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Title: The Attentional Demand of Automobile Driving Revisited: Occlusion Distance as a Function of Task- Relevant Event Density in Realistic Driving Scenarios

Year: 2016

Version:

Please cite the original version:

Kujala, T., Mäkelä, J., Kotilainen, I., & Tokkonen, T. (2016). The Attentional Demand of Automobile Driving Revisited: Occlusion Distance as a Function of Task- Relevant Event Density in Realistic Driving Scenarios. Human Factors, 58(1), 163-180. https://doi.org/10.1177/0018720815595901

Human Factors

THE ATTENTIONAL DEMAND OF AUTOMOBILE DRIVING REVISITED – Occlusion distance as a function of task-relevant event density in realistic driving scenarios

Journal:	*Human Factors : The Journal of the Human Factors and Ergonomics Society*
Manuscript ID:	HF-14-4051.R6
Manuscript Type:	Extended Multi-Phase Study
Keywords:	Driver behavior < SURFACE TRANSPORTATION, Vision < SENSORY AND PERCEPTUAL PROCESSES, Situation awareness < COGNITION, Attentional processes < COGNITION, ACCIDENTS, HUMAN ERROR, Cognitive modeling, cognitive architectures (e.g., ACT-R) < COGNITION, Experience < INDIVIDUAL DIFFERENCES, Intelligent vehicle systems < SURFACE TRANSPORTATION, Autonomous driving < SURFACE TRANSPORTATION, Human-automation interaction < AUTOMATION, EXPERT SYSTEMS

Extended Multi-Phase Study.

Text (excluding title page, abstract, key points, text in tables, references, bios): 7,989 words (tables 388 words)

References: 675 words (max 1,500)

Abstract: 250 words (max 250), Précis: 45 words (max 50)

2 tables and 10 figures

Running head: VISUAL DEMAND OF DRIVING REVISITED

THE ATTENTIONAL DEMAND OF AUTOMOBILE DRIVING REVISITED – Occlusion distance as a function of task-relevant event density in realistic driving scenarios

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Précis: Visual occlusion technique is an established method for assessing visual demands of driving. In this paper, we present support for our hypothesis of the utility of occlusion distance as a function of task-relevant event density in realistic traffic scenarios with driver-controlled speed and occlusion times.

Keywords: driver, task demands, visual occlusion, event rate, event density, distraction, inattention, driving experience, expectancy

Abstract

(a) Objective We studied the utility of occlusion distance as a function of task-relevant event density in realistic traffic scenarios with self-controlled speed. **(b) Background** The visual occlusion technique is an established method for assessing visual demands of driving. However, occlusion time is not a highly informative measure of environmental task-relevant event density in self-paced driving scenarios because it partials out the effects of changes in driving speed. **(c) Method** Self-determined occlusion times and distances of 97 drivers with varying backgrounds were analyzed in driving scenarios simulating real Finnish suburban and highway traffic environments with self-determined vehicle speed. **(d) Results** Occlusion distances varied systematically with the expected environmental demands of the manipulated driving scenarios whereas the distributions of occlusion times remained more static across the scenarios. Systematic individual differences in the preferred occlusion distances were observed. More experienced drivers achieved better lane-keeping accuracy than inexperienced drivers with similar occlusion distances, however, driving experience was unexpectedly not a major factor for the preferred occlusion distances. **(e) Conclusion** Occlusion distance seems to be an informative measure for assessing task-relevant event density in realistic traffic scenarios with self-controlled speed. Occlusion time measures the visual demand of driving as the task-relevant event rate in time intervals, whereas occlusion distance measures the experienced task-relevant event density in distance intervals. **(f) Application** The findings can be utilized in context-aware distraction mitigation systems, human - automated vehicle interaction, road speed prediction and design, and in the testing of visual in-vehicle tasks for inappropriate in-vehicle glancing behaviors in any dynamic traffic scenario for which appropriate individual occlusion distances can be defined.

THE ATTENTIONAL DEMAND OF AUTOMOBILE DRIVING REVISITED – Occlusion distance as a function of task-relevant event density in realistic driving scenarios

A novel taxonomy defines driver inattention as "*insufficient, or no attention, to activities critical for safe driving*" (Regan, Hallet & Gordon, 2011, p. 1775). Even if the taxonomy is a highly valuable effort to standardize the use and operationalization of the construct, Regan et al. (2011) admit that the definition remains open-ended because it does not define the critical activities for safe driving. The difficulties in coming up with a standard definition pinpoints the problem that in spite of over 40 years of research, we do not yet understand the demands of the driving task itself at the level that we would be able to inclusively define what is inattentive driving.

Even if there are certainly other types of task demands involved, automobile driving is first and foremost a visual-manual task requiring visual information. There is compelling evidence indicating a statistical relationship between individual off-road glance durations and the risk of safety-critical incidents in real traffic (Liang, Lee, & Yekhshatyan, 2012). The percentage of over-2-second off-road glances during in-car task completion is one of the limiting criteria for acceptable visual sampling behaviors in the verification guidelines for the visual-manual in-vehicle electronic devices of the National Highway Traffic Safety Administration (2013). However, already a 1-second glance away from the road could be an occurrence of visual inattention in some driving environments. In the terminology of the driver inattention taxonomy as posed by Regan et al. (2011): How much visual attention is required in order to sufficiently process the safety-relevant targets in different driving conditions at a given moment, at what frequency, and what are those targets? What are these visual demands of driving in a certain situation for different drivers?

Seminal work of Senders, Kristofferson, Levison, Dietrich and Ward (1967) on an interstate road and on a racetrack utilized the visual occlusion technique to intermittently occlude the visual field of the driver with an occlusion visor in order to acquire an understanding of the visual demands of driving. In four experiments, Senders et al. (1967) systematically varied either the vehicle velocity or the length of the occlusion interval (occlusion time, OT) in order to get a quantitative description of the relationship between vehicle speed and OT (Experiments 1 & 2: I-495), as well as road curvature and OT (Experiments 3 & 4: Motorsport park). They found that on a particular road OT and vehicle speed are inversely related if one of these and all other factors are controlled (Senders et al., 1967). Five hundred milliseconds seemed to be a sufficient visual sampling time (visor open) in between occluded periods for an experienced driver to keep the control of the vehicle in the studied driving environments.

Concerning the qualitative questions of what and where do drivers require visual information while driving, Mourant and Rockwell (1970, 1972) conducted pioneering work with eye tracking on real roads. Mourant and Rockwell found the effects of road familiarity (1970) and driving experience (1972) on the on-road fixation targets. Both of the factors seemed to move fixations from the right-hand side of the road towards the vehicle's distant field of travel but also free visual resources to inspect other safety-relevant targets such as mirrors.

Later in a driving simulator, Tsimhoni and Green (1999, 2001) utilized the occlusion technique in order to study visual demand of driving curves repeating the findings of Senders et al. (1967). Tsimhoni and Green (2001) have also applied the technique in an effort to determine how secondary in-vehicle activities affect visual sampling behavior while driving.

After Senders et al. (1967) and Wortelen, Baumann and Lüdtke (2013), we define the visual demand of the driving task as the event rate at which the driver has to update the focus of visual attention in order to decrease uncertainty of the task-relevant event states in the immediate field of view to a preferred level. In line with the framework of Wortelen et al. (2013), a task-relevant event state in driving is a source of visual information such that when its value is changed significantly, a response is required from the driver in order to achieve a subgoal in the driving task, for instance, to keep the vehicle in the lane. The task-relevant event states in driving can include, for example, lane position, headway distance, visibility of obstacles, signs or cues, as well as object trajectories, including one's own vehicle. The significance of the change depends on the particular goals of the driving task but the safety-related goals can be assumed to be fairly general across drivers and drives. In occlusion experiments, the expected rate of the significant task-relevant events in time (expectancies by Wickens, Helleberg, Goh, Xu, & Horrey, 2001) is in inverse relationship to OT.

