Changes in the Correlation Between Eye and Steering Movements Indicate Driver Distraction

Lora Yekhshatyan and John D. Lee

***Abstract*—Driver distraction represents an increasingly important contributor to crashes and fatalities. Technology that can detect and mitigate distraction by alerting distracted drivers could play a central role in maintaining safety. Based on either eye measures or driver performance measures, numerous algorithms to detect distraction have been developed. Combining both eye glance and vehicle data could enhance distraction detection. The goal of this paper is to evaluate whether changes in the eye–steering correlation structure can indicate distraction. Drivers performed visual, cognitive, and cognitive/visual tasks while driving in a simulator. The auto- and cross-correlations of horizontal eye position and steering wheel angle show that eye movements associated with road scanning produce a low eye–steering correlation. However, even this weak correlation is sensitive to distraction. Time lead associated with the maximum correlation is sensitive to all three types of distraction, and the maximum correlation coefficient is most strongly affected by off-road glances. These results demonstrate that eye–steering correlation statistics can detect distraction and differentiate between types of distraction.**

***Index Terms*—Driver distraction, driving performance, eye movement, eye–steering coordination, secondary task, time series analysis.**

I. Introduction

DRIVER distraction is an important safety problem. Analysis of naturalistic data suggests distraction contributes to approximately 43% of motor vehicle crashes and 27% of near crashes [1]. Analysis of fatal crashes shows that driver distraction contributed to an increasing proportion of crashes (i.e., 10% in 2005 and 16% in 2009, for a total of 5474 distraction-related fatalities in 2009) [2]. This increase may reflect the rapidly developing in-vehicle technology and other electronic devices that place additional demands on drivers and might lead to distraction and diminished capacity to perform driving tasks [3]. This situation threatens safe driving. Technology that can detect and mitigate distraction by providing drivers with feedback and alerts could play a central role in maintaining safety [4].

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Numerous algorithms have been developed to detect distraction [5]. Several distraction detection and mitigation systems are on the market or exist as advanced prototypes, including Saab's Driver Attention Warning System AttenD, Volvo's Driver Alert Control, Delphi's SAVE-IT system, Mercedes-Benz's Attention Assist, and Lexus' Driver Monitoring System, and there is a growing interest from automakers regarding the design of such systems. These systems aim to detect distraction based on visual behavior or driving performance. Identifying driver distraction in real time to predict dangerous situations associated with breakdowns in lane keeping control is a critical challenge in these systems' design. For this purpose, it would be useful to define the relationship between visual behavior and vehicle control. Distraction might change the relationship between glance patterns and steering that lead to breakdowns in vehicle control, resulting in lane departures. Changes in this visual behavior–vehicle control relationship might indicate distraction. Thus, it is crucial to evaluate this relationship for normal (nondistracted) driving and examine if it changes with distraction.

The assumption underlying our analysis of the visual behavior–vehicle control relationship is that this relationship reflects a fundamental perception–action control mechanism. In visually guided tasks, visual information is often sampled in a proactive manner to guide action preparation [6]. The perception–action control process plays a central role in driving [7], and a strong eye–steering correlation associated with this control process has been observed on curvy roads [8]. This paper evaluates the eye–steering correlation on a straight road with the assumption that it might show a qualitatively and quantitatively different relationship compared with curvy roads and that it might be sensitive to distraction.

A. Driver Distraction Detection Algorithms

Research has focused on two types of distraction: cognitive and visual, described as "mind-off-road" and "eye-off-road," respectively [9]. Although both can undermine driving performance, their effects can be quite different. Cognitive tasks tend to reduce lane position variance, whereas visual tasks tend to increase variance [10], [11]. Although cognitive distraction seems to improve some aspects of driver performance, it degrades longitudinal control and hazard perception. For the cognitive distraction detection, eye movement and performance measures have been summarized across a relatively long time interval using data mining techniques [12]–[15]. This approach estimates distraction as a discrete state, but does not predict the continuous level of distraction. Moreover, cognitive distraction detection is complex because the mechanisms involved in cognitive distraction have not been precisely described.

The challenges of detecting cognitive distraction have led most existing distraction detection systems to focus on visual distraction. The algorithms combine different glance behavior metrics to evaluate visual demands during predetermined time windows and predict risk associated with off-road glances [9], [16]–[22]. Another approach applied in distraction detection systems, such as Mercedes-Benz's Attention Assist and Saab's ComSense, use driver performance measures (e.g., speed, lane position, and steering) to assess the capability of the driver to drive safely [23], [24].

Approaches that have focused on glance behavior or on vehicle control hold great promise in detecting visual distraction. Nevertheless, considering a combination of both glance behavior and vehicle control might increase algorithm sensitivity in detecting different types of inattention. For example, eye movement data could be combined with vehicle path data to distinguish between drowsiness (e.g., eyes directed towards the road during path departures) and distraction (e.g., eyes directed away from the road during path departures). However, the relationship between visual behavior and driver performance measures is not well established. A better description of this relationship could contribute to new algorithms that consider the relationship between visual behavior and driver performance to detect driver distraction and predict breakdowns in lane keeping. This paper presents a new approach to algorithm design that focuses on the relationship between eye movements and steering wheel movements.

B. Eye–Steering Coordination

In perception–action control processes, such as driving, vision provides information to support action preparation and execution [6]. Two modeling approaches were applied to describe and predict the allocation of drivers' visual attention: 1) models of visual search and 2) models of visual sampling.

