CHALMERS
UNIVERSITY OF TECHNOLOGY

Understanding Driver Response Patterns to Mental Workload Increase in Typical Driving Scenarios

Citation for the original published paper (version of record):
Liao, Y., Li, G., Li, S. et al (2018). Understanding Driver Response Patterns to Mental Workload Increase in Typical Driving Scenarios. IEEE Access, 6: 35890-35900.
http://dx.doi.org/10.1109/ACCESS.2018.2851309

(article starts on next page)

IEEE Access
Multidisciplinary | Rapid Review | Open Access Journal

Received May 18, 2018, accepted June 20, 2018, date of publication June 28, 2018, date of current version July 19, 2018.

Digital Object Identifier 10.1109/ACCESS.2018.2851309

Understanding Driver Response Patterns to Mental Workload Increase in Typical Driving Scenarios

YUAN LIAO[1], (Student Member, IEEE), GUOFA LI[2], SHENGBO EBEN LI[1], (Senior Member, IEEE), BO CHENG[1], AND PAUL GREEN[3,4]

[1]Department of Automotive Engineering, Tsinghua University, Beijing 100084, China
[2]College of Mechatronics and Control Engineering, Institute of Human Factors and Ergonomics, Shenzhen University, Shenzhen 518060, China
[3]University of Michigan Transportation Research Institute, Ann Arbor, MI 48109, USA
[4]Department of Industrial and Operations Engineering, University of Michigan, Ann Arbor, MI 48109, USA

Corresponding author: Shengbo Eben Li (lishbo@tsinghua.edu.cn)

This work was supported in part by the NSF China under Grant 51575293, Grant 51622504, Grant 51577120, and Grant U1664263, in part by the National Key R&D Program of China under Grant 2016YFB0100906, in part by the Natural Science Foundation of SZU under Grant 2017033, and in part by the International Sci&Tech Cooperation Program of China under Grant 2016YFE0102200.

ABSTRACT As vehicles become more complex and traffic increases, the associated mental workload of driving should increase, potentially compromising driving safety. As mental workload increases (as measured by the detection response time task), does how people drive (as assessed by driving performance and eye fixations) change? How does driving experience impact on such response patterns? To address those questions, data were collected in a motion-based driving simulator. Two driving scenarios were examined, a stop-controlled intersection (high workload—16 participants, 320 trials) and speed-limited highway (low workload—11 participants, 264 trials). In each scenario, in half of the trials, the participants were required to complete or not to complete a distracting secondary task. Hierarchical cluster analysis was used to identify driver response patterns. For highway driving, they are: 1) increased eye fixation variability and unchanged driving performance and 2) unchanged fixation variability and increased mean speed. For intersection driving, they are: 1) increased; 2) decreased fixation variability both with decreased speed (mean and variance); and 3) increased fixation variability with increased speed. Eye fixation variability was more strongly associated with increased mental workload than other driving performance statistics. Furthermore, in contrast to prior research, changes in driving performance and eye fixations were not necessarily correlated with each other as mental workload increased. Novice drivers exhibit higher gaze variability, and they are more prone to maintain vehicle control than experienced drivers.

INDEX TERMS Driver distraction, driving performance, eye fixation, mental workload, multitask.

I. INTRODUCTION

Mental workload "is a multidimensional construct, generally defined as the level of attentional resources required to meet both objective and subjective performance criteria" (chapter 39-1 [1]). Attentional resources are the amount of attention available to perform cognitive tasks that require effort [2]. Mental workload is widely recognized as one of the most important human factors constructs; it is predictive of driving performance and safety [3]. It has been found that many traffic crashes are related to abnormal mental workload, when it is either too low (boredom-caused drowsiness) or too high (distraction) [4]. The mental workload can be inferred from objective measures of task performance and subjective ratings of mental effort [5].

Two common locations for crashes are highways and stop-controlled intersections [4], [6]. There is concern that as technology is added to vehicles, driver mental workload will increase [7]–[10], in particular at those two locations [11]. On highways, speed limit signs are often encountered and drivers should comply with those limits. An increase in mental workload tends to lead to decreased awareness of traffic signs, and therefore, low compliance with speed limits [12]–[14]. In urban driving, stop-controlled intersections are commonly encountered. Driving at non-signalized

intersections is a complex and highly interactive process, whereby each driver makes individual decisions about when, where, and how to complete the required maneuver [15]. Compared to highway driving scenarios, driving through intersections often leads to greater mental workload due to a presence of more traffic and the more complex process of approaching, stopping at, and departing from intersections [16]. Driving through a stop-controlled intersection imposes greater mental workload to drivers than complying with varying speed limit signs. The mental workload of primary driving task differs between those two scenarios. Faced with the increase of mental workload induced by a cognitive secondary task, the response patterns would manifest themselves in different ways [17].

Prolonged high mental workload driving leads to degraded situation awareness [18], but that does not mean that mental workload should always be reduced to relieve drivers from driving tasks. Studies show that decreased mental workload can lead to a driver directing his/her attention away from the primary driving task and thereby affecting his/her ability to retain control of the vehicle in emergency situations [19]. The connection between high driving risk and the low mental workload is complicated. Another mechanism is that boredom (low workload) could also result in dangerous situations due to driver's sleepiness [20]. Thus, driver mental workload should be controlled within an appropriate range to keep an optimal level for safety [21].

Prior research on mental workload and driving [22] has mainly focused on quantitative summaries of driving performance and driver eye fixation statistics. Despite the robust methods and meticulous analysis in prior research, identifying the relationships between those driving performance statistics and eye fixation statistics has not always been insightful. For real-world applications, the detection of driver's increased mental workload has begun incorporating various data sources into consideration [3], [23], enabling new insights into the relationships between those driving performance statistics and eye fixation statistics.

Current analyses of driver's distractions, assessed by either driving performance or eye fixations, are fundamentally stochastic [18]. Prior research concerning driver performance has examined the effects of the mental workload primarily at an aggregate level, by road category. Especially on highways, increased mental workload leads less smooth steering [24] but better lane maintenance [22], [25]. However, different outcomes can occur in complex traffic situations due to different maneuver requirements [11], [26]. Accordingly, one would expect that within road categories, the effect of mental workload on driving performance is maneuver specific. Moreover, the interaction between mental workload imposed by certain tasks and driver's capability is complex where many factors are involved [27]. For instance, one previous study observed that drivers tend to reduce their level of engagement in self-regulated mobile phone tasks to benefit driving performance, and such a tendency is associated with individual difference, e.g., gender [28]. Other efforts have been devoted to eye-related measures. Increased mental workload can lead to significant increases in blink latency [29], fixation duration [30], [31], pupil dilation [32], and decreases in blink duration [33]–[36] and fixation variability [36], [37].

Despite the abundance of research on either of the above-mentioned aspects, there is a shortage of research that provides a comprehensive understanding of driver response patterns to increased mental workload [18], [38]–[41]. As the driving of highways and at intersections are significantly different from each other [16], [17], drivers' response patterns in these two traffic situations need to be determined. Furthermore, as eye-fixation statistics and driving performance statistics are affected by mental workload, they need to be included in analyses of driver response patterns.

