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Predicting Driver Braking and Stopping Behavior using an Intelligent Speed Adaptation System

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***Abstract*—The efficacy of Intelligent Speed Adaptation systems (ISAs) hasbeen evaluated in mitigating excessive speeding in simulator and field operation experiments in Europe, and most recently in the United States.Different roadway scenarios have been used to mimic real-life driving conditions in simulation experiment performed using ISAs in virtual driving scenarios.This paper presents regression models for three types of ISAs: Warning, Mandatory and Advanced Vehicle Speed Adaptation System (AVSAS) on approach to a stop-controlled intersection and a curve.The dependent variables for the un-signalized intersection and curve approach were respectively stopping distance and approach speed. The resulting predictive behavior models have associated R^2 values ranging from 63% to 93%. These models could be used to enhance or refine the realism of the roadway designs for simulator-based ISA experiments. In addition, these models can be incorporated in the development of future ISA algorithms as predictors of driver behavior after being validated in field operational tests.**

Keywords: Intelligent Speed Adaptation Systems, Deceleration, Braking

INTRODUCTION

Over the past few years, various studies have been conducted aimed at predicting driver behavior on different highway segments. These studies have largely been developed to predict the speeding behaviors using the 85th percentile or average speeds of a population of drivers. Most simulation-based experiments use pre-designed roadway simulator graphics and systems with design elements that may not adequately reflect the real world driving scenarios. As a consequence, road segments employed in such experiments are often simulator-based designs which may fail to replicate real driving conditions. As a result, models which deal with specific roadway scenarios for a simulator would be useful in the prediction of driver behavior in a fixed-based simulator. The parameters thatcanbe influenced in a fixed-based simulator include speed, stopping distance and deceleration rate.

Intelligent Speed Adaptation systems (ISAs) are in-vehicle systems that are capable of either warning drivers of adverse speeding behaviors or limit them from exceeding a prevailing speed limit or advisory. Most ISAs have been tested using driving simulators.The adequate prediction of certain driver behaviors will aid in the design and development of ISA systems. This could potentially result in a more efficient system since they incorporate driver behavior under different scenarios in a fixed-based simulator. Most ISA systems developed to date have not relied on such models. In this paper, two types of predictive models for driving behavior using a driving simulator are presented. These are:

- Stopping distance at unsignalizedintersections, and
- Curve approach speeds

After conducting an experiment to compare the efficacy of three ISAs in a driving simulator, these models were developed based on data gathered during the experiment. The three ISAs are: 1) Warning, 2) Mandatory, and 3) AVSAS. The Warning ISA provides alarms and notifications when the system determines that a potentially hazardous situation is about to occur that requires immediate driver action. The Mandatory ISA controls the maximum speed that can be attained by the driver which cannot be overridden. Finally, the AVSAS technology was designed to limit the driver to a tolerable speed above the posted speed limit beyond which the driver will have to override the system.

LITERATURE REVIEW

It is essential to model deceleration rates associated with speeding maneuvers and associated change cycles to analyze fuel consumption, operating costs, and pollutant emissions. Moreover,it is also useful for determining geometric and queued components of overall delay [1]. Also, the modeling of deceleration characteristics and behavior of individual drivers is acritical issue in the development of traffic simulation models.

It was assumed that a deceleration rate of 16.4 ft/s^2 would be required to bring a vehicle to a stop, based on a study [2] conducted in 1960.. However, in 1980[3] another study suggested that a 9.8 ft/s^2 deceleration rate was more realistic.Several other studies in subsequent years[4,5] identified that deceleration rates between 6.9 ft/s^2 and 13.8 ft/s^2 are morer reasonable, depending on the mean approach speed.Meanwhile, the 2001 AASHTO A Policy on Geometric Design of Highways and Streets [6] that a deceleration rate of 11.2 ft/s^2 is typically comfortable for most drivers. These recommended deceleration rates assume that most drivers brake uniformly on approach to a road hazard or a stop sign. However, several studies [2, 6] have shown that drivers decelerate non-uniformly and that the deceleration rates are largely dependent on the approach speed.

A constant deceleration rate model was developed in a study conducted on 17 passenger cars [7].This model assumed that the drivers maintained an average deceleration rate throughout the time deceleration took place, in contrast to other studies. The model predicts the vehicle speed based on a linear relationship with the deceleration time. Bennett et. al [8] showed that higher speeds vehicular speeds assume the form of the following polynomial:

$$v = v_0 - a_0\, v_0 t^2 \qquad (1)$$

where v = vehicle speed (km/h)

v_0= vehicle approach speed (km/h)

t = deceleration time (s) and

a_0= model constant.