Models of visual search describe how people locate targets in the environment to complete the task [8]. The models of visual sampling describe a scanning pattern of particular areas to find relevant information. These models use visual feedback for error correction and path monitoring, i.e., drivers compare their current lane position with their desired lane position to determine the need for corrective steering input [25]. On a straight road, uncertainty about lane position grows less rapidly (low bandwidth) compared with curvy roads (high bandwidth) when more frequent sampling of information on lane position is required [26]. The changes in the bandwidth and parameters of such a model indicate changes in driver state, i.e., normal driving versus fatigued driving [25], [27]. Thus, the control-theoretic models of driving can represent a visual information–vehicle control behavior. Three different perspectives were considered to describe this relationship: 1) visual information framework; 2) oculomotor controller concept; and 3) intermittent control concept.

From the visual information perspective, information flow concerning the roadway and traffic situation guides a driver to control the vehicle. For curve negotiation, drivers fixate on the tangent point of an approaching curve to guide control through the curve [8]. These eye movements are coordinated with steering movements to keep a vehicle in lane. Drivers move their eyes to guide steering [28]. Changes in this coordination might lead to diminished vehicle control and to dangerous changes in vehicle state, such as lane departures.

An alternate perspective that explains strong eye–steering coordination observed on curvy roads is the oculomotor controller concept explained through the movement-centered framework [29]. This perspective assumes that the ocular control system feeds into the manual control mechanism to assist tracking: some neural centers produce and control eye movements that then engage neural centers that control steering. In diverse situations, the degree of coordination between eye movements and actions, and their relative timing, largely determine performance [30], [31]. For example, with reduced visibility, when the tangent point on a left-hand bend was not identifiable, drivers who moved their eyes to that area performed better than those who preferred to focus on the center part of the road, although they received no additional information by looking in that direction [32].

Another perspective on perception–action coordination in visually guided tasks is visual information intermittency in movement control. It assumes intermittent corrections such that each submovement is planned to reduce error developed in the previous step [33]. According to this perspective, the duration of visual information processing time reflects the time necessary for the visuomotor system to evaluate an error between current and target positions and initiate a correction to the ongoing movement. This intermittency paradigm explains task performance during visual occlusion or inattention when information about a target is eliminated. In the absence of visual information, perceptual memory enables people to act on target trajectories for about 2 s, resulting in almost perfect tracking even when they are not visible [34], [35]. This assumes that visual occlusion that exceeds this 2-s threshold would cause diminished performance, and this assumption matches the findings of Klauer *et al.* [16], where off-road glances of more than 2 s increase near crash/crash risk by approximately two times that of normal baseline driving.

Each of these perspectives suggests that eye movements play a crucial role in driver performance. However, they explain the eye–steering relationship in different (or complimentary) ways: 1) Eyes move to acquire the information for vehicle control; 2) eye movements produce steering movements; and 3) the time lead (TL) reflects visual information processing time. Together, these approaches indicate the following: 1) eye–steering coordination is highly consistent on curvy roads; 2) eye movements can be an input to the steering control; and 3) the changes in the visual behavior and vehicle control relationship might be indicative of distraction-related impairments and predictive of diminished driving performance.

Previous research suggests that driver impairment influences the coordination of eye movements and steering control. This coordination was measured through the cross-correlation coefficient (CC) and time by which eye movement precedes steering movement. The CC decreased while driving

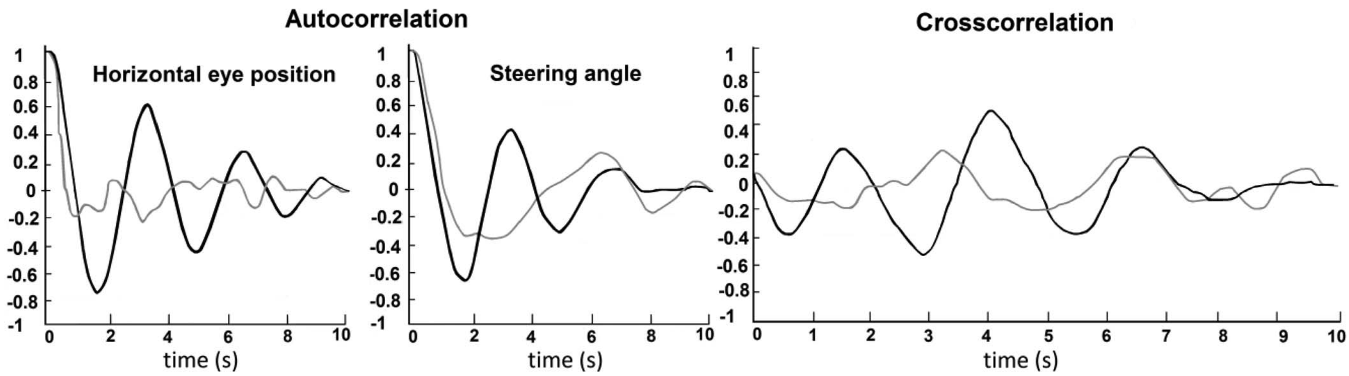

Fig. 1. Auto- and cross-correlation functions change with distraction. The grey lines represent the nondistracted condition and the black lines represent the distracted condition. The vertical axis is the correlation coefficient and the horizontal axis is the time lag.

on curvy roads with driver impairment, i.e., fixed or limited eye movements through restricted field of view [32], alcohol intoxication [36], or under high stress [31]. The TL decreased with diminished coordination associated with alcohol impairment [36].