We argue that a limitation of OT is that it is a function of the event rate only in the time domain, and cannot by itself (without considering speed) specify the density of task-relevant events in the spatial scenario. Because of the limitations of OT when applied to realistic driving scenarios with voluntary speed control, we propose a new measure of visual demand of driving environments, occlusion distance (OD). OD refers to the distance a driver feels comfortable driving with his or her eyes shut when the driver is fully concentrating on the driving task.

In order to illustrate the difference, Figure 1 shows the calculated ODs and vehicle speeds on predefined OTs after Senders et al. (1967) data for participant J.W.S. Given all the situational factors other than the speed are the same, the OD for this particular interstate road and driver seems fairly constant across different speeds. OD tells us simply that this particular driver can drive on average 30 meters on this particular road without visual information, regardless of speed. OT, on the other hand, describes the level of visual demand of driving with various speeds on the road as a function of the task-relevant event rate in time. With the same OT but at a higher speed, more OD is traveled blind.

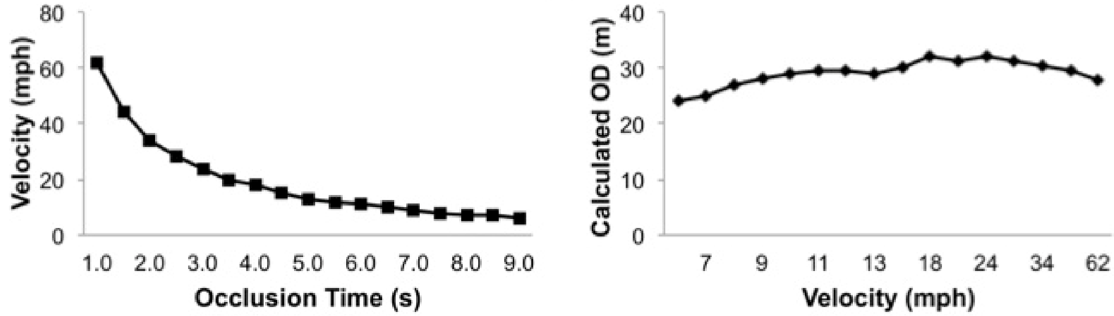

Figure 1. Calculated velocity points by occlusion time and the corresponding occlusion distances (OD) by velocity for the participant J.W.S. in Senders et al. (1967) Experiment 1 (I-495)

In this paper, we present support for our theoretical model of visual demand in driving and the utility of occlusion distance as a function of task-relevant event density in realistic traffic scenarios with driver-controlled speed and occlusion times.

Theoretical Model of Visual Demand in Driving

We define the visual demand of the driving task as the event rate at which the driver has to update the focus of visual attention in order to decrease uncertainty of the task-relevant event states in the immediate field of view to a preferred level. We specifically note that the event rate can be either in the time domain *or* in the space domain. That is, the updating may occur at specific time intervals, or at specific distance intervals. In the special case of constant speed, these two will be perfectly correlated.

In the following, we assume a driver (a cognitive agent) k with a perfect expectancy evaluation skill who pushes occlusion time to a constant maximum level of tolerated uncertainty in all scenarios.

After Wortelen et al. (2013), a task-relevant event $e(g,t)$ occurs if at time t visual information, which is relevant for a goal g is used by the cognitive agent k to achieve g. That is, event $e(g,t)$ occurs, if at time t a production rule is fired for goal g and thus, the visual information is used by the cognitive agent. A production can process perceived visual information from the environment, such as the headway distance, or features of a stored dynamic visuospatial mental representation of the environment, such as the imagined lane position of the vehicle. A production that processes visual information can also fire without producing a motor response. This would correspond to a real-world behavior of a driver perceiving something task-relevant in the environment such as a headway distance and making a judgment that the current headway distance is sufficient and no response is needed.

By our definition, the visual demand of a driving scenario is a function of the total number of events in the scenario per time or distance unit. With a perfect cognitive model of driving (similar to, e.g., Salvucci, 2006), the visual demand, that is, the number of events in the scenario per time or distance unit would correspond directly to the number of productions firing, in which visual information is used.

For the cognitive agent k, the field of view at a point x_i induces $E(x_i)$ task-relevant events. When the driver k moves along the road a distance Δx, the total number of processed events is $\sum_i E(x_i)$. In Figure 2, $\sum_i E(x_i) = E(x_1) + E(x_2) = 6$. The circles represent driving task relevant targets (i.e., event states) in the road environment, such as a traffic sign or an approaching car from the right at an intersection ahead. Each arrow represents task-relevant visual information for an event that is processed by the driver, such as the observed speed of the approaching car. Note that visual information of a single physical target can be processed in multiple events.

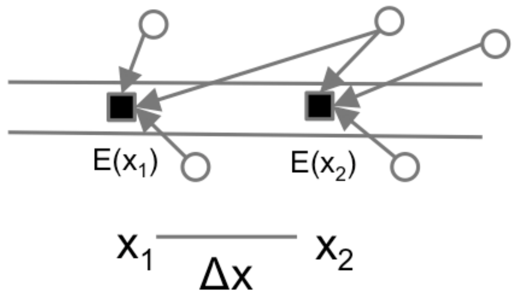

Figure 2. Illustration of task-relevant events at two points on the road (x_1 and x_2). Each circle represents a task-relevant source of visual information (i.e., event state) in the road environment.

The temporal event rate, $\sum_i E(x_i)/\Delta t$, is the time-based function that is traditionally studied in occlusion experiments. In general, the event rate in time is a function of both the number of events per distance, $\sum_i E(x_i)/\Delta x$, and the speed of the car, $\Delta x/\Delta t$. We can write this as an equation

$$\frac{\sum_i E(x_i)}{\Delta t} \approx \frac{\sum_i E(x_i)}{\Delta x}\frac{\Delta x}{\Delta t} \approx D(x)V(x) \qquad (1)$$

which is exact when Δt is very small. V(x) is then the momentary velocity of the car. We denote D(x) as the event density. It is the discrete version of the information density of the road *("events per mile"* rather than "*bits per mile*") as defined by Senders et al. (1967). The driver can adjust the event rate by scanning freely ahead and adjust speed so that a comfortable event rate is not exceeded. This is the key task in theoretical models of driving such as Fuller (2005) and Summala (2007).

However, the occlusion method makes the mathematical interpretation more complex compared to unoccluded driving. It is necessary to consider a new parameter: the driver's uncertainty $U(x)_k$ of the task-relevant event states during occlusion (Senders et al., 1967).

The uncertainty is hypothesized to be a function of the number of task-relevant events induced by the field of view. Increases in the observed event density in the field of view adds to the complexity of the stored dynamic visuospatial mental representation of the scenario that must be processed during the following occlusion. The more events that have to be processed while occluded, the faster the build-up of uncertainty.

Thus, uncertainty builds up in this model as a function of events, not time, as in the work of Senders et al. (1967). We make the simplifying assumption that the uncertainty of the task-relevant event states is linearly related to the number of processed (i.e., expected) events during the occlusion: $U(x)_k = \Delta x D(x)$, that is, $U(x)_k = \sum_i E(x_i)$ (see Eq. 1).

