DRIVER INATTENTION ALLOCATION DETECTION USING A PANEL DATA APPROACH

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ABSTRACT

Driver inattention has been regarded as an important contributing factor to serious roadway crashes, and as an emerging yet important field in highway safety study, driver inattention study is gaining increasing attention. Considering that driver inattention is closely related to the process of drivers allocating their attention between the primary driving tasks and the competing secondary tasks, this paper intends to develop a statistical model that can relate driver attention allocation to multiple explanatory factors. Real world data were collected using a test vehicle equipped with a commercial eye tracking device and on-board vehicle performance recording equipments. After the processes of data sampling and data reduction, a final dataset was obtained and three random effects ordered probit models were built based on different group definitions. Using the field data, the estimation results showed that traffic characteristics, road geometric characteristics, and time of day are statistically significant in relating to the driver attention allocation process; in addition, the prediction performances of the three models are investigated, showing that a workable driver inattention detection ability of the proposed model can be achieved given an appropriate calibrated threshold value. Discussions are provided on the driver attentional status indicator, the data collection approach, and the modeling approach with future work recommended for further investigating the driver attention allocation process. Potential applications of the proposed model are briefly discussed in the end.

Keywords: driver inattention, random effects ordered probit, attention allocation, crash, eye tracking system, eye movement

INTRODUCTION

Driver distraction, or more broadly, driver inattention, has been regarded as an important contributing factor to serious roadway crashes. Using the Crashworthiness Data System (CDS) data between 1995 and 1999, Stutts et al. (2001) reported that at least 15.5% of drivers were identified as distracted, looked but did not see, or sleepy. Therefore, as an emerging yet important field, driver inattention study is gaining increasing attention in highway safety study. Driver inattention is closely related to the process of the drivers allocating their attention between the primary driving tasks and the competing secondary tasks. The primary driving tasks usually relate to the operations that are necessary for maintaining safe driving conditions, such as lane keeping, driving speed control, or driving direction information acquisition. The competing secondary tasks are those that do not necessarily relate to driving, e.g., answering a cell phone, looking at road side advertising billboards, operating onboard instruments, text messaging, etc. In most situations when traffic conditions are predictable with no abrupt changes, the driver can maintain a safe driving through switching his/her attention between the primary driving tasks and the competing secondary tasks. However, in case of sudden changes in the driving condition, such as a sudden appearance of a crossing vehicle or pedestrian in front of the vehicle path, the misallocated attention on the competing secondary tasks at that moment might lead to the driver failing to correctly respond to the changing driving condition and hence create a high chance of traffic accident. Therefore, understanding the process of drivers allocating their attention during driving is essential for understanding the mechanisms of the driver distraction related highway safety issues.

The driver attention allocation process is complicated by many influencing factors. For example, it is hypothesized that driver attention allocation may be affected by driver characteristics, driving environment, vehicle driving performance, etc.; therefore, it is hypothesized that driver attention allocation can also be investigated through using these influencing factors. Considering that previous studies in psychology have indicated that eye movements and attentional deployment are intimately related (Wolfe 1998; Khurana and Kowler, 1987), it is possible to use the eye movement data to investigate the relationship between the driver attention allocation and those aforementioned hypothesized influencing factors.

Targeting the driver attention allocation process, this study intends to develop a statistical model that can relate driver attention allocation to various explanatory factors at the microscopic level and hence to detect driver inattention. As indicated above, in this study, eye movement data, or more specifically, the eye fixation positions, collected through a commercial eye tracking system will be used as the indicator of the driver attentional status that will be related to the influencing factors. Following a literature review on driver inattention detection, the data used in this study are described; afterwards, the methodology is presented, followed by the empirical results including model estimation and prediction performance investigation. Finally the paper is summarized with discussions and recommendations.

LITERATURE REVIEW

An emerging field in highway safety study, driver inattention detection has attracted great attention in the transportation research community, and a growing literature of studies have been reported, which can be broadly classified into image processing based approach and eye-tracking system based approach.