C. Eye–Steering Correlation for Eye Movement Types

Winding roads place a greater demand on the driver's eyes to follow approaching curves. When eye movements guide steering, the eye–steering relationship is very strong for normal driving. Drivers move their eyes toward the tangent point of an approaching curve to support steering. However, this relationship might change with driving environment and eye movement type. On straight roads, drivers scan the road ahead to be aware of the driving situation and less frequently to guide their steering. This scanning behavior is likely to be weakly correlated with steering because the "forcing" function is not strong enough to generate an appropriate output, i.e. the need for coordinated eye and steering movements is less. Thus, a low correlation between eye position and steering might not always indicate driver impairment, as demonstrated by Marple-Horvat *et al.* [36] and Wilson *et al.* [32].

Eye movements associated with visual distraction (glances away from the road and back to the road) have a qualitatively different relationship to steering. Glances away from the road might be associated with visual information loss that diminishes steering output. Glances back to the road influence subsequent steering movements that are needed to adjust the vehicle's lane position. Because of this eye–steering coupling, the correlation might be relatively large; but this correlation will differ fundamentally from that associated with a driver approaching a curve in the road when eye movements guide steering in a proactive and smooth fashion. Another expected difference is the association of eye–steering correlation with the direction of eye and steering movements. For curve negotiation, steering wheel and eyes move in the same direction, whereas with off-road glances, eyes and steering movements do not necessarily coincide. In the latter case, the large amplitude periodic visual and steering movements provoked by shifts from off-road to on-road glances will be associated with lapses in a vehicle control indicative of visual distraction.

Cognitive distraction will likely affect the relationship between eye and steering movements differently than visual distraction. Cognitive distraction tends to concentrate eye glances in the center of the road, and it will most likely reduce the association between eye and steering wheel movement [37]. This decrease in eye–steering coordination relative to normal driving will be associated with diminished attention to the road environment caused by cognitive distraction. Thus, it is important to consider not only the changes in eye–steering correlation but also the causes of these changes because such differences might represent important signatures of different types of driver distraction.

D. Correlation Analysis: Auto- and Cross-Correlation

The visual behavior–vehicle control relationship can be assessed with a correlation analysis that considers the relationship within a variable over time (autocorrelation) and the relationship between two variables (cross-correlation) [38].

Two parameters define the relationship between two variables: 1) the magnitude of a cross-correlogram peak (CC) and 2) relative timing (TL). Changes of these parameters might be associated with the effect of distracting activity on eye movements and steering wheel position (see Fig. 1). Thus, to assess the degree to which the correlation parameters are indicative of distraction, the correlation functions are calculated for each type of distraction.

II. Eye–Steering Correlation for Nondistracted and Distracted Conditions on a Straight Road

In this paper, the relationship within and between eye and steering movements is tested for four types of eye movements on a straight suburban arterial road: 1) scanning the road ahead during nondistracted driving; 2) shifts of glances between on-road and off-road areas during visual distraction; 3) reduced eye movement (glances concentrated on the road center during cognitive distraction); and 4) glances concentrated in the road center combined with glances away from the road during combined cognitive and visual distraction, which occurs when a cognitively distracted driver looks toward an in-vehicle system.

As a measure of the eye movement, the horizontal eye position is used. It was shown previously that vertical eye position changes little for different driver states [31], and it was not correlated with steering wheel position [32]. Therefore, horizontal eye position is considered in this paper.

A. Simulator Study

For the analysis, data from a simulator study conducted by Liang [11] were used. The study includes a sample of 16 active drivers (eight male and eight female) between 35 to 55 years old who have held a valid driver U.S. driver's license for at least 5 years. Eye movement (eye position) and steering movement (steering angle) signals were collected while the participants drove on a straight five-lane suburban arterial roadway comprised of two lanes in each direction separated by a center turning lane. Both the faceLab eye tracking system (Seeing Machines, Version 4.1) and the driving simulator collected data at 60 Hz. Participants performed 8-min drives for each nondistracted (baseline) and distracted (visual/manual, cognitive, and combined cognitive/visual tasks) conditions.

For the visual task, participants were instructed to match the direction of a given arrow within a 4×4 arrow matrix using a 7-in liquid crystal display touch screen interface located on the right side of the dash 25° laterally and 20° vertically below the drivers' line of sight.

For cognitive task, participants listened to direction information from the navigation system (e.g., turn left, then turn right, then turn right) and then verbally identified which direction (e.g., east, north, south, and west) they would face after following the directions. Participants were instructed to speak the direction out loud as soon as possible after hearing each turn and to press a button on the steering wheel at the same time. The task required auditory input, verbal and manual output, and spatial working memory.

For the combined cognitive/visual task, participants listened to audio clips similar to those in the cognitive task and selected the orientation using the interface similar to the visual task. The timing of the three tasks was the same: participants had 5 s to respond. If they responded in less than 5 s, another task would follow immediately. Otherwise, the next task would begin after 5 s. In this, the participants were constantly distracted by the secondary tasks during the 6-min task period.