Driving experience, related to the individual differences, presents great impacts on in the response to increased mental workload. The youngest drivers had the highest rate of involvement in all police-reported crashes [42], [43]. Given this, and their greater use of technology, it is appropriate that distracted driving research has focused on young drivers [44]. As shown by previous research [45], both novice drivers and more experienced drivers attempt to regulate their behavior in a risk-reducing direction when under added cognitive demand. However, it remains an open question that the extent to which such a self-regulation fully compensates for the impact of added cognitive demand. The effect of risk compensation has been widely observed in the cognitively distracted driving [37], [46]. A comprehensive understanding of underlying mechanisms behind those factors is imperative.

Thus, this paper addresses the following questions.

Q1: As mental workload increases, does how drivers respond change (as assessed driving performance and eye fixations)?

Q2: How does driving experience impact on such response patterns?

We began by constructing highway and stop-controlled intersection scenarios in a driving simulator to imitate real driving situations. A total of 27 participants were recruited to drive through the intersections and on highways with and without a concurrent secondary task. Such a cognitive task is applied to induce mental workload increase. Both driving performance and eye fixation statistics were collected to characterize drivers' response patterns. To quantify a driver's mental workload, we collected driver response times to an LED light, the Detection Response Task (DRT) [17], [26], [47], [48], the standard method identified by ISO Technical Committee 22/Subcommittee 39 (Ergonomics of Road Vehicles) for that purpose. The theory behind DRT is that visual attention narrows as mental workload increases [48]. That method has been shown to be low-demand, minimally intrusive, and reliable in assessing driving mental workload [47], [48].

Driver response patterns to increasing mental workload have two facets, the change of value regarding their driving performance and eye fixations, and the correlations of such changes across different types of statistics. Previous efforts

focus on how the mean or variance of some performance measure changes with the increased mental workload. In this study, we explored drivers' response patterns to two levels of mental workload (non-distracted and cognitively distracted), on highways and at intersections, as characterized by several statistics of driving performance and eye fixation measures examined using clustering analysis. Cluster analysis is a descriptive data mining method that can produce new, non-trivial information based on the available data set [49]. The main objective of clustering analysis is to organize data into sensible groups/patterns. We found two patterns for highway and three patterns for stop-controlled intersection situations. We then analyzed the correlation between indicators within each pattern to reveal how driving performance, eye fixation statistics, and mental workload relate to each other.

II. METHODS

A. ETHICS STATEMENT

The experimental procedures were approved by Tsinghua University's institutional review board. The authors performed these procedures in accordance with the approved guidelines, obtaining informed consent from each participant before conducting the experiments.

B. PARTICIPANTS

Twenty-six licensed drivers (17 male, 10 female) from 20 to 53 years old, participated in the experiment. Eleven participated in the scenario of stop-controlled intersections; 6 ages 20 to 30 (4 male, 2 female) and 5 ages 46 to 53 (3 male, 2 female). Sixteen participated in the speed-limited highway; 8 ages 20 to 30 (5 male, 3 female) and 8 ages 46 to 53 (5 male, 3 female). Within each scenario, there were two age groups with a balanced gender distribution; a young group (20-35 years old) and an older group (above 45 years old). Driving experience, represented by license year, was found significantly correlated with age (Pearson correlation test, $r = 0.68, p = 0.022$) where p represents how significant the test result is ($p < 0.05$ represents significant result, same following). Between the two driving scenarios, there was no significant differences in the age (Independent T-test, $t_{26} = 0.1$, $p = 0.9$) or gender distribution (Chi-square test, $p = 1.000$).

C. APPARATUS

A motion-based driving simulator was used in this study (Figure 1). It consists of a visual simulation unit, an audio simulation unit and a motion simulation unit [50]. The Visual simulation consists of 5 screens, 3 for the front and 2 for rear view, providing 200 degrees forward and 55 degrees rear field of view. The motion simulation unit is a six degree-of-freedom hexapod. The audio system provides simulated engine, road, and traffic sounds. The location of vehicles and driving performance data (calculated from speed, acceleration/deceleration, steering angle, etc.) were automatically logged.

FIGURE 1. Motion-based simulator.

The location of vehicles in the scene, vehicle movement parameters (e.g., speed, acceleration/deceleration) and driver control actions, (e.g., steering angle) were automatically recorded. A Smart Eye Pro 5.8 was adopted to collect and process the eye fixation data. A Quality Indicator, between 0 (poor) and 1 (excellent), was provided by the eye tracker software. To increase the data quality, a filtering process was applied where each data point with quality indicator that was less than or equal to 0.5 was replaced by the mean of two other closest valid samples in the sequence that had quality indicators greater than 0.5.

The cognitive secondary task was embedded in an in-vehicle tablet located on the right side next to the dashboard. The secondary task would be automatically triggered by serial communication between the tablet and the simulator. All the data were logged at 60Hz and synchronized with the driving data.

Detection response task (DRT) was used to assess the mental workload imposed by a concurrent task, with longer response times indicated greater mental workload [51]. Based on our previous studies [17], the DRT was implemented using a head-mounted LED stimuli. In this study, DRT was implemented in all the experiment trials. The mean response time was used to quantify the mental workload of drivers.

D. EXPERIMENT DESIGN

1) DRIVING SCENARIOS

a: SPEED-LIMITED HIGHWAY

See Figure 2 (right half). In this low-workload scenario, participants were required to drive in the middle lane of a straight, flat road. There was no turning, no change of direction, and changing lanes was not permitted. Adjusting their speed was the primary task in this scenario. Participants were instructed to comply with varying posted speed limits (minimum 60 kmh to 80 kmh, maximum speed 80 kmh to 100 kmh). Participants were encouraged to save time, driving from one location to another one within the encountered speed limit. The segment of the trial examined was from 300 m before to 150 m after the speed limit sign.

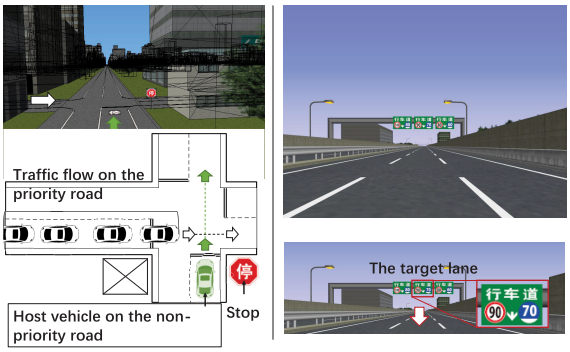


FIGURE 2. Driving scenarios (left to right: stop-controlled intersection, speed-limited highway).

b: STOP-CONTROLLED INTERSECTION

See Figure 2 (left half). In this high-workload scenario, participants were instructed to cross a stop-controlled intersection along a straight, flat, and non-priority road. They maintained a speed of approximately 40 km/h and complied with all traffic rules. On the priority (intersecting) road, there were 4 crossing vehicles driving at a speed of 40 km/h. The time headway [52] between each two vehicles varied randomly from 1 s to 3 s. The appearance of these 4 vehicles was triggered by the location of the host vehicle passing 60 m before the center of intersection. The segment of the trial examined was from 130 m before to 30 m after the intersection center.