The image processing approach mainly relies on the processing of the driver facial video stream for generating driver visual behavioral data and hence to infer the driver attentional status. Ji et al. (2004) proposed a real time driver facial video stream processing algorithm for driver fatigue monitoring. In their work, visual cues, including eyelid movement, gaze movement, head movement, and facial expression, were first extracted and then tracked with a Kalman filter; afterwards, a probabilistic Bayesian networks model was developed to relate fatigue to multiple visual cues for a robust and accurate fatigue prediction. Bergasa et al. (2006) proposed a real-time driver vigilance monitoring system, in which visual behaviors was generated through real-time processing of the driver facial video stream, including percent eye closure, eye closure duration, blink frequency, nodding frequency, face position, and fixed gaze; then the level of inattentiveness of the driver was inferred using a fuzzy classifier. D'Orazio et al. (2007) presented a neural classifier to recognize the eyes in the driver facial images and a probabilistic model to recognize the anomalous behavior of driver inattention or sleepiness. Based on image processing, Eriksson and Papanikolopoulos (2001) presented a vision-based approach to automatic diagnose driver fatigue, using micro-sleeps as the criterion of detecting driver fatigue.

The eye-tracker based approach mainly relies on a commercial eye tracking system to generate visual behavior data so that the researchers can focus exclusively on the issue of driver inattention detection. Liang et al. (2007a) used support vector machines for non-intrusively detecting driver cognitive distraction, and showed that the proposed support vector machine approach outperformed the traditional logistic regression model. The data used in their study were collected in a driving simulator equipped with the Seeing Machines' faceLab eye tracking system that collects eye movement data at 60Hz. Ten subjects were selected in the test. Using the similar simulation environment as in Liang et al. (2007a), Liang et al. (2007b) applied dynamic Bayesian networks for detecting driver cognitive distraction, and they found that blink frequency, fixation duration, and fixation's horizontal and vertical distribution play more important roles than smooth pursuit.

According to the review above, the eye movement data or visual cues, collected either from image processing algorithms or commercial eye tracking devices, have been widely used in driver inattention detection. However, many of these work relies on infer driver inattention from solely the eye movement data; in contrast, this study intends to infer driver inattention from multiple influencing factors through developing a statistical model at the microscopic level that can relate eye movement data (eye fixation) to the influencing factors.

DATA

In this section, the data used in this study are described, including data collection, data sampling, data reduction, and a summary of the data.

Data collection

The data used in this study was collected together with a study sponsored by the Federal Highway Administration (Molino et al 2009), and the following is a description relating to the present study. The data collection was conducted in Reading, PA, in September 2009, using a field research vehicle that was a 2007 Jeep Grand Cherokee sport utility vehicle. This test vehicle was instrumented with a Smarteye dashboard-mounted infra-red eye-movement measuring system and outfitted with equipments to record vehicle performance parameters. The data collection area includes two routes (indicated as Route A and Route B), covering both divided highways and urban streets, and each of the test run took about 20 to 30 minutes to complete.

Multiple drivers were selected from the local area to serve as test subjects. For each driver, a field calibration was conducted so as to fine-tune the testing environment to each driver. In order to minimize the impact of the testing on the driver visual behavior, the drivers were instructed to operate the vehicle normally, with two experimenters sitting inside the vehicle operating the testing instruments. The data collection time periods included both nighttime and daytime. After each run, the experimenters downloaded and archived the collected data, including a single panoramic video file of fps (frame per second) at 25 Hz with the eye fixation positions on the frames and the accompanying digital data files. Moreover, the vehicle performance data was collected for each test run, e.g., the global positioning system (GPS) data at 1Hz.

In the digital data files, three categories of events were logged by the experimenters during the test. The first category includes potentially distracting incidents, such as a disabled vehicle on roadside, a fire truck or ambulance on the road, etc. The second category includes driver errors, defined as minor driving anomalies or conflictions that occurred mainly at on and off ramps or other merging areas. The third category includes serious and potentially unsafe driving maneuvers such as sudden swerving or braking. These three types of events were identified and logged solely according to the judgment of the experimenters and will serve in this study as a filtering variable to identify sections of the test runs that might have a higher probability of inattention. Note the potential judgment bias of the experimenters will only affect the number of sections of the test runs that are to be used in this study, while it will not affect the mechanism of the modeling approach to be discussed below in this paper, and hence this judgement bias is not dealt with in this study.

Sampling

The Smarteye system used in the data collection effort is effective in logging eye fixations in bright sun lights and when driver is looking ahead, while it is likely for the system to lose track of eye fixations when the driver is looking further away from the forward view, causing missing values or dropouts of eye movement data in the panoramic video.

