications, particularly with the availability of signal processing already incorporated in many process-control systems.

From the three types of sensors above it seems that an ultrasonic transducer is the best way to go. It has much greater range than a capacitive or inductive proximity sensing device which has only a short range of accurate sensing of metallic objects. Also with these sensors the environment in which they work is very critical. It must be clean and free of any dust or debris. Consequently using these sensors outdoors under a driving environment just won't work. The sensors are made for accurate measuring in a controlled environment like an automated factory and would not be useful in an environment such as ours.

An ultrasonic sensor looks like the way to go. It is very versatile and can be used in a variety of different mediums. It has a wide range of sensing distances and is the sensor of choice for automotive manufactures for detecting obstructions while backing up. The only problem will be in setting up the sensors so that they can detect objects while moving which is the problem that is trying to be solved.

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