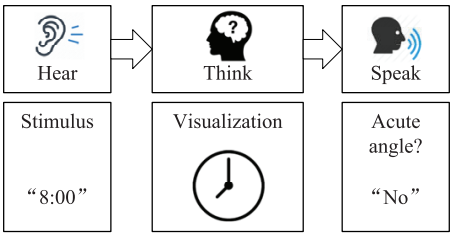


FIGURE 3. Clock task. Upon hearing a clock time (e.g., 10:30), a participant is required to visualize the location of the hour and minute hands and say whether those hands form an acute angle.

2) COGNITIVE SECONDARY TASK

The clock task is applied to induce increased mental workload. The clock task involves the visualization of the clock hands related to visuospatial working memory [53], [54]. See Figure 3. When participants approach an intersection or a speed limit sign, the secondary task was automatically triggered. Participants were presented a series of 3 randomized clock times (1:00-12:59) with 5 s between successive presentation. Two seconds before each intersection, participants were given an auditory prompt [54]. They were required to provide correct answers to the three clock times as quickly as possible.

3) EXPERIMENT ARRANGEMENT

For both driving scenarios, the secondary task presence (clock task = distracted/no clock task = not distracted) was treated as a within-subject factor, and thus, the experiment was a repeated-measure design. To minimize learning effects, the order of the two scenarios was counterbalanced between participants. Before data collection, participants practiced the clock task and simulator driving until they were proficient. For each participant, 24 trials were collected for the intersection scenarios and 20 for the limited highway scenario.

E. HIERARCHICAL CLUSTERING

In this study, the driving performance and eye fixation data were regarded as an integrated output to characterize driver response patterns to mental workload increase.

Hierarchical clustering was adopted with the data of 7-dimensional feature vector. The clustering procedure involved 1) data standardization, 2) distance calculation, 3) linkage establishment and 4) splitting the linkage into clusters. For data standardization, the z-score method was applied to all observations of each feature. For the distance calculation, the squared Euclidean distance, widely adopted in previous studies, was applied [55]. To establish cluster linkages, Ward's method was used where the decrease in variance for the cluster being merged [56]. In that method, sensible clustering is measured by the small sum of squares of deviations within the same cluster. By limiting the cluster number less than five, the final clusters of all collected feature vectors were formulated.

F. STATISTICAL ANALYSIS

Through clustering, the patterns of those variance changes can be extracted. As a typical multivariate data in this study, Andrews' Curves were used to code and represent multivariate data by linear transformed curves displayable as 2D structures [57]. For every cluster, each multivariate observation $\triangle D_i = [\triangle d_{i,1}, \triangle d_{i,2}, \ldots, \triangle d_{i,n}]$ $(n = 7)$ is transformed into a curve as follows:

$$f_i(t) = \frac{\triangle d_{i,1}}{\sqrt{2}} + \sum_{k=2}^{n} \triangle d_{i,k} \{[\mathrm{mod}(k/2) + 1] \cdot \sin(\lfloor k/2 \rfloor \cdot 2\pi t) + \mathrm{mod}(k/2) \cos(\lfloor k/2 \rfloor \cdot 2\pi t)\} \quad (1)$$

such that the observation represents the coefficients of a so-called Fourier series ($t \in [0, 1]$), where the $f_i(t)$ represents the indicator by Fourier transform from a measure i.

The feature distributions within each cluster reveal how driving performance and eye fixations change corresponding with mental workload. Subsequently, the distributions of feature's value change can be interpreted and summarized into patterns. Using the correlations between features within each cluster, the interacting mechanisms of mental workload, driving performance and eye fixations were revealed.

To explore how the mental workload of the primary driving task affects driver response patterns to increased mental workload, the quantified mental workload for non-distracted driving serves as an independent variable. The patterns are assumed as dependent on the mental workload of driving environment.

III. RESULTS

One event sample refers to crossing a speed limit sign and stop-controlled intersection respectively in the two scenarios; speed-limited highway and stop-controlled intersection. We collected 20 speed limit sign encounters and 24 intersection crossings for each participant. Therefore, we collected 320 samples from the speed-limited highway (16 participants) and 264 samples from the stop-controlled intersection (11 participants). The number of distracted driving episodes and non-distracted driving episodes was equal for every participant in each scenario.

Four driving performance statistics, three eye-fixation statistics, and mental workload determined using the DRT task were analyzed (Table 1). Previously, we found that eye fixation statistics predict of cognitive distraction in both scenarios. Furthermore, we found that for the stop controlled intersections, use both eye fixation and driving performance data led to the best workload predictions whereas for the speed-limited highway, using both sets of statistics did not lead to significantly better predictions than just using the eye-fixation data alone [17]. So, in this study, we (1) added the standard deviation of head heading angle and eye fixation, and (2) modified the selection of driving performance statistics based on our further research.

All the calculated statistics as denoted by d were regarded as paired data; non-distracted driving (d_n) and distracted driving (d_s) within each participant. As the only difference was the mental workload associated with cognitive distraction, their differences, $\triangle d$ ($\triangle d = d_s - d_n$) were adopted as the features to characterize the driver response patterns. Therefore, for speed-limited highway, the number of observations involved into clustering is 160. For stop-controlled intersection, the number of observations involved into clustering is 132. The analysis target in our study is the response effects, in terms of defined features, caused by the increased mental workload in comparison with the baseline driving (non-distracted driving).

As shown in Table 1, the changes of driving performance and eye fixation statistics in response to increased mental workload are defined as "patterns." Driving performance and eye fixation statistics form the feature set of driver response pattern to mental workload [4], [17], [26]. RT (response time) was used to directly quantify the driver mental workload during distracted driving and non-distracted driving, as an explanatory variable for the observed driver response patterns. The driving performance was decomposed into lateral control (steering) assessed by S_{std} and L_{std}, and longitudinal control (speed) assessed by V_{std} and V_m, whereas the eye fixations consisted of two directions, vertical and horizontal. For instance, some drivers may display more abrupt steering control but smoother speed control with increased fixation variability along vertical direction but decreased along the horizontal direction.

TABLE 1. Definitions of applied measures and statistics.

Category	Measure		Statistic
Driver response pattern	Driving performance	V_{std} (km/h)	Standard deviation of velocity
		V_m (km/h)	Mean velocity
		S_{std} (°)	Standard deviation of steering angle
		L_{std} (m)	Standard deviation of lateral position
	Eye fixation	Gx_{std} (°)	Standard deviation of horizontal gaze location
		Gy_{std} (°)	Standard deviation of vertical gaze location
		H_{std} (rad)	Head heading angle
Ground truth	Measured mental workload	RT (ms)	Mean response time to the LED stimuli

TABLE 2. Clustering results: cluster center and *RT*. N represents number of observations within each cluster; one cluster of the stop-controlled intersection is removed due to its size being below 10. ** denotes significance at 95% confidence interval. * denotes significance at 90% confidence interval.