In order to handle this disadvantage caused by the missing eye movement data, a sampling strategy was designed to increase the likelihood of including more inattention samples. Recall that in the data collection effort described above, the experimenters registered three categories of events that might indicate a higher probability of inattention. Therefore, in this study, the video frames that were flagged as events were sampled from all the videos. In addition, 50 frames ahead of the first flagged frame for each event were also selected for the analysis. Afterwards, the selected frames were scrutinized individually so that the frames with missing eye fixations were removed from the final sample.

Using the sampling approach described above, a total of 4,048 video frames were identified from the entire video database that covers 18 subjects and 31 test runs with an estimate of totally around 1.4 million video frames. A typical video frame is shown in Figure 1, and the detailed information on the selected subjects and test runs are listed in Table 1 and 2, respectively.

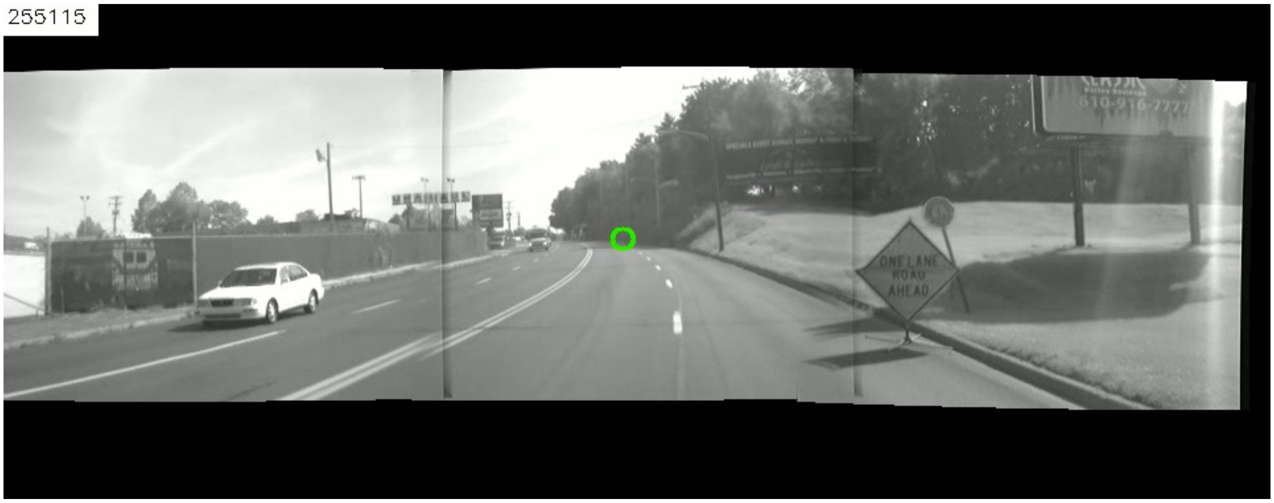

Figure 1 Video frame illustration (green circle indicates the driver eye fixation at this moment)

Table 1 Subject information

Subject	Gender	Age	Driving Experience
7	F	39	21
8	M	55	31
9	M	39	3
10	M	46	5
13	M	49	32
15	F	59	43
17	F	52	35
18	F	31	15
19	M	18	2
20	F	54	30
21	F	46	30
24	F	53	36
27	M	63	5
36	M	64	48
38	M	62	45
44	F	20	3
45	F	64	48
48	F	55	37

Table 2 Test runs information

Subject	Route	Frame Subtotal	Time of Day
7	A	97	Day
7	B	144	Day
8	A	168	Night
8	B	265	Night
9	A	108	Day
9	B	139	Day
10	B	84	Night
13	A	128	Day
13	B	139	Day
15	A	9	Day
15	B	343	Day
17	A	117	Day
17	B	149	Day
18	B	45	Night
19	A	329	Day
19	B	138	Day
20	A	8	Night
21	A	194	Day
21	B	304	Day
24	A	4	Night
27	A	47	Day
27	B	45	Day
36	A	32	Day
36	B	23	Day
38	A	187	Day
38	B	121	Day
44	A	149	Day
44	B	391	Day
45	A	41	Night
48	A	64	Day
48	B	36	Day
Sum		4,048	

It can be seen from Table 1 and 2 that the selected video frames are scattered across multiple test runs and multiple drivers, which is desirable in that the selected sample includes more variations across subjects. In addition and as described above, no eye fixation data were used in performing the sampling process so that no bias towards either inattention or attention was introduced into the final sample. Moreover, no road side information such as roadside digital billboards was used in the sampling process, and hence no bias towards any road side information was introduced into the final sample. This is desirable for developing a scenario independent driver attention allocation model.