B. Data Processing

The raw data were processed to assess the quality, remove artifacts, and assure that the datasets accurately represent driver visual behavior during all types of distraction. The criteria for exclusion included: 1) data points that fall unreasonably far from the locations associated with the task performance [9], [21]; 2) data points that distributed in a very unusual way (e.g., more than 50% of glances fall out of driving scene); and 3) sharp spikes in the rate of eye movement that exceeds the threshold of three standard deviations defined for each driver. These spurious data often occur when the eye tracker fails to detect an eye movement and then reacquires the eye at another location. These criteria define the outliers that can have a disproportionate effect on the correlation analysis.

The missing data points associated with the outliers were replaced with interpolated estimates when the length of a segment did not exceed 400 ms (i.e., 25 data points). Because the fixation durations range between 200 and 400 ms [39], segments up to 400 ms can be interpolated without significant distortion of eye movement information. Otherwise, the segments were deleted and treated as missing data. Based on these criteria, the resulting data differed across the drivers. On average, the 6-min segments decreased by 50 s, with a range of 0.10–165 s. The postreduction scatter plots showed that excluding outliers reduced the number of "unexpected" glances, i.e., those that do not relate to the task performance, for all but four drivers. Thus, the data from these four drivers were not considered in this paper, reducing the number of participants considered in this analysis to 12.

The measurement of steering wheel angle in the simulator is without noise and precise to 0.1°, which is very small relative to the drivers' typical steering wheel adjustments. Drive-by-wire technology will also make very accurate measurement of steering wheel position feasible in cars while driving in the real world. The eye tracking technology also provides measurements of eye movement accurate up to 0.05°. The actual precision is likely less and varies between drivers and within drivers over time, making the data processing steps a particularly important part of the analysis.

III. Results

A. Signal Length and Sampling

The accuracy of correlation analysis depends on the number of samples, i.e. signal length and sampling rate. The choice of a sampling rate is based on the spectral analysis. Spikes of spectral density function define cycles in time series. The lowest frequency is associated with a fundamental frequency. A cycle length, which is reciprocal of the fundamental frequency, determines the time associated with glance shifts, e.g., between on-road and off-road areas.

Based on the spectrum analysis performed with Signal Processing Toolbox Software (Version 6.13 of Matlab R2010a), the fundamental frequencies of horizontal eye position and steering angle for nondistracted driving are 0.03 and 0.07 Hz, respectively (see Table I). The fundamental frequency increases to 0.26 and 0.18 Hz, respectively, and the cycle length decreases with visually distracted driving, meaning that the signals include high-frequency components associated with shifts between on-road and off-road areas.

Both horizontal eye movement and steering angle are dominated by very low frequency components, less than 1 Hz, meaning that both variables could be resampled to lower frequencies (see Table I and Fig. 2). However, in this paper, the initial sampling rate of 60 Hz is kept unchanged. Previous studies examined eye and steering movements using a high-frequency signal of 200 Hz [36], [40]. The resolution of 5 and 16 ms that corresponds to 200 and 60 Hz, respectively, is much smaller than the time constant of the eye and steering wheel

TABLE I
MEAN VALUES OF FUNDAMENTAL FREQUENCIES AND CYCLE LENGTHS

	No distraction		Visual distraction	
	Horizontal eye position	Steering angle	Horizontal eye position	Steering angle
Fundamental frequency (Hz)	0.03	0.07	0.26	0.18
Cycle length (s)	38.5	14.3	3.8	5.5
Signal length (s)	192.3	71.4	19.2	27.8

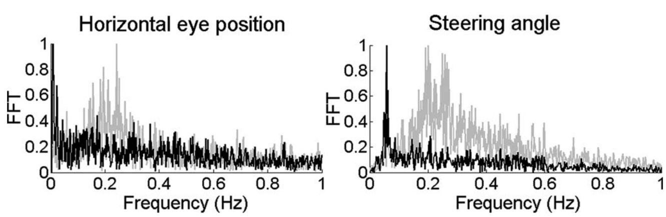

Fig. 2. (a) Steering angle and (b) horizontal eye position spectra for nondistracted (black line) and visually distracted (grey line) conditions.

movements, and the resolution of 16 ms is much smaller than previously observed lead times between eye and steering movements [8], [36]. Thus, the main reason for the relatively high sampling rate is timing accuracy, i.e., more precise estimation of TL of eye movements relative to steering movements.

Signal length should be long enough to capture several glances. On the other hand, the signal length should be short enough to detect changes in driver state in a timely manner. The signal length for the correlation analysis should contain a number of cycles of the fundamental frequency component, i.e., five [38]. Based on these assumptions and calculations presented in Table I, a signal length of 30 s is chosen for the correlation analysis. For consistency, the same sample length is used for all the driving conditions.

The mean glance cycle length of 3.8 s for visually distracted driving is consistent with a model of visual sampling behavior developed by Wierwille [41]. According to Wierwille's model, if a glance away from the road cannot extract the requisite information in approximately 1.6 s, drivers tend to glance back to the roadway before looking away again. Confirming this result, a best fit of a task switching model to human behavior with visual distraction was achieved with a 1.5-s interval [42]. If we assume the on-road glance of about 1.6 s, the cycle of approximately 3.8 s reflects the time of glance shifts from and back to the road.