The driver k will ask for additional visual information as soon as the driver's uncertainty of the task-relevant event states during the occlusion has reached the driver's maximum level of uncertainty tolerated, $U(x)_k = Umax_k$. For our perfect cognitive agent k the constant $Umax_k$ would correspond to the maximum processing capacity of the human visual memory for moving scenes (Thomson, 1983). For any real driver, $Umax_k$ could be affected by other personal factors, such as tolerance of ambiguity (Furnham & Marks, 2013) and risk tolerance. The driver will thus end the occlusion when $U(x)_k = Umax_k$. Then, for a constant speed V(x), we have the equation

$$U(x)_k = D(x)V(x)OT(x)_k = Umax_k \qquad (2)$$

In this paper, we are interested in estimating D(x). In most occlusion studies so far (Senders et al., 1967: Experiments 1 and 3; Tsimhoni & Green, 1999; 2001), the situation has been simplified considerably by holding the drivers to a constant speed. The driver can control occlusion time OT so that the event rate is kept within the limits of preferred uncertainty. In this special case of constant speed OT can be used to estimate D(x).

However, these results would be limited, for example, to visual demand of negotiating a curve with a constant speed. Driving on a road with realistic curvature with a forced static speed is fundamentally a different task than driving the same road with a voluntary speed control, at the operational level as well as from the perspective of visual demands. As an example, in our upcoming data speed is strongly dependent on the curvature of the road, since drivers decelerate when they enter a curve.

On the other hand, if both V and OT can vary, then OT can not be used to estimate D(x) without considering changes in speed. For these cases, however, we can define a new function that has not been used in earlier research: the occlusion distance $OD(x)_k$, defined as the distance the driver drives during an occlusion (see Figure 3). This is very close to $OT(x)_k*V(x)_k$, but the relationship is not exact because the driver may accelerate or decelerate during the occlusion (i.e., react according to the preceding unoccluded field of view).

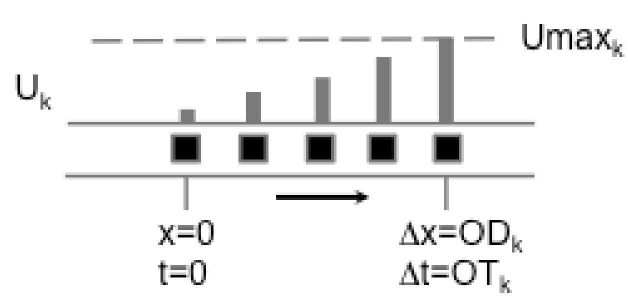

Figure 3. The relationships between U_k, $Umax_k$, OD_k, and OT_k. Driver k's uncertainty (U_k) reaches k's maximum level of uncertainty tolerated ($Umax_k$) when the distance Δx traveled equals OD_k and the time Δt traveled equals OT_k.

The occlusion distance combines the two driver-controlled variables in this setup into one:

$$Umax_k = D(x)OD(x)_k \tag{3}$$

and allows a prediction for driver behavior to be made:

$$OD(x)_k = \frac{Umax_k}{D(x)} \qquad (4)$$

We call the $Umax_k$ factor as the subjective uncertainty acceptance threshold that should be fairly static for driver k across different traffic scenarios. It describes the threshold at which the driver feels that the comfortable safety margins have been crossed (Summala, 2007). That is, the driver k is capable of processing (or willing to process) at most $Umax_k$ events per $OD(x)_k$. $Umax_k$ of a given driver can be estimated in a visual occlusion experiment with a sufficient sample of drivers.

Both OT and OD are imperfect measures for visual demand, but each has its own strengths. OT varies with the inverse of the task-relevant event rate in the time domain (i.e., dynamic visual demands of driving), but cannot determine whether the changes are due to changes in speed or to changes in the number of events in the scenario. OD varies with the inverse of the event density in the space domain from one unoccluded view to another (i.e., static visual demands of the driving environment), but does not give information on how the driver is processing information in the time domain.

In the following, we seek to demonstrate that the three specific hypotheses supporting our theoretical model are justified by the data set collected in two driving simulator experiments with intersection, suburban, and highway scenarios:

H1. With self-determined speed and OT, median ODs will increase across environments of progressively reduced event density from intersections to suburban to highway scenarios whereas OTs will vary significantly less. Highways have larger built-in safety margins (e.g., less curvature, no crossings, wider one-way lanes) to enable safe driving at higher speeds than suburbs. Intersections have more task-relevant targets to scan for than the other two scenarios, such as signs, lights, crossing roads, crosswalks, and lanes to select. H1 would support the model of OD as a function of task-relevant event density in space and OT as a function of the preferred task-relevant event rate. It would support the idea that drivers try to keep the visual demands of driving (i.e., event rate) at a general comfortable range across scenarios of varying event density.

H2. OD varies systematically with a nearly constant individual factor for the same driver across driving scenarios. The finding would give support for the consistency of the subjective uncertainty acceptance threshold $Umax_k$ within a driver and for the generalizability of OD across driving scenarios.

H3. Curvature of the road ahead has a significant inverse relation to OD. The specific environmental demands of road curvature should have an effect on OD if OD is a measure of the task-relevant event density of the environment.

By validating these three hypotheses, we can demonstrate that OD can be effectively used to define the environmental and driver-specific task-relevant event density with a generalizable metric over a wide variety of drivers and dynamic real-world scenarios.

Occlusion in Simulated Realistic Driving Scenarios

Because nowadays ethical research boards will not approve on-road occlusion studies, and with good reason, we used a motion-platform driving simulator to mimic Finnish suburban and highway driving as realistically as possible.

Research Method

Participants. A total of 130 volunteers were recruited by contacting private and public sector employees in Central Finland, the University of Jyväskylä student mailing lists, and vehicle inspection stations in the city of Jyväskylä. Driving schools in Jyväskylä, as well as the Central Finland educational consortium, were contacted in order to reach novice drivers. Motion sickness was monitored during the experiments with the Simulator Sickness Questionnaire (SSQ, Kennedy, 1993). Thirty-three participants withdrew from the study or had to be excluded from the data because of simulator sickness symptoms, or as outliers (driving at least 30% of the time the scene was constantly unoccluded). The final sample included 40 women and 57 men between the ages of 18 and 61 (*M*=30.8; *SD*=9.9). They all had a valid driving license and lifetime driving experience from 0 to 43 years (*M*=13.0; *SD*=9.9). Participants drove weekly from 0 to 2,500 kilometers (*M*=237; *SD*=432) and in a year from 50 to 130,000 kilometers (*M*=14,262; *SD*=19,322). All the participants had a normal or corrected to normal vision. The experiments were conducted in Finnish with fluent Finnish-speakers. All the participants were rewarded with a movie ticket.

Environment and tools. The motion-base medium-fidelity driving simulator is located at the driving simulator laboratory of the Department of Computer Science and Information Systems in University of Jyväskylä (see Figure 4). The CKAS Mechatronics 2DOF motion platform provided movements for the simulator, simulating accelerations and decelerations of the vehicle in order to make the maintenance of speed more natural and less visually demanding by minimizing the need to observe the speedometer to keep the speed constant. The virtual driving scene was displayed on three 40” (95.6 cm x 57.4 cm) LED displays with a resolution of 1440 x 900 pixels. The simulator was equipped with a Logitech G27 force feedback steering wheel, accelerator, and brake. A right side paddle shifter in the steering wheel was used for unoccluding the driving scene for 500 ms for each press.