Reduction

After the sampling process, the selected frames were reduced to generate the dataset for the study, including two procedures: digital data reduction and video frame reduction. In digital data reduction, the video frames were related to the GPS record based on time, and a vehicle speed was associated with each frame. This operation was facilitated through developing codes using the SAS software.

In video frame reduction, each video frame was viewed individually, with factors, such as traffic characteristics and road geometric characteristics, determined manually by the researchers. In addition, an environmental measure, termed as edge density, was also used to bring the environmental effect into the analysis. In this study, the environmental factor was selected as image complexity, describing the complexity of each video frame. Rosenholtz et al. (2007) proposed three image complexity measures, including subband entropy, edge density, and feature congestion, and showed that the three measures works comparably in quantifying image complexity. Edge density is defined as the percentage of the pixel points that are on the edges of an image, and in this study, the edge detection was computed using the conventional Canny approach (Canny 1986) for each frame in MATLAB©. Understandably, high edge density indicates more edges and hence more objects in the video frame, i.e., more complex of the driving environment.

Data summary

The final dataset reduced from the selected video frames were summarized in Table 3 and 4. Table 3 describes the variables to be investigated in this study and their definitions. Note that in Table 3, the ATTENTION variable is the dependent variable with the definitions of attention or inattention determined based on the position of eye fixation, and the explanatory variables include driver characteristics, vehicle performance, traffic characteristics, road geometric characteristics, and environmental factors. In Table 4, the statistics of these variables were presented for providing an overview of the final data set.

Table 3 Variable description

Variable	Description
Dependent Variable	
ATTENTION	1 if the eye fixation position is on ✓ Road ahead (vehicle ahead, curb, barrier, or shoulder) ✓ Traffic control devices (signs or signals) ✓ On-street Parking ✓ Pedestrians within the right of way 2 if the eye fixation position is on ✓ Roadside advertisements (billboard or on-premise signs) ✓ Building environment (buildings or off-street parking) ✓ Natural environment (trees) ✓ Approaching vehicles on divided highway
Driver characteristics	
AGE	Integer in years
GENDER	1 for male; 2 for female
EXPERIENCE	Integer in years
Vehicle performance	
SPEED	Floating number in mph
Traffic characteristics	
LIGHT	1 for light traffic (vehicles in one lane or occasional passing vehicle), 0 otherwise
MEDIUM	1 for medium traffic (visible vehicles in multiple lanes) , 0 otherwise
HIGH	1 for high traffic (many vehicles in multiple lanes) , 0 otherwise
Road geometric characteristics	
CURVE	1 for freeway or divided highway curve, 0 otherwise
STRAIGHT	1 for freeway or divided highway straight segment, 0 otherwise
WEAVE	1 for freeway or divided highway merging and weaving segment, 0 otherwise
MLSTREET	1 for street with two-way left turn lane, 0 otherwise
TWSTREET	1 for two-way street divided by single yellow line, 0 otherwise
SSTREET	1 for two-way street without dividing yellow line, 0 otherwise
RAMP	1 for freeway ramp, 0 otherwise
Environmental factors	
EDGEDENSITY	Floating number between 0 and 1
TIME	1 for video frames collected in daytime, 2 otherwise

Table 4 Data statistics

Variable	Mean	Standard deviation	Minimum	Maximum
Dependent Variable				
ATTENTION	1.0978	0.2971	1	2
Driver characteristics				
AGE	43.2517	15.6130	18	64
GENDER				
EXPERIENCE	23.1759	16.2151	2	48
Vehicle performance				
SPEED	32.0746	16.6785	0.0186	64.2436
Traffic characteristics				
LIGHT	0.6005	0.4899	0	1
MEDIUM	0.3305	0.4705	0	1
HIGH	0.0689	0.2534	0	1
Road geometric characteristics				
CURVE	0.0692	0.2538	0	1
STRAIGHT	0.1601	0.3667	0	1
WEAVE	0.1025	0.3034	0	1
MLSTREET	0.0526	0.2233	0	1
TWSTREET	0.4074	0.4914	0	1
SSTREET	0.1109	0.3141	0	1
RAMP	0.0973	0.2965	0	1
Environmental factors				
EDGEDENSITY	0.0642	0.0093	0.0413	0.0934
TIME	1.1519	0.3590	1	2