Scenario	Highway		Stop-controlled intersection		
Cluster	OSC	NSI	OSC	USC	OSI
N	113	47	41	46	37
$\triangle V_{std}$	0.029	-1.872**	-1.988**	-1.889**	3.512**
$\triangle V_m$	0.15	1.917*	-4.432**	-4.130**	8.976**
$\triangle S_{std}$	0.231**	0.124	-0.462**	-0.506**	0.363
$\triangle L_{std}$	0.195**	0.322	-0.010*	-0.016*	0.011
$\triangle H_{std}$	0.002**	-0.012**	0.002	-0.042**	0.009*
$\triangle Gx_{std}$	0.137*	-0.109	-0.214	-3.407**	0.113
$\triangle Gy_{std}$	0.925**	-0.272	1.455**	-0.448	1.038**
RT_B	552.9	695.4	703.4	977.9	721.8
$\triangle RT$	266.8**	275.3**	197.7**	56.4	114.9*

A. CLUSTER ANALYSIS TO CHARACTERIZE DRIVER RESPONSE PATTERNS

For each driving scenario, there are a couple of clusters with a different number of observations (Table 2). To find whether a cluster feature displays significant value change affected by mental workload increase, the Single T test was adopted on the value difference (i.e., $\triangle d$) to test if there is a significant difference between distracted driving and non-distracted driving. Response time (RT, ms) is also reported as a reference quantifying driver mental workload.

The stop-controlled intersection has higher mental workload, which is confirmed by the measured mental workload of non-distracted (baseline) driving (RT_B). However, within each driving scenario, the mental workload of either non-distracted driving or distracted driving, varies between clusters. associate with the cognitive distraction is $\triangle RT$, the increase above the baseline.

According to the change in descriptive statistics for each cluster, we can name each cluster based on their driving performance (control) and eye fixation (scan) change in response to the mental workload increase (Table 3). The fixation

TABLE 3. Explanations of cluster name.

Scenario	Cluster	Explanation
Highway	overscan-control (OSC)	Increased fixation variability and unchanged driving performance
	Neutral-scan-control (NSI)	Unchanged fixation variability and increased average speed
Intersection	overscan-control (OSC)	Increased fixation variability and decreased speed (mean value and variance)
	Under-scan-control (USC)	Decreased fixation variability and decreased speed (mean value and variance)
	overscan-inability (OSI)	Increased fixation variability and increased speed (mean value and variance)

variability refers to $\triangle Gx_{std}$ and $\triangle Gy_{std}$, and the driving performance refers to the main tasks in the two scenarios, i.e., speed control (adjusting speed in the speed-limited highway and the slowing down in the stop-controlled intersection). The speed control performance consists of its mean value and variance during the time history of each trial ($\triangle V_{std}$, $\triangle V_m$).

To illustrate how those clusters/patterns differ with each other, the clustering results are further presented through Andrew's Curves [58], an approach of dimension-reducing visualization. Multiple variables are fed into a Fourier transform to be represented with one variable. More details can be found in section Statistical Analysis. See Figure 4.

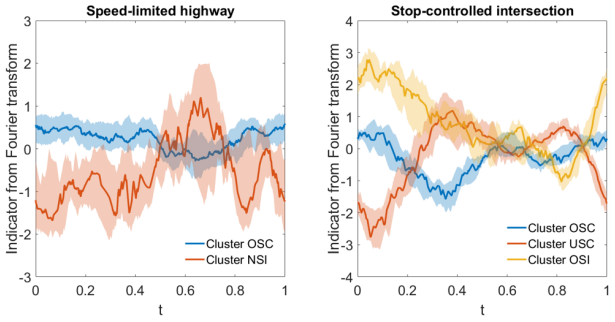


FIGURE 4. Andrews' curves of clusters' observations (standardized, 25%-75% data range). It is observed that different clusters/patterns differ with each other significantly in their profiles for both scenarios.

1) SPEED-LIMITED HIGHWAY

In this scenario, the eye fixations along the vertical direction are associated with frequently glancing at the speed limit sign. The gaze along horizontal direction is focused on lane keeping when steering is needed.

The extracted two clusters on highways could be summarized as overscan-control (OSC) and neutral-scan-control (NSI) (Figure 5, left). Cluster OSC shows significantly increased abruptness of lateral control, increased vertical fixation variability with unchanged longitudinal control. As for cluster NSI, its observations show smoother longitudinal control (with increased speed), more abrupt

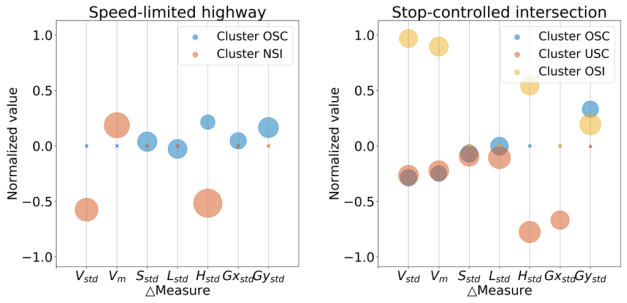


FIGURE 5. The normalized value of cluster centers. The marker 'x' represents the value of measure change that is not significantly different with zero as shown in Table 2.

lateral control and decreased fixation variability. Regarding the mental workload for non-distracted driving, cluster NSI is significantly larger than cluster OSC (ANOVA test, $F(1, 158) = 9.37, p = 0.003$) where the larger the F statistic, the more significant difference (same following). However, the mental workload increase of two clusters are similar according to RT_B.

2) STOP-CONTROLLED INTERSECTION

In this scenario, the safe execution of the major task is to slow down to avoid conflict with the traffic on priority road. Eye fixations along the vertical axis (looking ahead) are the most relevant. Similarly, with the speed-limited highway, the gaze along horizontal direction is focused on lane keeping.

The extracted three clusters at stop-controlled intersections could be summarized as overscan-control (OSC), under-scan-control (USC), and overscan-inability (OSI). All clusters have a similar number of observations. See Figure 5 (right). Cluster OSC is characterized by increased vertical and decreased horizontal eye fixation variability with improved vehicle control; speed is lower and control abruptness is decreased. Cluster USC has decreased fixation variability vertically and horizontally, similarly existing improved vehicle control. Cluster OSI is far different with the other clusters; it displays increased fixation variability and impaired vehicle control indicated by increased speed, more abrupt speed control (larger standard deviation). Except for cluster OSC and OSI, the mental workload of all clusters differ from each other (multi-variable paired T-test, corrected using LSD, $p < 0.01$). Unlike the speed-limited highway, all the patterns with decreased speed also show improved lateral control (less abrupt steering).

B. INTERACTION MECHANISMS BETWEEN MENTAL WORKLOAD, EYE FIXATION, AND DRIVING PERFORMANCE

After describing the extracted patterns, in this section, we present within-cluster correlation analysis between those value changes to explore the interaction mechanism between mental workload, eye fixations, and driving performance statistics. See Figure 6. All correlations are statistically significant ($p < 0.05$).