From this model, it was inferred that the deceleration rate, which is the first derivative of equation (1), is directly proportional to the approach speed. Thus, the higher the approach speeds, the higher the deceleration rates. Another polynomial model [9] recommended for use in practice implied that drivers generally decelerate over a longer distance especially at higher speeds.

Haas et. al [10], developed a deceleration model using data gathered during a 1996 Intelligent Cruise Control (ICC) Field Operational Test in Michigan. The model rate predicted the average deceleration ratefor each driving event. The analysis of the data showed a statistically significant dependence of the deceleration rate on the initial speed. However, other factors such as final speed, driver gender, and street type had little influence on the deceleration rates. The analysis also showed that there is a large and stochastic component in the deceleration ratewhich is influenced by driver choice.

A field experiment conducted by El-Shawarby et al.[11], involved volunteer drivers who drove an instrumented vehicle based on which deceleration rates were predicted. This involved a 1 mile downgrade roadway. The results showed that a motorist's deceleration rate is impacted by the roadway grade, gender, and age and concluded that driver deceleration is unlikely to be adequately modeled by employing average deceleration rates. The study suggested using a distribution of model parameters instead of fixed values.

In 2007, two deceleration rate models for curves on two-lane rural roads were developed [9]. In that study, which used data on 18 two-lane rural road horizontal curves, the results showed that the approaching speed, curve length, and the radius are correlated to deceleration rate. The first deceleration rate model was defined as a function of the impending curve radius while the second estimated it as a function of speed reduction and approaching speed. The authors contended that the models predicted deceleration rates consistent with observed speed reduction behavior and implied they can be used for operating speed profile construction.

The required overall safe stopping distance, D, depends on a driver's perception and reaction time, the grade of the roadway, as well as the vehicle reaction and braking capability [12]. Typically, D is computed as a sum of two distances, namely, perception reaction distance (D_1) and the distance needed to stop the vehicle from the instant the brakesare applied (D_2).

Stopping distance is an important design parameter that defines the minimum distance that must be provided at critical points along aroadway to bring a vehicle to stop safely, particularly on approach to signalized and un-signalized intersections. A basic model for calculating stopping distances was first developed in 1940.

Apostolopoulou et al [13], contended that existing stopping distance models are based on daytime driving and thereby rendering the model's output unrealistic for nighttime driving. The analysis of a stopping distance data obtained from a nighttime driving experiment showed that the influence of night visibility is critical for a safe stopping sight distance. It was determined that, overall, there are shorter sight distances during nighttime driving which could potentially lead to unsafe driving conditions. The authors suggested that design policies should be reconsidered to address the issue of safe stopping sight distance at night time.

In the development of ISA's, there is the need to identify the potential system requirements in order to adhere to expected deceleration rates as well as stopping distances. For most of ISA systems developed and tested using simulator experiments, existing or potential deceleration rate and stopping distance models validation have not been addressed.

OVERVIEW OF AVSAS AND OTHER ISA FEATURES

Underlying AVSAS Architecture

During the first phase of the simulator experiment, a clustering algorithm was developed to assessdrivers behavior. This algorithm is presented in Figure 1.At thisstage, subjects drove the simulator without any active ISA system. Drivers' average and maximum acceleration, deceleration, and speeds on different roadway segments were analyzed. The results showed three clusters of drivers:conservative, normal, or aggressive. Thevalues for excess speed above the speed limit and maximum deceleration rates were extracted for each of these groups of drivers, which formed the input for AVSAS' cluster algorithm, that run continuously while the vehicle is in motion.

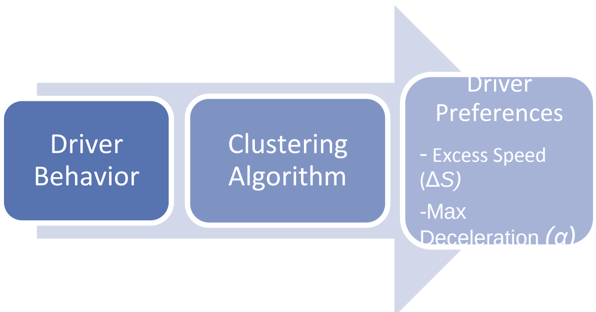

Figure 1: Driver Behavior Clustering

This processbegun with a determination of a target speed based on adriver'sclassification and current roadway information as shown in Figure 2.