METHODOLOGY

In this section, a microscopic statistical model is presented for relating the dependent variable ATTENTION to the explanatory variables. In order to investigate the relationship between the response variable and the explanatory variables with respect to certain grouping criterion, three grouping strategies are designed as follows: Model I: two groups were defined according to the gender of the subject; Model II: four groups were defined according to the combinations of gender and driving experience of each subject; Model III: three groups were defined according to the speed the test vehicle was running for each video frame, as in Table 5. The three models and their grouping criteria are illustrated in Table 5.

Table 5 Group definition for Model II

Model	Group	Group Description		
		Gender	Driving Experience (in years)	Speed (mph)
I	1	Male		
	2	Female		
II	1	Male	<5	
	2	Male	≥5	
	3	Female	<5	
	4	Female	≥5	
III	1			0-30
	2			30-45
	3			≥45

Based on above description and the discrete response nature of the dependent variable, the random effects ordered probit model was selected in this study. The random effects ordered probit model is a powerful statistical tool for modeling discrete response variables with the effects of the groups (panels) modeled as randomly distributed across the groups (Greene 2000; SAS Institute Inc. 2000), and has been widely used in econometrics, social studies, and transportation related studies as well (Greene 2000, Shafizadeh and Mannering, 2006; Qi et al. 2007; Alsakka and Gwilym 2010). The random effects ordered probit model is specified based on a latent regression as below.

$$y_{it}^{*} = \mathbf{x}'_{it}\boldsymbol{\beta} + u_i + \varepsilon_{it}, \quad i = 1,..., N; t = 1,..., T_i \tag{1}$$

where:

y_{it}^{*} unobserved component;

$\mathbf{x}$ the vector of explanatory variables;

$\boldsymbol{\beta}$ the vector of parameters, including the constant intercept across defined groups;

u_i the unobserved random effects of defined group *i*, which is constant within each group and different across groups, and $u_i \sim Normal(0, \sigma_{\mu}^{2})$;

ε_{it} the random errors and $\varepsilon_{it} \sim Normal(0,1)$;

N total number of groups;

T_i total number of observations for group *i*.

In equation (1), the unobserved component y_{it}^{*} is associated with the explanatory variables, and based on y_{it}^{*}, the observed driver attentional status y_{it} of group *i* for observation *t*, i.e., attention or inattention, is defined as below.

$$y_{it} = \begin{cases} 1 & \text{if } y_{it}^* \leq 0 \text{ (attention)} \\ 2 & \text{if } y_{it}^* > 0 \text{ (inattention)} \end{cases} \tag{2}$$

Based on the normality assumption of the random error terms, the following probabilities can be derived as below:

$$\text{Prob}(y_{it} = 1) = \Phi[-(\mathbf{x}'_{it}\boldsymbol{\beta} + u_i)] \tag{3}$$

$$\text{Prob}(y_{it} = 2) = 1 - \Phi[-(\mathbf{x}'_{it}\boldsymbol{\beta} + u_i)] \tag{4}$$

where $\Phi(\cdot)$ is the standard normal cumulative distribution function. Based on equation (3) and (4), the log-likelihood function for this model can be obtained, and the parameters can be estimated using the maximum likelihood method. In addition, given the parameter estimates, for each realization of the explanatory variables, the probability for each response can be predicted. In the data set used in this study, for each observation, the covariates were collected and assembled for each video frame, and therefore the predicted probabilities are for the instance of each video frame, i.e., at the microscopic level.

EMPIRICAL RESULTS

The empirical results are presented in this section, including the estimation results and the prediction performances for the three models.

Estimation results

The estimation results were presented in Table 6, 7, and 8 for Model I, II, and III, respectively, and following observations can be drawn from the results. First, it can be seen from the results that the random effects are not found to be statistically significant for all the three models. Though disappointing for this study, it is not surprise considering the limited number of groups for all the three models, i.e., 2 for Model I, 4 for Model II, and 3 for Model III, which might limit the statistical variations needed for estimating the random effects.