If the total number of observations is N, where N is a product of sampling rate and cycle length, then the autocorrelation is typically calculated for the first $N/4$ lags in the data set because higher order autocorrelations become increasingly unstable [43]. Therefore, the autocorrelation functions for eye and steering signals are calculated for the first 8-s lags for the 30-s segments of data. The 30-s segment at frequency of 60 Hz includes 1800 samples. The correlation functions are calculated for the first 480 lags (8 s).

B. Autocorrelation Analysis of Eye and Steering Movements

Auto- and cross-correlation functions are calculated using Signal Processing Toolbox Software (Version 6.13 of Matlab R2010a). For this analysis, the data from 12 drivers were divided into 30-s nonoverlapping segments. To calculate the properties of the signals, all the segments were detrended to remove any slope and mean.

Autocorrelation analysis shows association between observations as a function of the time separation between them (time lag). Visual inspection of the calculated autocorrelation functions for baseline condition shows that these signals are close to but not completely random. The function decreases quickly from its peak value at zero lag, but has values that exceed the 95% confidence interval (CI) [see Fig. 3(a)]. The CI is computed as $0 \pm 1.96/N$ following an assumption that the sample correlations are normally distributed with mean 0 and variance 1/N, where N is a sample size. For the 0.05 α-level and two-tailed test, the value of 1.96 is the 0.975 probability point of the cumulative distribution function [44].

The short-term correlation, i.e., the large values of autocorrelation function that follow the peak value at zero lag and tend to get smaller, was expected and can be accounted for the dependency of the eye and steering wheel current positions on their preceding values. For some segments, the autocorrelation coefficient outside the 95% CI at larger lags can be associated with different types of eye movements, i.e., glance shifts between on-road and off-road. In general, the correlation between horizontal eye position and steering wheel position is low. This implies that visual "input" and associated steering demands on the straight road are not strong enough to generate a strong eye–steering relationship as it does on curvy roads [45].

Visual distraction changes the autocorrelation function for both signals. Signs of periodicity appear and are indicated by the peaks beyond the 95% CI at nonzero lags [see Fig. 3(b)]. This is more apparent for horizontal eye position compared with steering angle. The peaks are higher for the eye signal than for the steering signal. This periodicity in eye movements reflects the glance shifts between on-road and off-road areas. The relatively lower correlation in steering movement implies that drivers do not lose their lane keeping control with every off-road glance, and hence, they do not steer with the same periodicity and amplitude to correct their position in the lane. This could be a reason for the low correlation between eye and steering movements.

The autocorrelation functions calculated for cognitively and cognitively/visually distracted conditions differ from the ones for baseline and visual conditions [see Fig. 3(c) and (d)]. The correlation was stronger for some nonzero lags than it was for the baseline condition, but the functions are not periodic. This indicates that these two types of distraction have substantially different effects on the correlation characteristics (e.g., strength of observations dependence) of the time series.

To assess how the autocorrelation function changes with distraction, the autocorrelation coefficient, i.e., the magnitude of the first peaks that follow the zero-lag peak and exceed CI, and the associated time lags were compared. The analysis

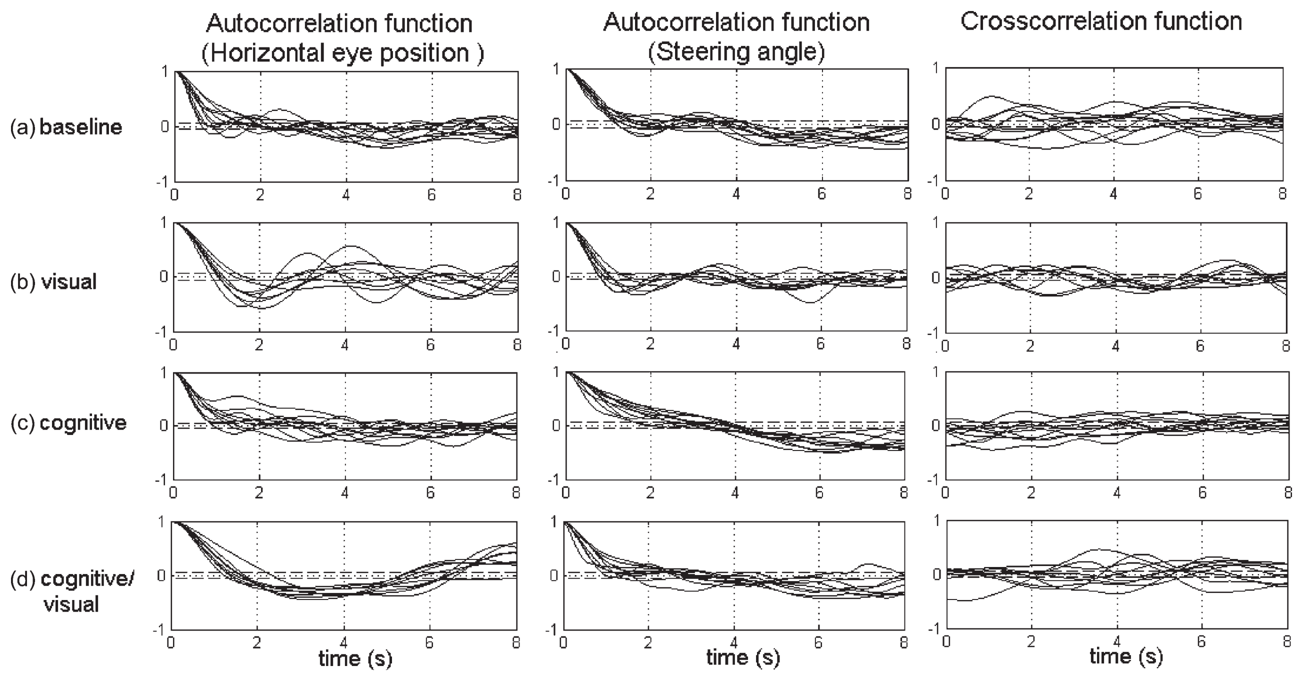

Fig. 3. Auto- and cross-correlation functions for detrended steering angle and horizontal eye position for nondistracted and distracted conditions. The functions were calculated for all the 30-s segments. The dashed lines are 95% CI.