The following equation is used to determine the Target Speed (*TS*):

TS = min $\{SL + \Delta S.\sqrt{\{(SL' + \Delta S)^2 + 2\ \alpha d\}}\}$ (6)

where:

- *TS* is the target speed in m/s
- *SL* is the speed limit for the current segment of roadway in m/s,
- ΔS is the driver's preferred exceding speed in m/s,
- *SL'* is the speed limit on the next segment of roadway in m/s,
- α is the driver's preferred deceleration rate ($\alpha > 0$), in m/s^2, and
- *d* is the distance between the vehicle and the beginning of the next segment of roadway in meters.

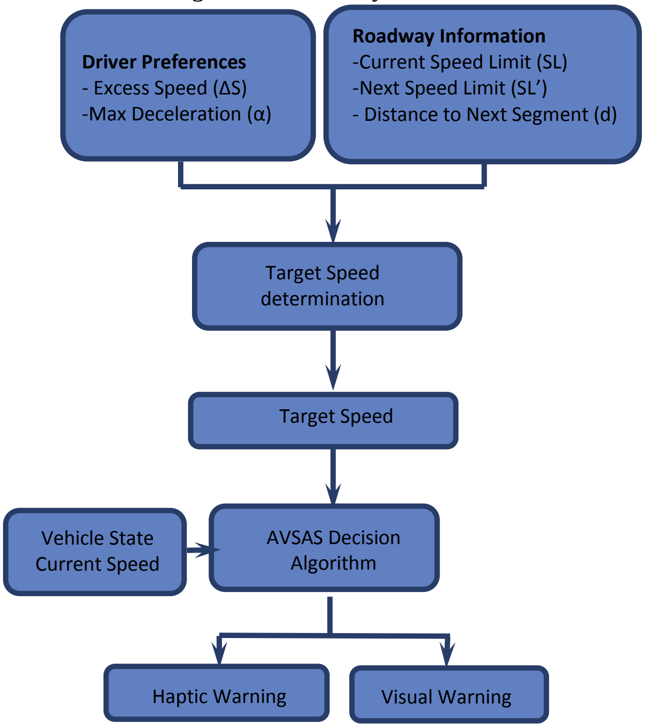

Figure 2: AVSAS Speed Regulation Process

The determination of the TS allows AVSAS to adapt to individual speed profiles, driving scenario and roadway geometry and condition. When drivers approach potential scenarios that require a reduction in speed such as intersections, work zones, and curves, AVSAS takes into consideration drivers' preferred deceleration rates to determine a target speed at the given moment.AVSAS considers the speed limit for curves to be equal to the posted advisory speed. For cases where vehicles are required to come to a complete stop, e.g., a red light or stop sign, AVSAS considers the Speed Limit and the preferred excess speed to be equal to 0.The computed TSform the basis for system generated warnings.

METHODOLOGY

Using a driving simulator software program, (STISM), speed data was collected from21 drivers for each of the ISAs (warning, mandatory, AVSAS). AVSAS was developed by the Center for Intelligent System Research atGeorge Washington University as hybrid of the Warning ISA and the Mandatory ISA [13]. The Warning ISA provides alarms and notifications (voice or visual) when the system assesses that a driver has exceeded the speed limit or advisory.Information to the driver such as the current recommended speed based on the prevailing road and weather conditions, is provided by the advisory systems. The Mandatory ISA, which is an automatic control system, uses mechanical systems and techniques such as throttle control and braking to prevent the driver from exceeding a prevailing speed limit.It is effective in ensuring compliance with speed limits; however, it is viewed extremely negatively by drivers. On the contrary, the Warning ISA system is significantly less effective when reducing driver speeds [13].

AVSAS functions as a speed management system based on individual driver speeding preferences under different roadway scenarios rather than a complete speed limiting system. AVSAS allows a driver to exceed the prevailing speed limit up to a certain threshold beyond which it functions as a Mandatory ISA, with override capability. It also has the all the features of a Warning ISA including advance hazard warning displays.

The driving simulator experiment involved six (6) types of road classes: freeway (65 mph), collector (45 mph), local (35 mph), residential (25 mph), rural (55 mph), and urban roads (35 mph). The driving scenarios included five curves (with 20, 35, 45 and 55 mph posted advisory speed limits), three stop-controlled intersections, a fog zone, and an accident zone.

Data was gathered for 21 drivers using the three ISAs, based on which the regression models were developed. The ISA development and evaluation data, as mentioned earlier, included several other scenarios. Multiple regression analysis method was used with all model indicators tested at 5% level of significance. The significance and adequacies of these models were examined using a number of tests including the F-test, t-test, the two-sample Kolmogorov-Smirnov test (KS test), associated p-values, homoscedasticity, and normality.