Second, the driver characteristics and vehicle performance are not found to be statistically significant by all the three models, indicating that these factors investigated in this study do not significantly relate to driver attention allocation. This finding is interesting in meaning that within the data range of this study, there are not many differences in attention allocation for the drivers driving at different speeds.

Third, Model II and Model III found that the traffic characteristic, i.e., the HIGH variable, is significantly related to the driver attention allocation process. The negative sign of the HIGH variable estimate indicates that high traffic requires more eye fixation for the drivers on the primary driving tasks. According to the assumption in this study on using eye fixation as the attentional deployment indicator, this implies that drivers are more attentive when driving in high traffic.

For the road geometric characteristics, all the three models found statistically significant relationship between road geometric characteristics and the driver attention allocation process. Specially, except for the CURVE variable, the negative sign of the STRAIGHT, WEAVE, and RAMP variable estimates indicates that driver are more likely to direct their eye fixations at the primary driving tasks and hence are more attentive when driving on these types of road segments. In addition, the positive sign of the MLSTREET, TWSTREET, and SSTREET variable estimates indicates that drivers are more likely to direct their eye fixations at the non-driving related tasks. Compared with the finding for the above STRAIGHT, WEAVE, and RAMP types of roads, this finding might indicate that drivers have to visually search more widely when driving on these types of roads, which sheds some lights on a higher expectation of accident happening on these roads.

Finally, for the environmental factors, the edge density is not found to be statistically significant for all the three models, and TIME is found to be statistically significant for Model II; in addition, the negative sign of the TIME variable estimate indicates drivers are more attentive when driving in the night.

In summary, the model estimation results showed that traffic characteristics, road geometric characteristics, and time of day are statistically significant in relating to the driver attention allocation process.

Table 6 Estimation results for Model I

Parameter	Estimate	Std. Error	*t*-statistic	*p*-value	
CONSTANT	-0.1115	0.2733	-0.41	0.7533	
Driver characteristics					
AGE	-0.0105	0.0050	-2.10	0.2832	
EXPERIENCE	0.0074	0.0046	1.62	0.3529	
Vehicle performance					
SPEED	-0.0053	0.0022	-2.36	0.2550	
Traffic characteristics					
LIGHT	-0.0285	0.1118	-0.26	0.8409	
MEDIUM	0.2084	0.1128	1.85	0.3157	
HIGH	-0.2914	0.1304	-2.23	0.2679	
Road geometric characteristics					
CURVE	0.1090	0.1132	0.96	0.5120	
STRAIGHT	-0.5157	0.1027	-5.02	0.1252	*
WEAVE	-0.3473	0.1087	-3.19	0.1931	
MLSTREET	0.2314	0.1069	2.16	0.2755	
TWSTREET	0.2049	0.0723	2.83	0.2159	
SSTREET	0.3810	0.1182	3.22	0.1915	
RAMP	-0.1748	0.0937	-1.87	0.3132	
Environmental factors					
EDGE DENSITY	-0.1073	0.0448	-2.40	0.2518	
TIME	-0.1241	0.0947	-1.31	0.4149	
Random effects					
σ_μ	0.0003	0.0278	0.01	0.9934	

Note: * - significant at 15% level.

Table 7 Estimation results for Model II

Parameter	Estimate	Std. Error	*t*-statistic	*p*-value	
CONSTANT	-0.2537	0.2817	-0.90	0.4343	
Driver characteristics					
AGE	-0.0054	0.0036	-1.51	0.2283	
Vehicle performance					
SPEED	-0.0036	0.0022	-1.62	0.2030	
Traffic characteristics					
LIGHT	-0.0780	0.1146	-0.68	0.5451	
MEDIUM	0.1724	0.1155	1.49	0.2322	
HIGH	-0.3481	0.1340	-2.60	0.0806	**
Road geometric characteristics					
CURVE	0.0858	0.1152	0.74	0.5103	
STRAIGHT	-0.6071	0.1056	-5.75	0.0105	***
WEAVE	-0.3493	0.1107	-3.16	0.0511	**
MLSTREET	0.2498	0.1114	2.24	0.1108	*
TWSTREET	0.2134	0.0745	2.86	0.0644	**
SSTREET	0.3802	0.1191	3.19	0.0496	***
RAMP	-0.2266	0.0982	-2.31	0.1044	*
Environmental factors					
EDGE DENSITY	-0.0803	0.0453	-1.77	0.1745	
TIME	-0.1976	0.1005	-1.97	0.1438	*
Random effects					
σ_μ	0.1158	0.0670	1.73	0.1825	

Note: * - significant at 15% level; ** - significant at 10% level; *** - significant at 5% level.