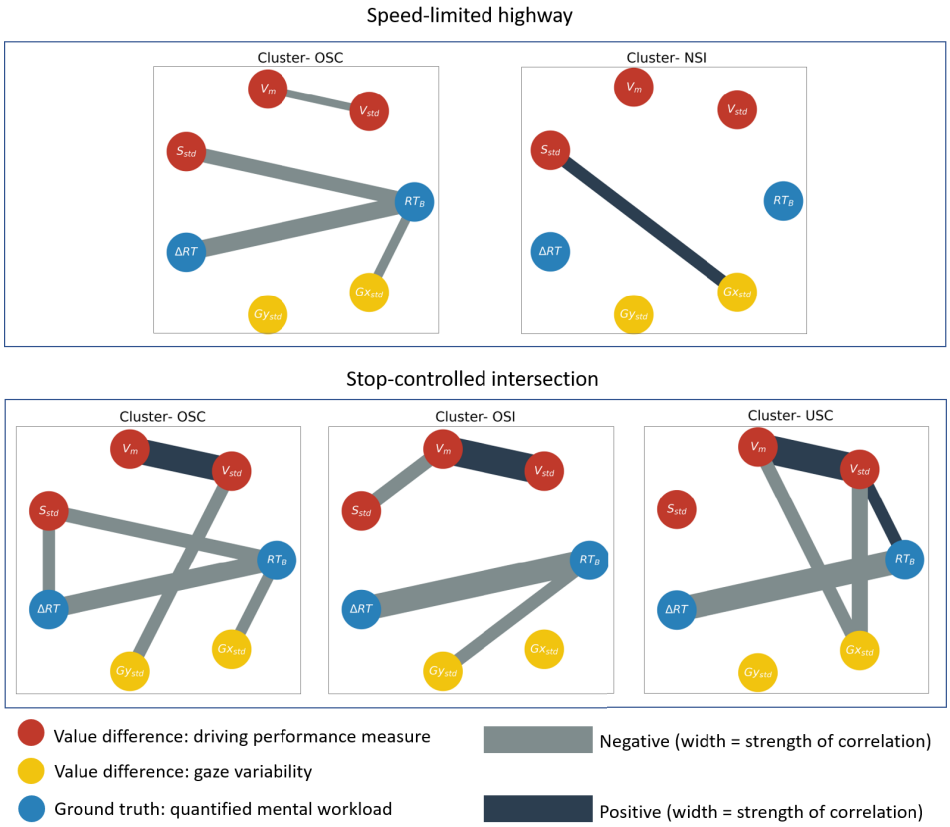


FIGURE 6. Results of within-cluster correlation analysis. Each node represents the value change of a certain statistic including driving performance, gaze variability, and quantified mental workload. The connection between a pair of nodes represents a significant correlation, either negative or positive, where the width of connection is proportional to the absolute value of correlation coefficient.

1) SPEED-LIMITED HIGHWAY

For cluster OSC, RT_B has a significant effect on the change of horizontal fixation variability and the change of steering angle variance. For such OSC pattern, higher mental workload during non-distracted driving indicates less change in the latter two indicators in response to cognitively distracted driving. For cluster NSI, the change of horizontal fixation variability and the change of steering angle variance have a significant positive correlation. Cluster NSI displayed higher mental workload than cluster OSC. In cluster NSI, the increased fixation variability did not improve lateral control as the steering angle variance tends to increase.

2) STOP-CONTROLLED INTERSECTION

Compared to a low-workload speed-limited highway, more correlations within each cluster are observed for the stop-controlled intersection. Increased mental workload ($\triangle RT$) due to the clock task is correlated with the mental workload of the primary driving task (RT_B). When RT_B increases, $\triangle RT$ decreases, although sometimes it does not change significantly. Similarly, longitudinal control; the change of V_m and V_{std} due to cognitive distraction change in the same direction.

Response time, as the measured mental workload can explain the change of eye fixation variability and driving performance. For cluster OSC, RT_B has a negative correlation with the change of both steering variance and horizontal fixation variability. The similar effect of the mental workload of the primary driving task can be found within cluster USC; higher mental workload for non-distracted driving is correlated to improved driving performance, in particular, longitudinal control (decreased speed). For cluster OSI, there is no correlation found between mental workload and driving performance. For the overscan- patterns, a higher mental workload of the primary driving task is associated with the decreased change of fixation variability. For control patterns alone, correlations between the change of fixation variability and the change of driving performance are found; larger change of vehicle control is associated with a smaller change of fixation variability.

C. IMPACTS OF DRIVING EXPERIENCE

The cluster distribution explained by age group for two driving scenarios is shown in Table 4. Indicated by Chi-square test, the distribution between novice group and experienced group significantly differ with each other for both

TABLE 4. Cluster distribution of observations across two age groups. Chi-square test (two-sided) for the impact of age group on the frequency distribution of clusters: Speed-limited highway has $\chi_1^2 = 21.962$, $p < 0.001$, and Stop-controlled intersection has $\chi_2^2 = 15.903$, $p = 0.001$.

Age group	Highway		Intersection		
	OSC	NSI	OSC	USC	OSI
Young / novice	70	10	25	17	28
Older / experienced	43	37	16	29	9

driving scenarios. For speed-limited highway, experienced drivers have more observations belonging to NSI. While for stop-controlled intersection, experienced drivers have most observations that are categorized into cluster USC contrary to which, most observations of novice drivers belong to OSC and OSI.

IV. DISCUSSION

Primary driving task affects drivers' response patterns to increased mental workload imposed by cognitive secondary task. In this study, speed adjustment (longitudinal control) is the major task, either changing speed to a regulated range in speed-limited highway or slowing down at the stop-controlled intersection. The stop-controlled intersection has a higher mental workload of the primary driving task. Among identified six clusters, response time (RT_B) is widely correlated with driving performance and eye fixation statistics. One implication here is the importance of doing task analysis for different driving scenarios to create red lines of mental workload.

The change of driving performance and eye fixation statistics for characterizing driver response patterns to increased mental workload were found to occasionally correlate with each other. Many previous studies suggests decreased fixation variability tends to impair driving safety [36], [59]. In the cluster IN-USC, decreased fixation variability was associated with increased mental workload. However, that decrease was not always linked to degraded driving performance. Therefore, driving performance indicators are not sufficient to predict potential risk imposed by a mental workload increase, which is more consistently associated with minimized fixation variability. In the stop-controlled intersection scenario, Cluster USC has observations of a high mental workload for non-distracted driving. The mental workload imposed by the cognitive secondary task is not detected by DRT (no significant change on $\triangle RT$). When the resource supply is reaching the upper limit due to increased mental workload, the supplying efficiency decreases [18]. In the Cluster USC of the stop-controlled intersection, the driver chooses to dramatically slow down in advance to compensate for the decreased supply of attention resources. In that case, driving performance is consequently improved as the main task of passing through a stop-controlled intersection is to efficiently slowing down to avoid a collision. However, considering the equivalent real-world scenario, what if there is rear traffic queue behind the subject vehicle where slowing down too early is not advisable or not socially accepted? It is more likely to obtain accurate prediction by combining eye fixation statistics with driving contexts. It is also suggested that directly monitoring driver eye fixation is promising as compared to the highly diversified driving behavior of compensation for the decrease supplying of attention, increased mental workload is more consistently associated with the change of fixation variability.