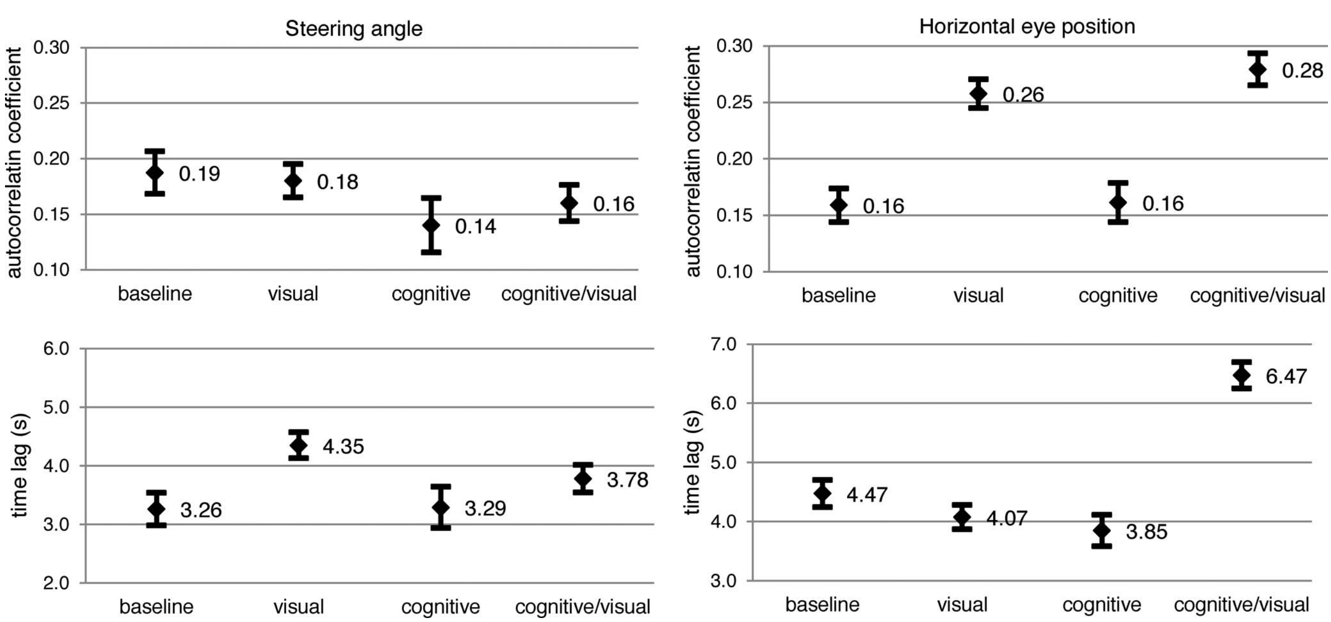

Fig. 4. Autocorrelation coefficient and time lag change with distracted condition (mean values with standard error bars).

was performed through a within-subject analysis of variance with repeated measures using the SAS 9.2 PROC MIXED procedure. The analysis shows that, for the horizontal eye position, both measures change significantly (autocorrelation coefficient: $F(3, 31) = 18.05, p < 0.0001$; time lag : $F(3, 31) = 35.34, p < 0.0001$). For steering angle, time lag changes significantly $(F(3, 28) = 5.40, p = 0.005)$, but the autocorrelation coefficient does not: $F(3, 28) = 1.86$, $p = 0.16$ (Fig. 4). For horizontal eye position, cognitive/visual distraction leads to the largest time lag compared to other conditions, but visual distraction does not affect the time lag significantly. In contrast, for steering angle, visual distraction increases the time lag but cognitive/visual distraction does not.

The results of pair-wise comparison (Tukey's test) between distracted conditions indicate that the autocorrelation coefficient of the horizontal eye position time series is sensitive to distraction associated with off-road glances. The autocorrelation coefficients for visual and cognitive/visual conditions are significantly different from those for baseline and cognitive conditions (see Table II). Off-road glances affect the time lag of both the horizontal eye position and the steering angle time series. However, this influence differs for these two variables. For visual condition, time lag decreases for steering angle and increases for horizontal eye position; for cognitive/visual condition, time lag substantially increases for steering angle and slightly for horizontal eye position.