Table 8 Estimation results for Model III

Parameter	Estimate	Std. Error	*t*-statistic	*p*-value	
CONSTANT	-0.3271	0.3049	-1.07	0.3956	
Driver characteristics					
AGE	-0.0094	0.0057	-1.66	0.2380	
GENDER	-0.0094	0.0714	-0.13	0.9071	
EXPERIENCE	0.0068	0.0052	1.31	0.3196	
Traffic characteristics					
LIGHT	-0.1096	0.1146	-0.96	0.4396	
MEDIUM	0.1304	0.1240	1.05	0.4033	
HIGH	-0.3480	0.1411	-2.47	0.1325	*
Road geometric characteristics					
CURVE	-0.0044	0.1118	-0.04	0.9719	
STRAIGHT	-0.5678	0.1019	-5.57	0.0307	***
WEAVE	-0.4072	0.1078	-3.78	0.0635	**
MLSTREET	0.2868	0.1186	2.42	0.1368	*
TWATREET	0.2132	0.0783	2.72	0.1125	*
SSTREET	0.3665	0.1201	3.05	0.0927	**
RAMP	-0.2142	0.1000	-2.14	0.1654	
Environmental factors					
TIME	-0.1100	0.0975	-1.13	0.3763	
EDGE DENSITY	-0.0924	0.0453	-2.04	0.1782	
Random effects					
σ_μ	0.0720	0.0452	1.59	0.2518	

Note: * - significant at 15% level; ** - significant at 10% level; *** - significant at 5% level.

Prediction performance

Based on the estimation results, the prediction performance of the three models are investigated for demonstrating their applicability in detecting driver inattention. Note that for discrete response models, the predicted values are usually in the form of likelihood in that the probability of each response is generated for each observation using the values of independent variables, and a threshold is needed to determine the discrete response based on this probability. In this study, a base threshold of 0.097826 was selected as the percentage of inattention samples in the dataset, and the threshold was multiplied by 1.1, 1.2, 1.3, 1.4, 1.5, 1.6, 1.7, 1.8, 1.9, and 2.0, respectively, to demonstrate the behavior the prediction ability with respect to varying thresholds. In addition, the prediction performance was computed as the percentage of correctly predicted inattention observations, i.e.,

Performance=Count(correctly detected inattention samples)/Count(Inattention samples)×100%.

The prediction results are presented in Figure 2. It can be seen from the prediction performance curves that the three models have similar behavior with respect to the varying thresholds. When the threshold is low, the prediction performance is around 30%, while when the threshold increase to 1.4 times the base threshold, the prediction performance reaches around 60%, and if the threshold increases to 1.6 times the base threshold, the prediction performance reaches around 80%. This prediction performance showed that the proposed models might be workable for detecting driver inattention given an appropriated calibrated threshold value.