RESULTS

Stopping Distance Models at Un-signalized Intersection

A standard multivariate regression analysis was employed to assess the relationship between the following variables: approach speed, maximum deceleration rate, stopping distance and the deceleration time. These values were extracted from the STISM program at the approach of the intersection being analyzed. The model was determined to assume the following form:

$$D = \alpha_0 + \alpha_1 a + \alpha_2 V + \alpha_3 t \quad (7)$$

where

D = distance to stop sign when braking is initiated (stopping distance, ft),
a = maximum deceleration rate (ft/s^2),
V = approach speed (ft/s), and
t = deceleration time (s).

The constants α_0, α_1, α_2 and α_3 are the coefficients of the regression model with an associated error of ε [$\varepsilon \sim N(0, \sigma^2)$].

The resulting regression models developed for the Warning, Mandatory and AVSAS intelligent speed adaptation systems are presented in Table 1.

ISA Type	Model	R^2
Warning	$D = 103.6 - 13.8\,a + 4.3\,V + 6.9t$	0.91
Mandatory	$D = 46.2 - 8.2\,a + 3.1\,V + 8.6t$	0.88
AVSAS	$D = 37.7 - 13.6\,a + 4.8\,V + 11.9t$	0.87

Table 1: Summary of Regression Models for Stopping Distance at Stop Signs.

From the KS Test, the resulting D-statistic and corresponding p-values for each model show that the models adequately predict the observed values. Further, the results of the regression analysis show that the models adequately predict the stopping distance for all the drivers on approach to the stop-controlled intersection, with $p < 0.05$ for the t-statistics for the corresponding coefficients, while the F-statistic indicated a statistically significant model.

Deceleration Rate Model on Curve Approach

Regression models were also developed for the driver deceleration rate on approach to a curve with a radius of 489 feet used in the simulator. The curve had a posted speed limit of 35 mph. Aregression model was developed to assess the relationship between the approach speed, maximum deceleration rate, and the deceleration time. These values were obtained for each driver onapproach to the curve. The model assumed is of the form:

$$\sqrt{V} = \beta_0 + \beta_1 a + \beta_2 t^2 \qquad (8)$$

where

V = approach speed (ft/s), and
t = deceleration time (s).
a = maximum deceleration rate (ft/s^2),

The constants β_0, β_1, and β_2 are the coefficients of the regression model with an associated error of ε [$\varepsilon \sim N(0, \sigma^2)$]. The resulting predicting models for the ISAs are presented in Table 2.

ISA Type	Model	R^2
Warning	$\sqrt{V} = 7.994 + 0.0636\,a - 0.0532t^2$	0.66
Mandatory	$\sqrt{V} = 9.249 - 0.0016\,a - 0.5492t^2$	0.90
AVSAS	$\sqrt{V} = 10.02 + 0.015\,a - 0.77t^2$	0.93

Table 2: Summary of Regression Models for Simulation based Deceleration Rates at Curves.

The deceleration rate was determined by obtaining the first derivative of the approach speed, V. For these models, the residual plots showed evenly distributed random plots about the zero line, confirming that the model fit the data sets well. Further, the KS tests showed that there is no statistically significant difference between the predicted and observed values, at 5% level of significance.The associated p-values for the t-statistics for the coefficients were less than 0.05, indicating that the approach speed in the regression models on approach to the curve for the three ISAs were adequately predicted by the maximum deceleration rate and the deceleration time.

CONCLUSIONS

Future ISA tests mayinclude the driver-simulator models presented in this paper for the design of road segments for the applicable scenarios.This could help to achieve a more realistic driving behavior in the driving simulator by determining the metrics needed in the ISA's design process.From the analysis of the stopping distance regression models for each of the ISA scenario,they adequately predicted the stopping distance for all the drivers on approach to the stop-controlled intersection in a driving simulator. The coefficient of determination for all the models (R^2) range from 87% to 91% indicating that the models adequately predicted the observed values. Similarly, the regression models for the drivers on approach to the curve for the three ISAs scenariosshowed that the approach speed can be adequately predicted by the maximum deceleration rate and the deceleration time. The R^2 values ranged from 66% to 93%. Residual plots for all models showed randomness about the zero line indicating their viability, in addition to the normal probability plots showing data points near a straight line. Furthermore, the KS Test results indicated that the models adequately predicted the observed values.

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