Figure 4. The motion-base medium-fidelity driving simulator

The driving simulation software was provided by Eepsoft (www.eepsoft.fi). The experiments were driven in a virtual environment simulating real-life Finnish suburban and highway traffic environments in Martinlaakso, Vantaa (see Figure 5). The virtual environment included Head-Up-Display (HUD) speedometer, RPM gauge, and a rear-view and side mirrors. The virtual car's transmission was set to automatic. Driving log data were logged and saved at 10 Hz. Additional research equipment included a head-mounted Dikablis eye-tracking system with a 50 Hz sampling rate (eye-tracking data not reported here).

Figure 5. Examples of 6 simulated locations (numbered) compared to real ones (below). 1: intersection with traffic; 2: junction to highway; 3, 4, 5: suburban roads; 6: intersection with traffic lights.

Procedure. After the collection of demographic data, all the participants completed a practice session followed by three experiments in different environments. The practice session was driven in an urban environment until the participant felt comfortable, on an average about 10 minutes per practice, first unoccluded and then occluded. After the practices, the participant first drove a Suburban experiment for approximately 25 minutes, after a break a 15 minute Highway experiment, and finally 5 minute suburban experiment in snowfall conditions (snowfall results not reported here). The driving scene was occluded by default and participants were able to unocclude the scene for 500 milliseconds by pressing the right-hand paddle behind the steering wheel. To keep the scene continuously unoccluded the paddle had to be repeatedly pressed.

A speed limit of 60 km/h was instructed for the Suburban experiment and 80 km/h or 120 km/h for two different types of road in the Highway experiment. Driving directions were provided by Finnish voice guidance at predetermined points on the tracks. The instructions were given two times before each street corner or junction and the participant had the possibility to ask the experimenter to repeat the instructions. In order to make the participants focus on the driving task but still to try to maximize the comfortable occlusion time, they were informed that the 30 most accurate participants in the driving task and with the least unoccluded time would be rewarded with another movie ticket. Driving task accuracy was defined by the number of lane excursions that were scored in real-time by the experimenter. The accuracy of lane keeping was assessed by how many times the HUD speedometer (Figure 4) crossed a white lane marking, but this was not explicitly stressed in order to avoid unnatural visual demand for an experienced driver through fixating on the lane markings.

In this setup, lane-keeping accuracy could be determined independently from the OD because lane excursions were monitored covertly. Although it is not a direct measure of safe driving as such, the lane-keeping accuracy differed dramatically from driver to driver (from 2 to 120 excursions). The accuracy parameter was thus defined as (120-number of excursions)/120, being normalized between 0 and 1. Participants were also instructed to obey traffic rules, to choose their preferred driving speed, beware of unexpected events and react as in real situations. No completion time limits were given. Participants were told that they could withdraw from the experiment whenever they wish.

Data set. The final data set consisted of 97 drivers who drove through the Suburban and Highway experiments. Four other drivers finished both experiments, but were found to have often (at least 30% of the time) clicked the unocclusion paddle at intervals that were less than 500 milliseconds, meaning the scene was constantly unoccluded. The other drivers did not indicate such behavior or only 1-2% of the time, so the four outliers were easily identified and excluded from the analysis. The sample size in the following statistical tests varies between 93, 95, and 97 because of missing data due to technical problems with four participants. For the Suburban and Highway experiments N=95.

The data set consisted of two types of scenarios (Suburban and Highway, see Table 1). The tracks, that is, road segments, were divided into separate segments by defining trigger points on the road at points where the user was instructed to turn at an intersection. Another trigger point was set where the driver had cleared the intersection. The tracks were thus defined as segments between the last trigger line marking the end of an intersection and the first trigger line of the consecutive intersection. The drivers accelerated at the beginning of each track in order to reach a velocity preferred by the driver. In total, there were 13 tracks that were long enough to be usable to estimate the average behavior of drivers over the tracks. Nine of these were Suburban (60 km/h speed limit) and four were Highway (80 or 120 km/h) tracks. In addition, 19 of the intersections were studied. These varied considerably, but all contained an instruction for the driver to turn at an intersection. Driver behavior was highly variable. Some stopped at some intersections, while others never did. This confounding behavior could not be modeled. Therefore, the intersection data for speeds over 2 m/s were used for the OT-OD comparison, but not for a close-up analysis of the occlusion data. For the Intersection data N=97.

Table 1

Scenarios per Track [values are median, mean, (SD)].

Track ID	Length m	Winding (W) m/m	Speed m/s	Occlusion Time (OT) s	Occl. Distance (OD) m	Median OT * Median Speed	Traffic	Type
Experiment 1 – Suburban scenarios (*N*=95)								
M02	395	0.11 0.12 (0.06)	10.0 10.0 (2.4)	0.86 0.99 (0.64)	7.5 8.6 (5.8)	8.6	None	Suburban, almost straight, 60 km/h
M04	396	0.32 0.32 (0.15)	10.5 10.5 (2.3)	0.74 0.92 (0.67)	6.8 8.4 (6.4)	7.8	One approaching	Suburban, 60 km/h
M10	1059	0.012 0.020 (0.02)	13.0 12.7 (2.5)	0.97 1.20 (0.87)	10.7 14.1 (11.7)	12.6	High*	Suburban, almost straight, 60 km/h
M12	1039	0.038 0.039 (0.008)	12.3 12.4 (2.5)	0.90 1.10 (0.79)	9.9 12.6 (10.1)	11.1	Approaching	Suburban, almost straight, 60 km/h
M22	355	0.18 0.15 (0.05)	10.9 10.9 (2.1)	0.85 1.01 (0.71)	7.9 9.6 (7.5)	9.3	None	Suburban, 60 km/h
M28	423	0.34 0.33 (0.07)	9.7 9.5 (1.9)	0.60 0.74 (0.54)	4.8 6.1 (4.9)	5.8	High*	Suburban, narrow road, 60 km/h
M33	704	0.15 0.15 (0.04)	12.8 13.0 (2.6)	0.80 0.97 (0.70)	9.2 11.6 (8.8)	10.2	One approaching	Suburban, 60 km/h
M46	850	0.063 0.066 (0.016)	12.6 12.6 (2.5)	0.80 0.97 (0.70)	8.9 11.1 (8.6)	10.1	Approaching	Suburban, 60 km/h
M54	571	0.18 0.23 (0.14)	10.5 10.6 (2.8)	0.69 0.88 (0.67)	5.8 8.0 (7.1)	7.2	High*	Suburban, 60 km/h
Experiment 2 – Highway scenarios (*N*=95)								
M64	1208	0.041 0.037 (0.010)	21.0 20.5 (2.8)	0.51 0.64 (0.48)	8.4 10.7 (8.7)	10.7	High*	Highway, 80 km/h
M66	1015	0.028 0.027 (0.005)	21.2 21.2 (2.3)	0.81 0.97 (0.74)	14.2 17.6 (14.3)	17.2	None	Highway, 80 km/h
M71	1182	0.030 0.029 (0.007)	28.1 27.9 (3.9)	0.56 0.71 (0.54)	12.3 16.6 (14.2)	15.7	High*	Highway, 120 km/h
M73	1135	0.011 0.019 (0.014)	26.5 26.0 (4.7)	0.65 0.81 (0.65)	12.9 16.7 (15.2)	17.2	None	Highway, 120 km/h

Note. *: In cases of high traffic, cars with artificial intelligence driving in the same direction drove at the nominal maximum speeds, and thus usually outran drivers. Most tracks in fact were in practice empty except for the approaching cars.