Yet, knowing mental workload status is the first step for effective risk reduction. In a previous review [37], of mobile phone distraction, although engaging in phone use increased mental workload, the effects on crash involvement were not consistent, indicating either an increase in crash involvement or negligible effects. Such an inconsistency is partly due to the complexity of how drivers react on the increased mental workload, which is intermediated by many factors, such as driving scenario and driving experience that are explored in the present study. Although the causal relationship between mental workload and driving safety is not fully established in the present study, we do get some implications. For instance, the primary driving task can explain those extracted patterns to some degree. Therefore, the current study implies a more context-aware way of providing feedback to guide appropriate driving behavior. For example, the detected increased mental workload could be integrated based on specific driving environment considering historical records of compensation capability.

Previous research indicates that it remains an open question that the extent to which such self-regulation fully compensates for the impact of added cognitive demand [45]. In the present study, the results imply that in response to increased mental workload, novice drivers exhibit higher gaze variability and they are more prone to maintain vehicle control than experienced drivers. More observations from experienced drivers present insufficient compensation to increased mental workload. Consistent with that previous study, the age group where drivers were in their 40s exhibited higher tendency of risk-taking. Over-confidence and awareness of accumulated driving experience might lead to low willingness and less self-regulation in response to higher-workload driving.

There are two major ways to produce driver cognitive distraction: real-world secondary task and surrogate task [60]. Compared to real-world secondary tasks, those surrogate secondary tasks have advantages in easy implementation, repetition, and measurable and scalable workload production. The focus of current study is driver's response patterns to increased mental workload. Therefore, we chose to use surrogate secondary tasks. One way to generalize or extend the findings to various cognitive distractions is to apply DRT to measure mental workload and to apply metrics of driving performance and eye fixation as we did in the present study. However, real-world secondary tasks (e.g., mobile phone use) may make differences on drivers' behaviour [28], [37]. In further studies, real-world secondary tasks need to be considered.

V. CONCLUSION

We found 2 response patterns in the highway driving, and 3 response patterns in the urban driving. The patterns defined in this study were interpreted by the cluster centers in terms of the change direction of eye fixation and driving performance. In speed-limited highway (lower demand on mental workload), the two patterns are overscan-control and neutral-scan-inability. In stop-controlled intersection (higher demand on mental workload), the three patterns are overscan-control, under-scan-control and overscan-inability. Results indicate that unlike many previous studies, the tendencies of driving performance and eye fixation are actually not necessarily correlated with each other with increased mental workload. Compared to highly diversified driving performance, mental workload is more consistently associated with the change of eye fixation variability. Regarding the impact of driving experience, in response to increased mental workload, novice drivers exhibit higher gaze variability and they are more prone to maintain vehicle control than experienced drivers.

There are two main limitations of this study in terms of sample size and real-world verification. The sample size of this paper was relatively small; 27 participants were included. Observations of different drivers were mixed and fed to clustering process and followed analysis. However, given small sample size carefully considered, rigorous analysis methods were applied to avoid over-interpretation of obtained data sets. All the data were collected based on a driving simulator, the simulator was motion based with high fidelity scenes. Accordingly, further verification of those findings is needed in real-world traffic.

VI. ACKNOWLEDGMENT

(Yuan Liao and Guofa Li contributed equally to this work.)

REFERENCES

[1] M. S. Young and N. A. Stanton, "Mental workload," in *Handbook of Human Factors and Ergonomics Methods*, N. A. Stanton, A. Hedge, K. Brookhuis, E. Salas, and H. W. Hendrick, Eds. London, U.K.: Taylor & Francis, 2005, ch. 39.

[2] S. Blanchet, "Attentional resources theory," in *The Encyclopedia of Adulthood and Aging*. Hoboken, NJ, USA: Wiley, 2016.

[3] J. C. De Winter, R. Happee, M. H. Martens, and N. A. Stanton, "Effects of adaptive cruise control and highly automated driving on workload and situation awareness: A review of the empirical evidence," *Transp. Res. F, Traffic Psychol. Behav.*, vol. 27, pp. 196–217, Nov. 2014.

[4] K. A. Brookhuis and D. de Waard, "Monitoring drivers' mental workload in driving simulators using physiological measures," *Accident Anal. Prevention*, vol. 42, no. 3, pp. 898–903, 2010.

[5] T. B. Sheridan and R. Simpson, "Toward the definition and measurement of the mental workload of transport pilots," Dept. Aeronaut. Astronaut., Flight Transp. Lab., Massachusetts Inst. Technol., Cambridge, MA, USA, Tech. Rep. R79-4, 1979.

[6] T. Bryer, "Stop-controlled intersection safety through route activated warning system," Vehicle Res. Test Center, Federal Highway Admin. Office Safety, Nat. Highway Traffic Safety Admin., U.S. Dept. Transp. Federal Motor Carrier Safety Admin., Washington, DC, USA, Tech. Rep. FHWA-SA-11-015, 2011.

[7] S. P. McEvoy, M. R. Stevenson, and M. Woodward, "The prevalence of, and factors associated with, serious crashes involving a distracting activity," *Accident Anal. Prevention*, vol. 39, no. 3, pp. 475–482, 2007.

[8] P. M. Salmon and M. G. Lenné, N. A. Stanton, D. P. Jenkins, and G. H. Walker, "Managing error on the open road: The contribution of human error models and methods," *Saf. Sci.*, vol. 48, no. 10, pp. 1225–1235, 2010.

[9] A. Stuiver, K. A. Brookhuis, D. de Waard, and B. Mulder, "Short-term cardiovascular measures for driver support: Increasing sensitivity for detecting changes in mental workload," *Int. J. Psychophysiol.*, vol. 92, no. 1, pp. 35–41, 2014.

[10] V. D. Blondel, A. Decuyper, and G. Krings, "A survey of results on mobile phone datasets analysis," *EPJ Data Sci.*, vol. 4, p. 10, Feb. 2015.

[11] T. A. Ranney, "Driver distraction: A review of the current state-of-knowledge," Vehicle Res. Test Center, Federal Highway Admin. Office Safety, Nat. Highway Traffic Safety Admin., U.S. Dept. Transp. Federal Motor Carrier Safety Admin., Washington, DC, USA, Tech. Rep. HS-810 787, 2008.

[12] K. Brookhuis and D. de Waard, "Limiting speed, towards an intelligent speed adapter (ISA)," *Transp. Res. F, Traffic Psychol. Behav.*, vol. 2, no. 2, pp. 81–90, 1999.

[13] C. J. D. Patten, A. Kircher, and J. Östlund, and L. Nilsson, "Using mobile telephones: Cognitive workload and attention resource allocation," *Accident Anal. Prevention*, vol. 36, no. 3, pp. 341–350, 2004.

[14] J. Törnros and A. Bolling, "Mobile phone use—Effects of conversation on mental workload and driving speed in rural and urban environments," *Transp. Res. F, Traffic Psychol. Behav.*, vol. 9, no. 4, pp. 298–306, 2006.

[15] M. Liu, G. Lu, Y. Wang, and Z. Zhang, "Analyzing drivers' crossing decisions at unsignalized intersections in China," *Transp. Res. F, Traffic Psychol. Behav.*, vol. 24, pp. 244–255, May 2014.