TABLE II
STATISTICAL RESULTS OF THE CORRELATION PARAMETERS PAIR-WISE COMPARISON

CORRELATION CHARACTERISTICS	B vs. V	B vs. C	B vs. C/V	V vs. C	V vs. C/V	C vs. C/V
Horizontal eye position	*t*(31)	*t*(31)	*t*(31)	*t*(31)	*t*(31)	*t*(31)
Autocorrelation coefficient	**-5.03**	-0.11	**-5.84**	**4.47**	-1.13	**-5.26**
Time lag (s)	1.47	1.96	**-6.99**	0.75	**-9.04**	**-8.38**
Steering angle	*t*(28)	*t*(28)	*t*(28)	*t*(28)	*t*(28)	*t*(28)
Autocorrelation coefficient	-0.07	1.86	1.08	*2.10*	1.34	-1.09
Time lag (s)	**-3.54**	-0.07	-1.62	**2.84**	**2.08**	-1.28
Eye-steering correlation	*t*(32)	*t*(32)	*t*(32)	*t*(32)	*t*(32)	*t*(32)
Crosscorrelation coefficient	**2.01**	-0.88	**3.83**	**-2.83**	1.72	**4.64**
Time lead (s)	**2.56**	**2.05**	**-2.21**	-0.52	**-4.71**	**-4.22**

B, V, C, and C/V indicate baseline, visual distraction, cognitive distraction, and cognitive/visual distraction conditions.
Bolded values represent significant differences at α=0.05.

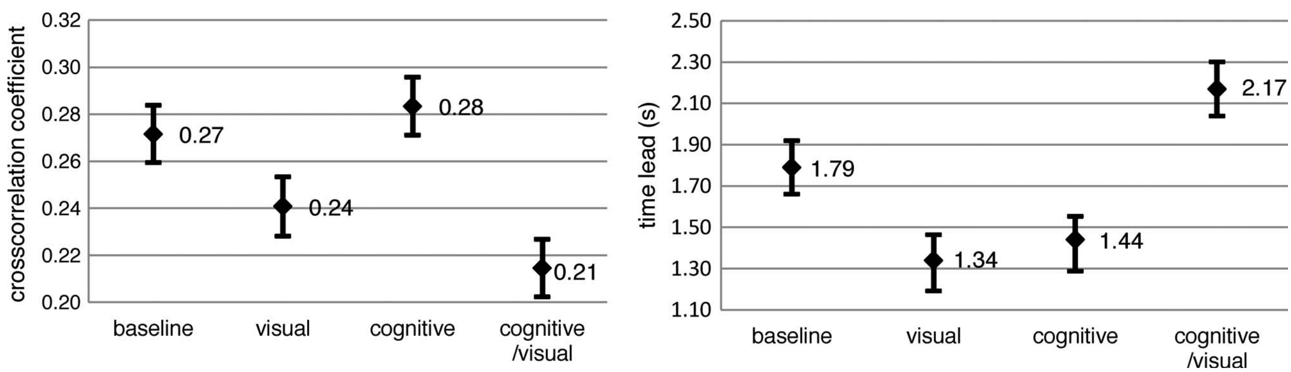

Fig. 5. Cross-correlation analysis statistics (mean values with standard error bar for correlation coefficient and TL).

C. Cross-Correlation Analysis of Eye and Steering Movements

To examine the correlation between horizontal eye position and steering angle for all four driving conditions, the magnitudes of cross-correlation function's first peak that follows the peak at zero time and exceeds CI (CC) and TL values were extracted. On straight roads, the departures from the centerline could happen in both directions regardless of the glance direction. These deviations lead to equally possible negative and positive changes in steering angle (i.e., steering to the left and to the right) and, consequently, negative and positive eye–steering correlation coefficient. Therefore, the absolute values of CC are examined.

The correlation parameters (CC and TL) are examined for all the driving conditions. The results show that driving condition has a statistically significant effect on both parameters, i.e., CC $(F(3,32) = 8.69, p = 0.0002)$ and TL $(F(3,32) = 9.16, p < 0.0001)$. Post hoc comparison between driving conditions shows that the correlation coefficient is significantly greater for baseline and cognitive task conditions than for visual and cognitive/visual distraction conditions (see Table II and Fig. 5).

The TL differs for all the conditions because it decreases with visual and cognitive distraction and increases with the cognitive/visual distraction condition. The post hoc pair-wise comparison indicates that the TL values for all the conditions are significantly different except for the visual and cognitive conditions (see Table II and Fig. 5). The smallest correlation coefficient and largest TL were for cognitive/visual distraction, indicating that this is a different type of distraction and it has a different effect on eye–steering correlation.

IV. DISCUSSION

Autocorrelation and cross-correlation functions of horizontal eye position and steering angle time series indicate distraction. Distraction affects the eye and steering time series, as well as their coupling (see Fig. 3). For visual distraction, the autocorrelation functions reflect the periodicity associated with glance shifts to and from the road and associated intensive steering movements. Cognitive and cognitive/visual distraction also affects the autocorrelation functions. There are more peaks at nonzero lags than for the baseline condition, indicating changes in the strength of association between observations. Similar to the changes in autocorrelation functions, distraction also affects the cross-correlation function, and together, these changes identify the presence and type of driver distraction.

Changes in eye–steering relationship measured through CC and TL differentiate types of distraction. For visual distraction, both CC and TL decrease; for cognitive distraction, TL decreases and CC does not change; and for cognitive/visual distraction, CC decreases and TL increases (see Fig. 5). All the comparisons are relative to the baseline condition of a straight road. Thus, the CC and TL metrics not only differentiate distracted driving from nondistracted, but these metrics can also differentiate types of distraction including visual, cognitive, and cognitive/visual.