The study closest to ours, Tsimhoni and Green (1999), had the following restrictions: a simple predefined road with a radius of curvature measured at just a few points, constant speed, no other cars, and the participant only varying the occlusion time. The level of visual demand was defined as 0.5/(0.5+OT), and a linear model of visual demand with a radius of curvature and age was determined by averaging values over all drivers for the four well-defined curvature points.

In contrast, in our experiments the driver drove on simulated real-world roads that were not designed to prove any hypotheses and the driver was able to vary vehicle speed (only a nominal maximum for the road was defined) as well as the occlusion time. Furthermore, the driver was told to drive carefully and to obey traffic regulations. Additionally, other traffic in the form of cars controlled by artificial intelligence algorithms (AI cars) could move in the same or opposite direction (Figure 5: 1, 2) and there were intersections with potential traffic (Fig. 5: 1, 6), traffic lights (Fig. 5: 6), and various other signage (Fig. 5: 1, 2). The downside of this naturalistic driving simulation was that it introduced variables that could not be modeled. We suspect that intersections, zebra crossings, and road signs, in particular, may have caused highly variable effects, since the drivers were asked to be vigilant of crossing traffic and pedestrians.

Calculation of Winding. The calculation of road curvature for real-world roads is a numerically unstable parameter, a fact that could be ignored in Tsimhoni and Green (1999) where the simulated road was designed specifically for the purpose of the analyses of curvature on occlusion time. In addition, they only measured road curvature at four points, whereas we needed to measure it continuously.

The radius of curvature R of a natural road is not constant, but rather is constantly varying as the driver moves in and out of a curve. To improve measurements, we defined a related parameter we coined Winding, denoted by W. It is a measure of how much the driver needs to turn the steering wheel while driving along the track.

We suggest that the number of task-relevant events on a winding road is related to the amount of steering a driver anticipates as being required ahead. The Winding is related to the radius of curvature R, but is dimensionless and numerically more stable. For any infinitesimal distance dx, the dimensionless lateral deflection is dx/R(x). The total lateral deflection over a long distance L is then given by:

$$W = \frac{1}{L}\int_0^L \frac{dx}{R(x)} \tag{5}$$

The integral is divided by L in order to make W dimensionless and independent of the chosen value of L. The distance L must be defined empirically, but we found 100 meters to be practical. This is also consistent with the result of Tsimhoni and Green (1999), by which the closest 100 meters ahead before a curve included 70 % of the locations of the maximum visual demand. A value of 0.1 means that the road is on average deflected 10 cm per every meter driven. For the roads in our simulation the typical values of W were less than 0.2; only in the tightest corners did it exceed 0.4.

W is dimensionless but can be defined as (meters deflection)/(meters distance). Qualitatively, it describes how many meters the path is deflected per each meter that is traveled forward.

Effects of other cars. The effect of AI cars on driver behavior could not be meaningfully evaluated. Some of the tracks had AI traffic going in the same or opposite direction as the driver, but this had no practical effect on the results. The lead cars drove at the nominal speed limit of the scenario, while test subjects almost always drove at lower speeds. Thus, unexpectedly, there was little to no interaction with the AI traffic, and the AI traffic was ignored in this study.

Results

H1. With self-determined speed and OT, median ODs will increase across environments of progressively reduced event density from intersections to suburban to highway scenarios whereas OTs will vary significantly less. Median and mean OTs, ODs, and speeds per track are listed in Table 1. Over all the drivers, median ODs seem to vary in a similar systematic fashion between the tracks in Table 1 as median OT * median speed (Pearson's $r(11)=.98$, $p<.001$). This suggests that it is sufficient to approximate that OD(x)=V(x)*OT(x) although the exact distance travelled during OT is then somewhat under- or overestimated. It is, however, more interesting to look at the underlying distributions. Figure 6 shows the individual median OTs and ODs per scenario for the three different scenarios.

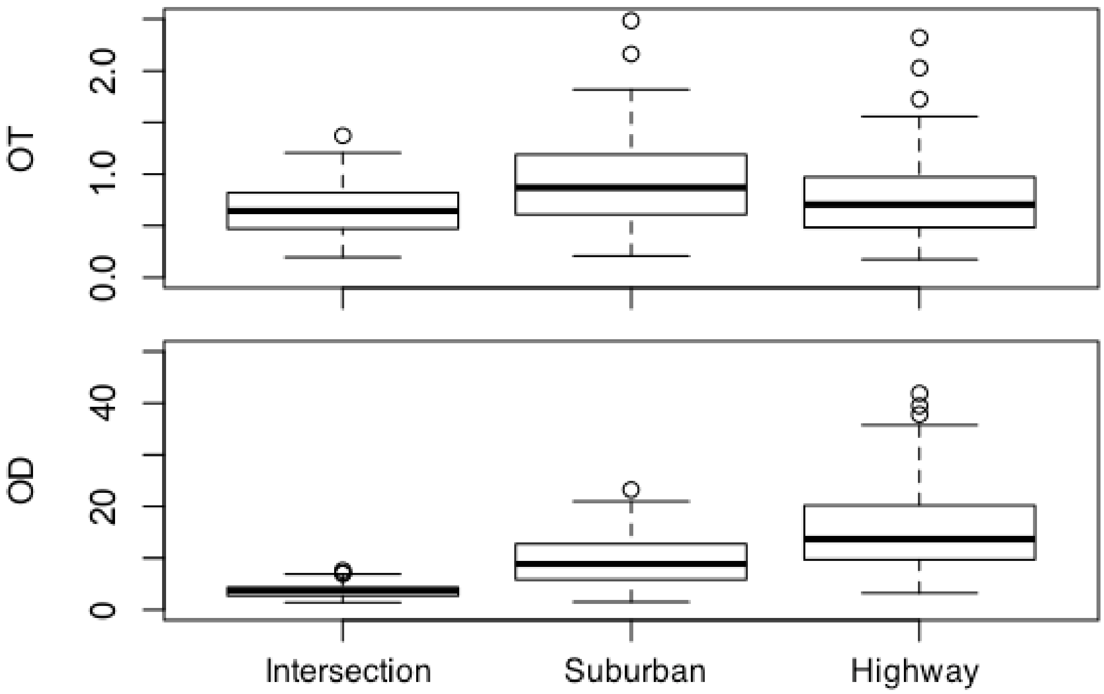

Figure 6. Tukey box-plots with medians and quartiles of individual median OT (s, top) and OD (m, bottom) for the Intersection (*N*=97), Suburban (*N*=95), and Highway (*N*=95) scenarios.

Analysis on the effects of the scenario (Intersection, Suburban, Highway) with one-way repeated measures ANOVA indicates significant differences between the scenarios in both mean OD, $F(2,184)=208.619$, $p<.001$, *partial* $\eta^2=.694$, as well as in mean OT, $F(2,184)=56.388$, $p<.001$, *partial* $\eta^2=.380$. However, Table 2 and Figure 6 indicate that the mean OD increases considerably from Intersection to Suburban to Highway scenarios whereas mean OTs stay within a range between .67 to .95 seconds.

Table 2

Mean OD and Mean OT per Scenario (SD).

	Intersection	Suburban	Highway	Mean Difference Sub-Int	Mean Difference High-Int	Mean Difference High-Sub
OD (m)	3.76 (1.40)	9.86 (4.78)	15.53 (8.38)	6.10***	11.77***	5.67***
OT (s)	.67 (.25)	.95 (.44)	.74 (.39)	.27***	.07*	-.20***

Note. ***: p<.001, *: p<.05. Int=Intersection (N=97), Sub=Subway (N=95), High=Highway (N=95).