[16] M. Plavšić, "Analysis and modeling of driver behavior for assistance systems at road intersections," Ph.D. dissertation, Fac. Mech. Eng., TU München, München, Germany, 2010.

[17] Y. Liao, S. E. Li, W. Wang, Y. Wang, G. Li, and B. Cheng, "Detection of driver cognitive distraction: A comparison study of stop-controlled intersection and speed-limited highway," *IEEE Trans. Intell. Transp. Syst.*, vol. 17, no. 6, pp. 1628–1637, Jun. 2016.

[18] M. S. Young, K. A. Brookhuis, C. D. Wickens, and P. A. Hancock, "State of science: Mental workload in ergonomics," *Ergonomics*, vol. 58, no. 1, pp. 1–17, 2015.

[19] N. A. Stanton, M. Young, and B. McCaulder, "Drive-by-wire: The case of driver workload and reclaiming control with adaptive cruise control," *Saf. Sci.*, vol. 27, nos. 2–3, pp. 149–159, 1997.

[20] K. Kircher and C. Ahlstrom, "Minimum required attention: A human-centered approach to driver inattention," *Hum. Factors*, vol. 59, no. 3, pp. 471–484, 2017.

[21] B. Reimer and B. Mehler, "The impact of cognitive workload on physiological arousal in young adult drivers: A field study and simulation validation," *Ergonomics*, vol. 54, no. 10, pp. 932–942, 2011.

[22] J. He, J. S. McCarley, and A. F. Kramer, "Lane keeping under cognitive load: Performance changes and mechanisms," *Hum. Factors*, vol. 56, no. 2, pp. 414–426, 2014.

[23] Y. Dong, Z. Hu, K. Uchimura, and N. Murayama, "Driver inattention monitoring system for intelligent vehicles: A review," *IEEE Trans. Intell. Transp. Syst.*, vol. 12, no. 2, pp. 596–614, Jun. 2011.

[24] I. Pavlidis *et al.*, "Dissecting driver behaviors under cognitive, emotional, sensorimotor, and mixed stressors," *Sci. Rep.*, vol. 6, May 2016, Art. no. 25651.

[25] Y. Liang and J. D. Lee, "Combining cognitive and visual distraction: Less than the sum of its parts," *Accident Anal. Prevention*, vol. 42, no. 3, pp. 881–890, 2010.

[26] J. L. Harbluk, Y. I. Noy, P. L. Trbovich, and M. Eizenman, "An on-road assessment of cognitive distraction: Impacts on drivers' visual behavior and braking performance," *Accident Anal. Prevention*, vol. 39, no. 2, pp. 372–379, 2007.

[27] R. Fuller, "Towards a general theory of driver behaviour," *Accident Anal. Prevention*, vol. 37, no. 3, pp. 461–472, 2005.

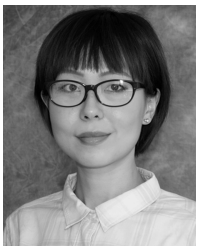
[28] O. Oviedo-Trespalacios, M. M. Haque, M. King, and S. Demmel, "Driving behaviour while self-regulating mobile phone interactions: A human-machine system approach," *Accident Anal. Prevention*, to be published.

[29] V. Faure, R. Lobjois, and N. Benguigui, "The effects of driving environment complexity and dual tasking on drivers' mental workload and eye blink behavior," *Transp. Res. F, Traffic Psychol. Behav.*, vol. 40, pp. 78–90, Jul. 2016.

[30] E. Schmidt, R. Decke, and R. Rasshofer, "Correlation between subjective driver state measures and psychophysiological and vehicular data in simulated driving," in *Proc. IEEE Intell. Vehicles Symp. (IV)*, Jun. 2016, pp. 1380–1385.

[31] Y. Liang, J. D. Lee, and L. Yekhshatyan, "How dangerous is looking away from the road? Algorithms predict crash risk from glance patterns in naturalistic driving," *Hum. Factors*, vol. 54, no. 6, pp. 1104–1116, 2012.