According to Land's theory and the oculomotor controller concept, eye and steering movements are highly coordinated on winding open roads and eye movement is a strong input to the steering control [29], [46]. On a straight road, this eye–steering relationship is different. Eyes scan the driving environment to maintain situation awareness and not to solely guide steering movements. This implies that, in general, the eye–steering correlation would be lower on a straight road compared with curvy road. The results of this paper confirm the hypothesis that the coordination between eye and steering movements on straight roads is not strong. However, even this weak relationship is sensitive to the distraction associated with off-road glances. This is consistent with other driver impairments, such as fatigue and alcohol intoxication, which diminish this coordination [30], [31], [36]. It was expected that the eye–steering correlation would increase slightly for visual and cognitive/visual conditions compared with baseline and cognitive conditions. This increase would be associated with coupling eye and steering movements driven by on-road and off-road glances that cause corrective steering movements to keep the vehicle in a lane. However, the correlation analysis shows the opposite: the correlation coefficient decreases with visual and cognitive/visual distraction compared with baseline and cognitive distraction.

The TL defined by the peak of the cross-correlation function is sensitive to all three types of distraction. Visual and cognitive distractions decrease the TL, which matches the results of driver impairment on curvy roads [31], [36]. In contrast, cognitive/visual distraction causes the TL to increase, and it is most likely due to changes in the oculomotor controller function. This type of distraction causes a delayed signal to the neural controllers for eye movement and a delayed response from oculomotor controller. Moreover, visual distraction is the only type of distraction where both TL and correlation coefficient changed significantly. This result indicates that cognitive/visual distraction affects eye and steering movements differently than visual and cognitive distraction, and this issue merits further investigation.

In this paper, the mean TL is 1.8 s for normal driving. In other studies, the TL associated with oculomotor controller was observed in the range of 200–300 ms for visually guided tracking and about 700 ms for normal driving on curvy roads [29]. This large discrepancy in TL most likely reflects the differences in the road demands and the nature of the task, which had a greater emphasis on monitoring rather than tracking [47].

This discrepancy suggests that although promising, the metrics of driver distraction were demonstrated only for straight roads in a driving simulator. Before these metrics can be incorporated into production vehicles, they need to be considered in different road situations, such as urban settings, nighttime driving, and curving roads. Specifically, the eye–steering coordination changes associated with distraction might depend on the information sampling rate (bandwidth) associated with road demand, i.e., straight road versus curvy road.

The drivers' information sampling rate increases with increasing road curvature, because uncertainty about lane position increases, and therefore, more frequent information and corrective steering input are needed, leading to an increased eye–steering correlation [26], [29], [46]. Different types of distraction might affect information sampling differently. In case of distraction associated with off-road glances, uncertainty about lane position increases, but the sampling rate decreases because drivers share attention between the driving and the distraction task. Thus, greater uncertainty regarding the sampling rate and uncertainty about lane position associated with curves might improve detection and discrimination of different types of distraction. Similar considerations need to be addressed for the full range of driving situations that might affect visual sampling, such as traffic density, time of day, lane width, and speed.

The sensitivity of the visual behavior–vehicle control relationship might also depend on driver experience. Visual scanning of the road changes with experience. The scan patterns of the novice drivers contribute to their higher crash rate largely through a failure to look at hazardous situations [48], [49]. The visual acquisition process of undistracted novice drivers tends to focus on the road ahead, and when distracted, they look away from the road for longer periods than experienced drivers. Such behavior might enable even more precise distraction detection and discrimination of distraction than was demonstrated in this paper. More generally, the visual behavior–vehicle control relationships described in this paper might provide a deeper understanding of the difference between experienced and novice drivers than that afforded by simple measures of glance location and duration.

V. Conclusion

This paper examined how three types of distraction affect visual behavior–vehicle control relationships on a straight road. A straight road that imposed minimal steering demands led to a low correlation between steering movements and eye glances. However, even this weak eye–steering relationship produces metrics, such as the cross-correlation of steering angle and eye position, that can detect distraction and discriminate between types of distraction. Based on CC and TL changes, it is possible to differentiate between not only distracted and nondistracted driving but also between the types of distraction: visual, cognitive, and cognitive/visual. Moreover, the most problematic type of distraction combines various levels of visual and cognitive distraction, e.g., phone dialing and text messaging, and it has the strongest effect on the distraction metrics introduced in this paper.

This paper makes an important contribution by demonstrating the value of considering the coupling of steering and eye movements over time in detecting distraction. This provides a new set of indicators that can be incorporated into vehicle-based systems that detect distraction in real time. A major benefit of these new indicators is that they differentiate between visual and cognitive distraction, and so they can support a broader range of techniques to mitigate distraction [4].

An important consideration in generalizing the results of this paper concerns its reliance on data collected in a simulator. Considering how the metrics described in this paper apply to driving on an actual road, i.e., the full range of roads and traffic situations drivers face on a daily basis, merits substantial further research. In addition, any driving simulator has a number of intrinsic limitations, i.e., restricted field of view (no rearview and side view mirrors), image resolution, and diminished vestibular cues. Because this paper considers fundamental visual control coupling, it seems likely that the primary outcomes of this paper will generalize to actual driving.

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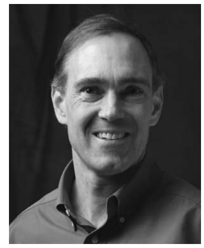

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