The mean difference in OT between Suburban and Highway scenarios is only .27 seconds, and the difference is to an opposite direction than in OD. The mean difference in OT between the Intersection and Highway scenarios is only .07 seconds. These findings suggest that even if OT is able to differentiate the high Intersection demands, OT varies as a function of task-relevant event rate in time and is not able to differentiate the spatial task-relevant event density between the Suburban and Highway environments that are built to allow safe driving at significantly different speeds. On the other hand, OD can indicate the differences in the expected spatial demands between the scenarios. However, OD cannot indicate that the visual demand of driving near the nominal speed limits in Suburban and Highway scenarios are nearly at the same level, with slightly higher demands on Highway driving and approaching the demands of the Intersection scenarios. Hence the two measures provide complementary information.

These findings support H1 and thus support the model of OD as a function of task-relevant event density in space whereas OT seems to be a function of preferred task-relevant event rate in time. The findings suggest, as expected, that by controlling speed according to the experienced event density, the drivers tend to keep the occlusion times on a similar comfortable range of approximately .50 to 1.00 seconds across different driving scenarios. The data and our theoretical model can provide an explanation why drivers' preferred range of off-road glance durations seem to reside within this time frame across driving scenarios (Wierwille, 1993). The task-relevant event densities of constructed real-world road environments are in a linear relationship with the drivers' preferred speeds in these environments such that the preferred off-road glance durations (a function of the task-relevant event rate) rarely exceed 2.00 seconds.

H2. OD varies systematically with a nearly constant individual factor for the same driver between driving scenarios. The Highway scenario differed from the others in that the Winding is extremely low (see Figure 7), there were no intersections to worry about, and driving was not affected by AI cars because in almost all cases the AI lead cars drove much faster than the participants. The within-scenario visual demand is thus for all practical purposes near constant. Any variations in the highway scenario should be due to individual differences. To eliminate issues with possible AI lead cars, we removed the first 200 meters of the highway tracks from the analysis. Therefore, in all except a few cases the lead cars had driven off, and do not confound the analysis of the visual demand.

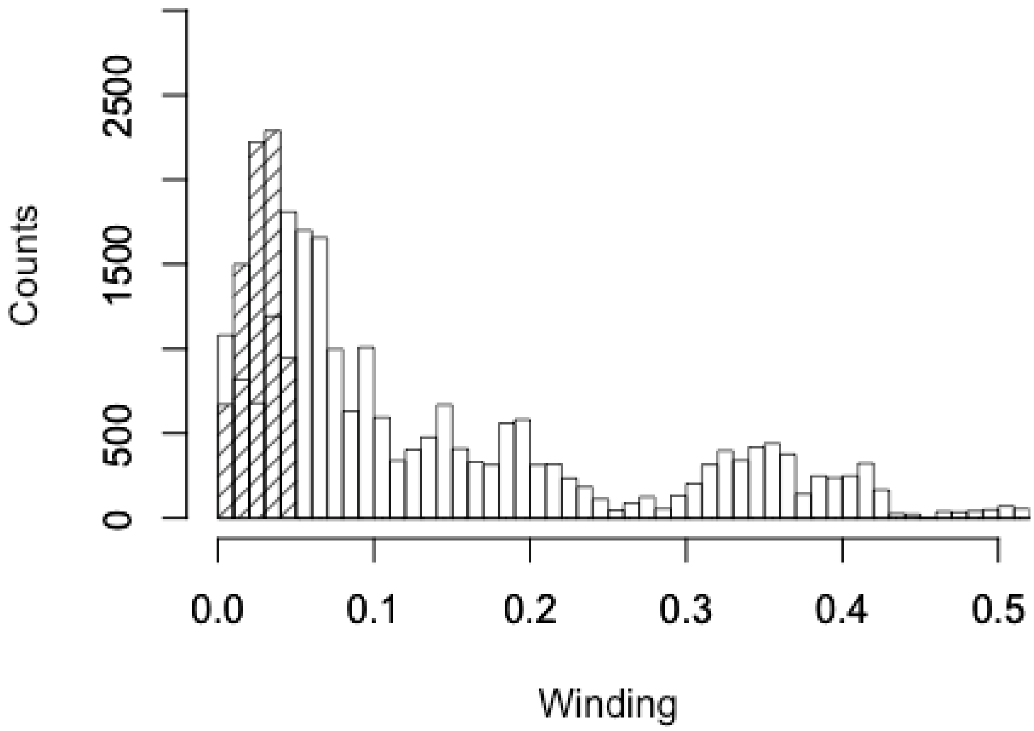

Figure 7. Winding (m/m) on the Highway track samples (lined) compared to the Suburban track samples (blank).

The median highway OD was 13.7 m, and the 15th and 85th percentiles were 7.1 and 23.4 m (see Figure 8). The median OT was .71 s, and the 15th and 85th percentiles were .36 and 1.10 s. The median OD (as well as OT) can thus vary by up to a factor of three between drivers. Since the drivers in the highway scenario did not modulate the speed rapidly (i.e. did not apply brakes sharply), the OD and OT are closely correlated ($r(91)=.95$, $p<.001$).