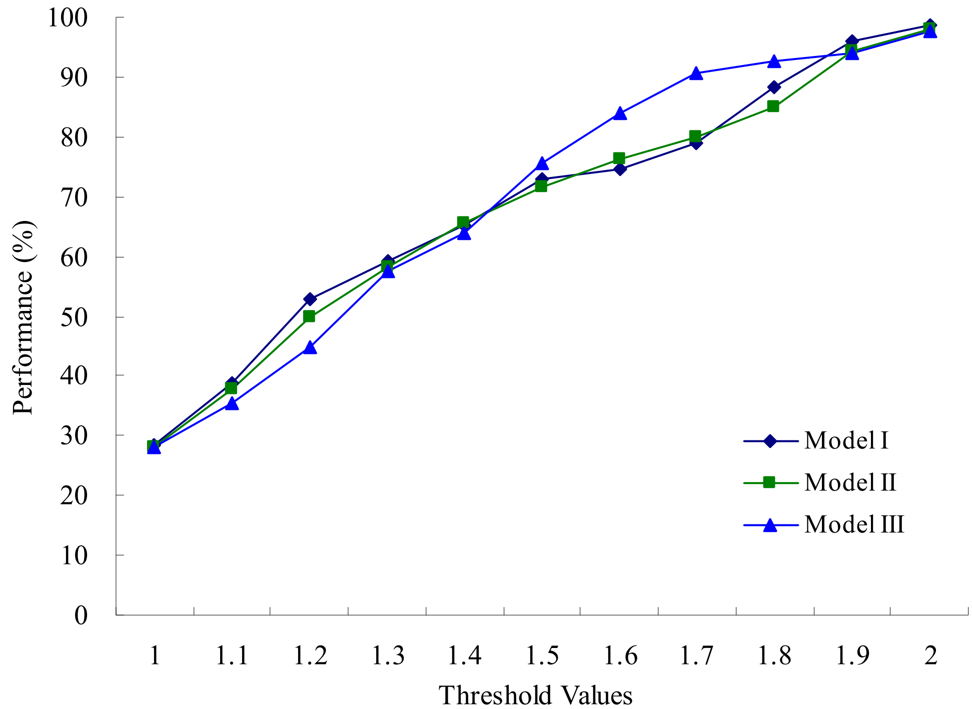

Figure 2 Prediction performance behavior

DISCUSSIONS AND RECOMMENDATIONS

Targeting the driver attention allocation process that plays a vital role in driver distraction research, this paper proposed a microscopic approach that can relate driver attention allocation to explanatory factors, including driver characteristics, vehicle speed, traffic characteristics, road geometric characteristics, and environmental factors indicated by edge density and time of day. Three random effects ordered probit models are designed and tested in this study according to different group definitions. Using the field data collected from in the real world, the estimation results showed that traffic characteristics, road geometric characteristics, and time of day are statistically significant in relating to the driver attention allocation process; in addition, the prediction performances of the three models are investigated, showing similar performance curves with respect to varying thresholds, which indicates a workable driver inattention detection ability of the proposed model can be achieved given an appropriate calibrated threshold value.

Concerning the study in this paper, several remarks can be made as follows. First, in this paper, a simple assumption was made on identifying driver attentional status using eye fixation positions based on a review on previous studies in the field of psychology. This assumption was made in light of the purpose of this paper, in which driver attentional status was used as the response variable for developing a model that can infer driver attentional status from explanatory variables. The authors are aware of many phenomena that have been treated as driver inattention, e.g., using cell phone while driving, listening to music, or fatigue; however, though all these phenomena can be and have been investigated in many studies, for example, in controlled driving simulator studies, they are not suitable for serving as a universal indicator of driver inattention. Therefore, even though this assumption is not true in many cases, e.g., in the so called look-but-not see situation, it is a simple yet workable assumption meeting the purpose of this paper. Concerning this remark, future research can be conducted to further investigate driver attention so as to identify a better attentional status indicator other than eye fixation that is used in this study; in doing so, the new indicator can be used to refine the work proposed in this study.

Second, the eye tracker used in this study will create missing values or dropouts when the driver is looking further away from the road ahead, and in this paper, a sampling strategy is developed for selecting the video frames to be used in the investigation. This strategy will increase the likelihood of selecting more inattention samples, while it will also break the continuity of the elapse of time in the final data sample, limiting the applicability of the model in time continuous applications. Concerning this remark, different types of eye tracking systems, such as head mounted eye trackers, can be used in future research to collect more time continuous eye movement data with wider visual search fields for developing a model that is more suitable for time continuous applications.

Finally, as discussed in the methodology section, the random effects ordered probit model is a powerful tool for discrete response analysis; however, as an emerging field, the authors are expecting to see more tools to be tested in modeling the driver attention allocation process.

In the end, though still in its infancy, driver inattention allocation is certainly an important topic in highway safety study. On one hand, together with an on-going effort by the authors on developing a model of describing the randomness of unexpected events happening in the road environment, the proposed model in this study could serve as a step towards unraveling the mechanisms of the happening of accidents on the highways. On the other hand, together with some auxiliary configurations, the proposed model in this study could be implemented in the on-board devices for vehicles, e.g., the long-haul trucks or the buses, to monitor the attentional status of the drivers based on simple variables that can be collected through on-board devices, so that alert could be provided when the drivers is found to be consistently not paying attention to the primary driving tasks.

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