[32] T. M. Gable, A. L. Kun, B. N. Walker, and R. J. Winton, "Comparing heart rate and pupil size as objective measures of workload in the driving context: Initial look," in *Proc. Adjunct Proc. 7th Int. Conf. Automot. User Inter. Interact. Veh. Appl.*, 2015, pp. 20–25.
[33] S. Benedetto, M. Pedrotti, L. Minin, T. Baccino, A. Re, and R. Montanari, "Driver workload and eye blink duration," *Transp. Res. F, Traffic Psychol. Behav.*, vol. 14, no. 3, pp. 199–208, 2011.
[34] N. Merat *et al.*, "Highly automated driving, secondary task performance, and driver state," *Hum. Factors*, vol. 54, no. 5, pp. 762–771, 2012.
[35] G. Borghini, L. Astolfi, G. Vecchiato, D. Mattia, and F. Babiloni, "Measuring neurophysiological signals in aircraft pilots and car drivers for the assessment of mental workload, fatigue and drowsiness," *Neurosci. Biobehav. Rev.*, vol. 44, pp. 58–75, Jul. 2014.
[36] G. Marquart, C. Cabrall, and J. de Winter, "Review of eye-related measures of drivers' mental workload," *Procedia Manuf.*, vol. 3, pp. 2854–2861, Jan. 2015.
[37] O. Oviedo-Trespalacios, M. M. Haque, M. King, and S. Washington, "Understanding the impacts of mobile phone distraction on driving performance: A systematic review," *Transp. Res. C, Emerg. Technol.*, vol. 72, pp. 360–380, 2016.
[38] Mercedes-Benz. (2008). *Mercedes-Benz to Introduce Attention Assist Into Series Production in Spring 2009*. [Online]. Available: http://www.emercedesbenz.com
[39] Volvo. (2007). *Driver Alert Control*. [Online]. Available: https://www.media.volvocars.com/global/en-gb
[40] L. Barr, S. Popkin, and H. Howarth, "An evaluation of emerging driver fatigue detection measures and technologies," Vehicle Res. Test Center, Federal Highway Admin. Office Safety, Nat. Highway Traffic Safety Admin., U.S. Dept. Transp. Federal Motor Carrier Safety Admin., Washington, DC, USA, Tech. Rep. FMCSA-RRR-09-005, 2009.
[41] Toyota. (2016). *The 2017 GX-Lexus Safety Features*. [Online]. Available: http://www.lexus.com/models/GX/safety
[42] J. Yang, F. Du, W. Qu, Z. Gong, and X. Sun, "Effects of personality on risky driving behavior and accident involvement for Chinese drivers," *Traffic Injury Prevention*, vol. 14, no. 6, pp. 565–571, 2013.
[43] W. Qu, Y. Ge, C. Jiang, F. Du, and K. Zhang, "The dula dangerous driving index in China: An investigation of reliability and validity," *Accident Anal. Prevention*, vol. 64, pp. 62–68, Mar. 2014.
[44] C. N. Pope, T. R. Bell, and D. Stavrinos, "Mechanisms behind distracted driving behavior: The role of age and executive function in the engagement of distracted driving," *Accident Anal. Prevention*, vol. 98, pp. 123–129, Jan. 2017.
[45] B. Reimer, B. Donmez, M. Lavallière, B. Mehler, J. F. Coughlin, and N. Teasdale, "Impact of age and cognitive demand on lane choice and changing under actual highway conditions," *Accident Anal. Prevention*, vol. 52, pp. 125–132, Mar. 2013.
[46] G. J. S. Wilde, "The theory of risk homeostasis: Implications for safety and health," *Risk Anal.*, vol. 2, no. 4, pp. 209–225, 1982.
[47] W. van Winsum, M. Martens, and L. Herland, "The effects of speech versus tactile driver support messages on workload driver behaviour and user acceptance," TNO Hum. Factors Res. Inst., Amsterdam, The Netherlands, TNO Rep. TM-99-C043, 1999.
[48] M. Martens and W. van Winsum, "Measuring distraction: The peripheral detection task," TNO Hum. Factors, Soesterberg, The Netherlands, 2000.
[49] M. Kantardzic, *Data Mining: Concepts, Models, Methods, and Algorithms*. Hoboken, NJ, USA: Wiley, 2011.
[50] G. Li *et al.*, "Effectiveness of flashing brake and hazard systems in avoiding rear-end crashes," *Adv. Mech. Eng.*, vol. 6, p. 792670, Jan. 2014.
[51] *Road Vehicles—Transport Information and Control Systems—Detection-Response Task (DRT) for Assessing Attentional Effects of Cognitive Load in Driving*, Standard 17488, International Organization for Standardization, Oct. 2016.
[52] *Operational Definitions of Driving Performance Measures and Statistics*, SAE Int., Warrendale, PA, USA, 2015.
[53] B. Schlorholtz and F. Schieber, "Assessment of age differences in mental workload while driving using verbal versus visual-spatial subsidiary tasks," in *Proc. Hum. Factors Ergonom. Soc. Annu. Meeting*, vol. 50. Los Angeles, CA, USA: Sage, 2006, pp. 2378–2382.
[54] Y. Wang, B. Reimer, J. Dobres, and B. Mehler, "The sensitivity of different methodologies for characterizing drivers' gaze concentration under increased cognitive demand," *Transp. Res. F, Traffic Psychol. Behav.*, vol. 26, pp. 227–237, Sep. 2014.
[55] M. M. Deza and E. Deza, "Encyclopedia of distances," in *Encyclopedia of Distances*. Berlin, Germany: Springer, 2009, pp. 1–583.
[56] J. H. Ward, Jr., "Hierarchical grouping to optimize an objective function," *J. Amer. Statist. Assoc.*, vol. 58, no. 301, pp. 236–244, 1963.
[57] W. Härdle and L. Simar, *Applied Multivariate Statistical Analysis*. vol. 2. Berlin, Germany: Springer, 2007.
[58] D. F. Andrews, "Plots of high-dimensional data," *Biometrics*, vol. 28, no. 1, pp. 125–136, 1972.
[59] M. Sodhi, B. Reimer, and I. Llamazares, "Glance analysis of driver eye movements to evaluate distraction," *Behav. Res. Methods, Instrum., Comput.*, vol. 34, no. 4, pp. 529–538, 2002.
[60] Y. Liao, S. E. Li, W. Wang, Y. Wang, G. Li, and B. Cheng, "The impact of driver cognitive distraction on vehicle performance at stop-controlled intersections," in *Proc. IEEE Intell. Vehicles Symp. (IV)*, Jun./Jul. 2015, pp. 946–951.



YUAN LIAO (S'15) received the B.E. and M.S. degrees in automotive engineering from Tsinghua University, Beijing, China, in 2013 and 2016, respectively. She is currently pursuing the Ph.D. degree with the Division of Physical Resource Theory, Department of Space, Earth and Environment, Chalmers University of Technology, Gothenburg, Sweden. From 2013 to 2013, she was an Intern Student with Nissan Motor Corporation, where she was involved in a research project for the development of driver-centered autonomous driving. Her active research interests include intelligent transportation, vehicular human factors, and human mobility patterns. She received the Excellent Graduate Student and Excellent Master Thesis of the Year from Tsinghua University in 2016.

GUOFA LI received the B.S. degree from the Beijing Institute of Technology, Beijing, China, in 2010, and the Ph.D. degree from Tsinghua University, Beijing, China, in 2016. From 2012 to 2013, he was a Visiting Scholar with the University of Michigan Transportation Research Institute, where he was involved in an NSF project for the development of driver behavior models at signalized intersections. He is currently an Assistant Professor with the Institute of Human Factors and Ergonomics, Shenzhen University. His active research interests include driver behavior modeling, autonomous vehicle technologies, and human factors in transportation systems.

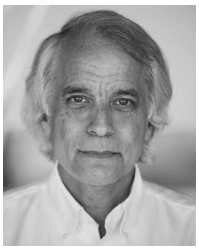
SHENGBO EBEN LI (SM'16) received the M.S. and Ph.D. degrees from Tsinghua University in 2006 and 2009, respectively. He was with Stanford University, the University of Michigan, and the University of California Berkeley.

He is currently a tenured Associate Professor with Tsinghua University. His active research interests include intelligent vehicles and driver assistance, reinforcement learning and distributed control, and optimal control and estimation.

He has authored over 100 peer-reviewed journal/conference papers, and the co-inventor of over 20 Chinese patents. He was a recipient of the Best Paper Award in 2014 IEEE ITS Symposium, the Best Paper Award in 14th ITS Asia Pacific Forum, the National Award for Technological Invention in China in 2013, the Excellent Young Scholar of NSF China in 2016, and the Young Professorship of Changjiang Scholar Program in 2016. He serves as an Associate Editor for the *IEEE Intelligent Transportation Systems Magazine* and the IEEE TRANSACTIONS ON INTELLIGENT TRANSPORTATION SYSTEMS.

BO CHENG received the B.S. and M.S. degrees in automotive engineering from Tsinghua University, Beijing, China, in 1985 and 1988, respectively, and the Ph.D. degree in mechanical engineering from Tokyo University, Japan, in 1998.

He is currently a Professor with Tsinghua University and the Dean of Tsinghua University-Suzhou Automotive Research Institute. He has authored over 70 journals/conference papers, and the co-inventor over 20 patents. His active research interests include autonomous vehicles, driver assistance systems, active safety, and vehicular ergonomics. He was a Chairman of the Academic Board of SAE-Beijing, the Member of the Council of Chinese Ergonomics Society, and the Committee Member of National 863 Plan.



PAUL GREEN received the M.S. and Ph.D. degrees from the University of Michigan, Ann Arbor, MI, USA, in 1974 and 1979, respectively. He is currently a Research Professor with the Driver Interface Group, University of Michigan Transportation Research Institute, Ann Arbor, MI, USA, and an Adjunct Professor with the Department of Industrial and Operations Engineering, University of Michigan. He teaches automotive human factors and human-computer interaction classes. He is the Leader of the University's Human Factors Engineering Short Course, the flagship continuing education course in the profession, now in its 59th year. His research interests include driver interfaces and driver workload, and the development of standards to get research into practice. He was the President of the Human Factors and Ergonomics Society.