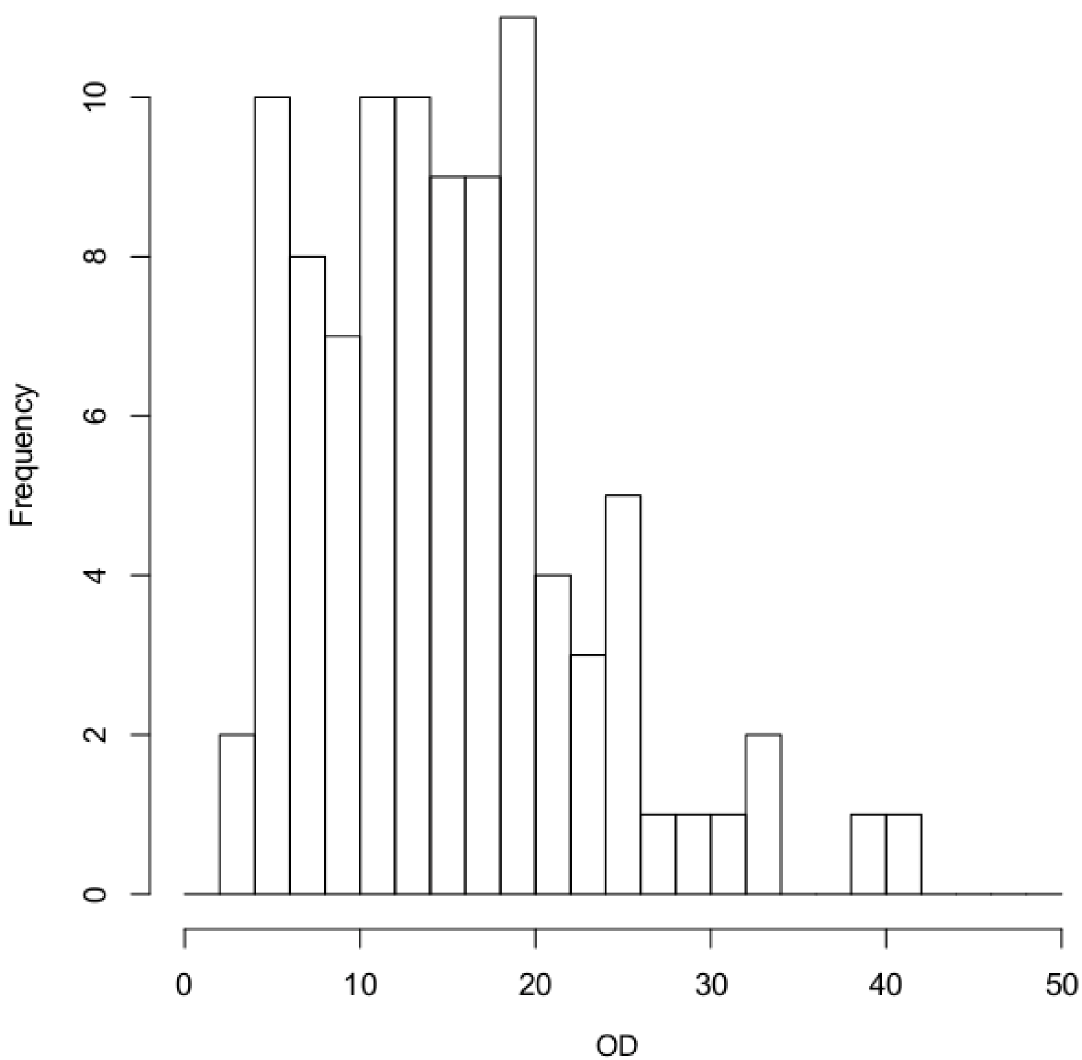

Figure 8. Distribution of median OD (m) of each driver in the Highway scenarios (*N*=95).

The scenario-dependent visual demand in all the Highway scenarios was assumed to be constant, and the significant variations seen in OD thus show differences in the drivers' perceptions of the task-relevant event density, which are in fact not present in the objective distribution of the events in the external scenario. Based on our theoretical framework, we interpret these differences to describe the subjective uncertainty acceptance threshold $Umax_k$, so that for any individual driver k on the Highway scenario $OD(x,highway)_k=Umax_k*13.7$.

H2 suggests that across scenarios OD(x) varies systematically (because the event density varies with the distance x), and that across subjects $Umax_k$ varies systematically. Let

h_m = 13.7 m be the median OD of the sample for the Highway scenarios and s_m = 8.9 m the median OD of the sample for the Suburban scenarios. Then the normalized values of $OD(x,highway)_k$ and $OD(x,suburban)_k$ for the driver k are:

$$\frac{OD(x, highway)_k}{h_m} = Umax_k \tag{6}$$

$$\frac{OD(x, suburban)_k}{s_m} = Umax_k \tag{7}$$

Then we can rewrite $OD(x, suburban)_k$ as a linear function of $OD(x, highway)_k$ using the above equations:

$$OD(x, suburban)_k = \frac{s_m}{h_m} OD(x, highway)_k \tag{8}$$

Now we can show that for any individual driver, the value of $Umax_k$ remains almost constant across all scenarios. Figure 9 shows a scatter plot of the per-driver relative values for the two scenarios (Highway and Suburban). The data points are normalized to the median OD for all drivers in the scenario. It is seen that a driver with a low OD on the Highway tracks will also have a low OD on the Suburban tracks ($r(91)$=.85, p<.001). The correlation between Highway and Intersection tracks is slightly lower ($r(93)$=.71, p<.001). However, we can state that the measured value of $Umax_k$ for a given driver will be relatively constant over different scenarios.

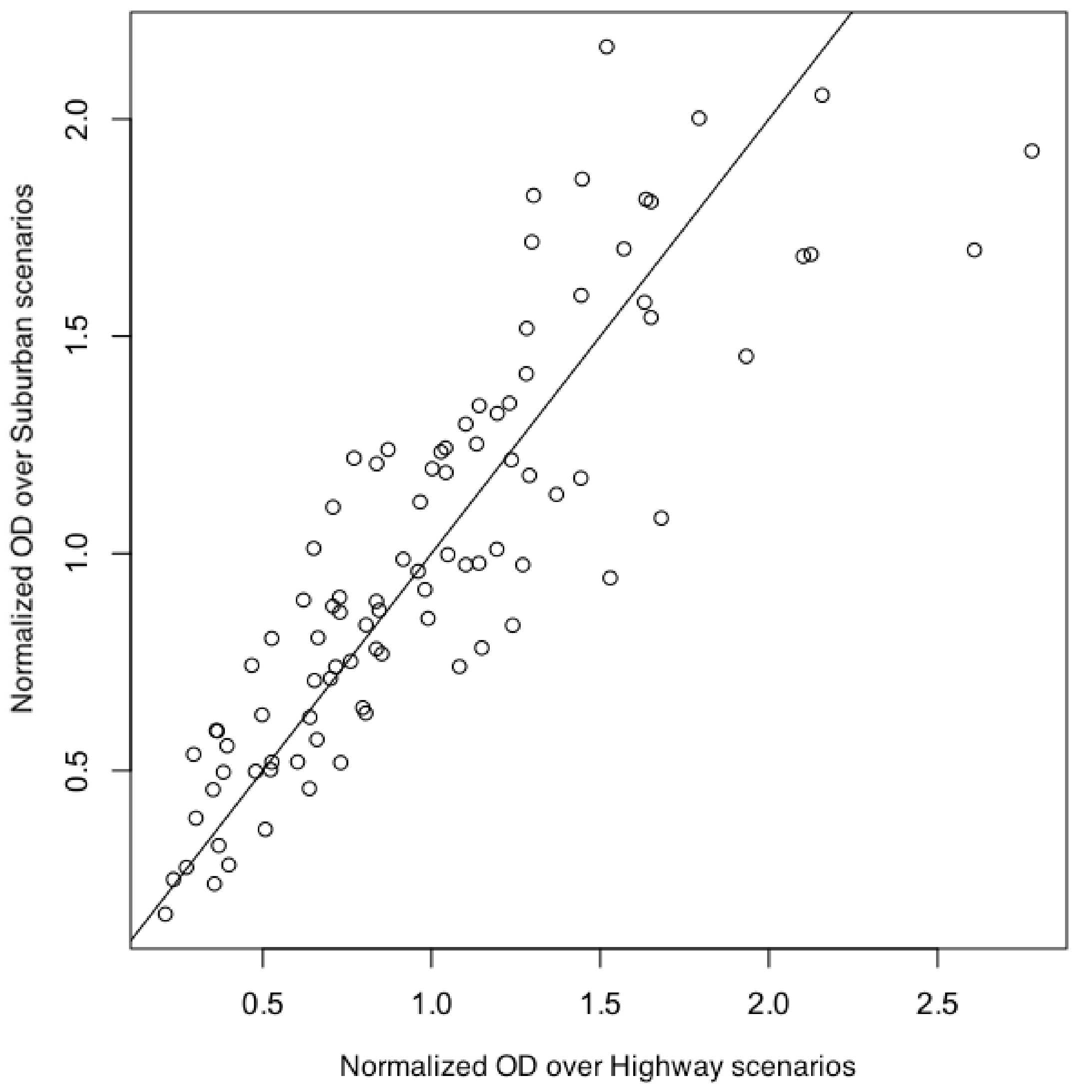

Figure 9. Normalized OD (m) for each driver, Suburban vs. Highway scenarios (N=93).

Note that the correlations are approximately the same for OT across scenarios as they were for OD ($r(91)=.82$, $p<.001$ and $r(93)=.71$, $p<.001$ respectively). There are also statistically significant correlations between median speeds ($r(91)=.48$, $p<.001$ for Highway vs. Suburban, and $r(93)=.29$, $p=.003$ for Highway vs. Intersection), although these correlations are much lower than for OT and OD. Nevertheless, fast drivers seemed to drive fast in all scenarios: high-occlusion-time drivers had high occlusion times across all scenarios.

However, high-OT drivers may not be high-speed drivers. For both the Highway data and the Suburban data, the correlation of OT and speed is statistically insignificant (Highway: $r(93)=-.03$, $p=.740$; Suburban: ($r(93)=-.08$, $p=.420$). For the Intersections the calculation of median speed and the correlative analysis is not appropriate due to the much stronger and highly variable acceleration and deceleration behaviors compared to the Highway and Suburban scenarios.

Based on earlier research, it was expected that driving experience would affect the choice of OD (and OT), since novice drivers require more frequent updates of focal visual attention for lane keeping than experienced drivers (Mourant & Rockwell, 1972; Summala, Nieminen, & Punto, 1996). The analysis was made for the Suburban scenarios. The participants were divided into three classes according to self-reported lifetime driving experience: under 50,000 km ($n=36$, median OD=7.0), 50,000-200,000 km ($n=28$, median OD=7.3), and over 200,000 km ($n=33$, median OD=6.3). In addition, we studied the effects of gender and age on drivers' median ODs in the Suburban scenarios ($N=95$). One-way between-subjects ANOVAs were conducted for analyzing the effects of driving experience (<50,000 km; 50,000-200,000 km; >200,000 km) and gender (male; female).

The choice of OD level does not seem to be affected by driving experience ($F(2,93)=1.31$, $p=.270$) or gender ($F(1,94)=.23$, $p=.630$). Neither did age and OD correlate significantly, $r(93)=-0.17$, $p=.090$.

In line with previous research, a Welch t-test shows a significantly lower median lane-keeping accuracy for the least experienced group than for the most experienced one (.69 versus .81), $t(61.793)=-2.9677$, $p=.004$, 95% CIs [-.21,-.04], two-tailed. The effect is still significant at $p<.05$ but much smaller when the least experienced group is compared to all the others: $t(67.184) = -2.1386$, $p=.036$, 95% CIs [-.17,-.005], two-tailed.

Interestingly, drivers' median OD and driver accuracy were significantly inversely correlated ($r(93)=-.64$, $p<.001$) in the Suburban scenarios. Figure 10 shows the OD-accuracy relationship by experience category, together with the least-squares fits for each experience category.

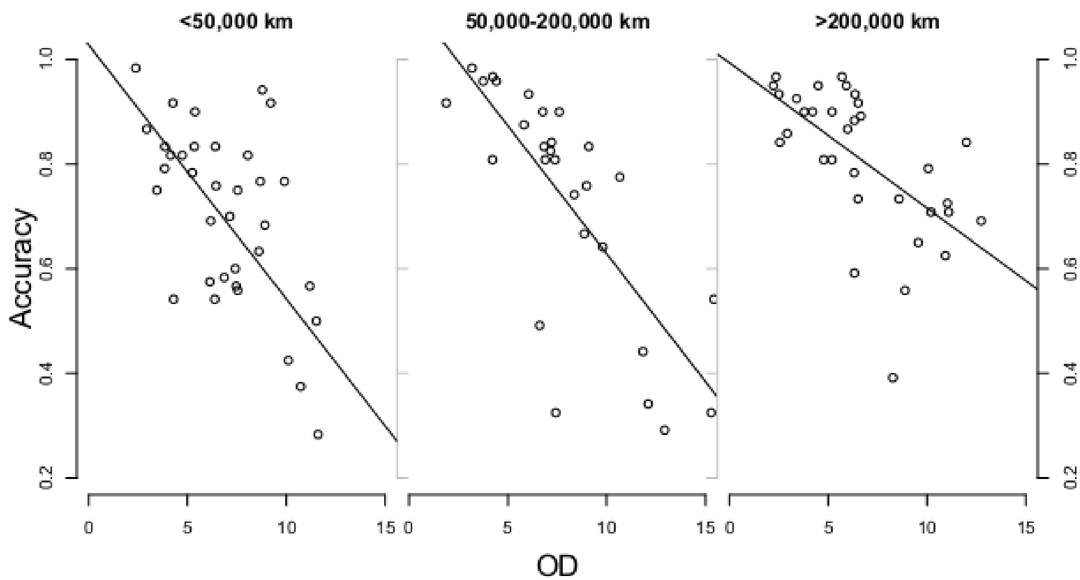

Figure 10. Lane-keeping accuracy in the Suburban scenarios by OD (m, median) and the driving experience category.

As noted earlier, there was no direct correlation between driving experience and OD (or OT). Based on our theoretical framework, we interpret this result to suggest that the subjective uncertainty acceptance threshold $Umax_k$ of a driver is not in a direct relationship with driving experience. A higher OD seemed to systematically lead to a lower lane-keeping accuracy regardless of the level of driving experience. However, higher level of driving experience may result in better lane-keeping accuracy for a given OD value. No other individual effects could be found.

H2 is supported by the data. The findings suggest that OD is a generalizable measure across the studied driving scenarios and the consistency of the subjective uncertainty acceptance threshold $Umax_k$ over different driving scenarios is supported. This means that if we know a driver's $Umax_k$ value, we can make predictions of the driver's visual behavior in road environments with known median OD values.

H3. Curvature of the road ahead has a significant inverse relation to OD. Next, we modeled the dependence of OD on scenario parameters. This analysis was made with only the Suburban tracks. To eliminate between-subject differences, ODs of the individual driver k were normalized by dividing by the median OD of the driver k for the Suburban scenarios:

$$ODN(x, suburban)_k = OD(x, suburban)_k \,/\, median(OD(x, suburban)_k) \quad (9)$$

Thus, whether the driver is high-OD or low-OD, the normalized ODN for that driver will be centered at a value of 1.

The tracks were digitized at ten-meter intervals. For each of the 10-meter intervals, an average Winding W(x) was then calculated. The normalized OD values of all drivers were also averaged, giving a single value

$$OD(x, suburban) = \frac{1}{N}\sum_k ODN(x, suburban)_k \quad (10)$$

A least-squares fit gives OD(x,suburban)=1.20-1.03*W, with R^2=.23. 95% CIs [1.17, 1.23] for the intercept, [-1.18,-0.87] for W. The median OD of all drivers over all suburban tracks is 8.9 meters, so that this can be transformed into meters: OD(x,suburban)=10.7-9.1*W, 95% CIs [10.4,11.0] for the intercept, [-10.5,-7.7] for W. This gives support for H3: road winding has a significant effect on OD as it should if OD is a measure of task-relevant event density of the environment. The finding shows that it is possible to estimate the task-relevant event density of a driving environment by knowing its task-relevant environmental parameters, such as road winding in this particular case.

General Discussion

In this paper, we studied the utility of occlusion distance as a function of task-relevant event density in realistic dynamic driving scenarios with driver-controlled speed and occlusion times by testing three hypotheses (H1-H3).

The fairly short range of mean OTs for the different driving scenarios (670-950 milliseconds) is in the ballpark with the visual sampling model by Wierwille (1993). According to Wierwille, in most real world self-paced driving scenarios drivers try to keep off-road glances between 500 to 1,600 milliseconds. OT as well as OD indicated that the Intersection scenarios were the most demanding (Figure 6), although the mean difference in OT between the Intersection and Highway scenarios was only 70 milliseconds.

However, ODs as well as driving speeds varied considerably more than OTs between all the scenarios. According to OD, the Intersection scenarios had the highest event density, followed by Suburban, and then Highway scenarios (means 3.8-9.9-15.5 meters, Figure 6). These findings give support to our model of OD as a function of task-relevant event density in space and that by controlling speed according to the experienced event density, the drivers tend to keep the event rate in time on a similar comfortable range across different driving scenarios (H1 supported). Near the road speed limits, the OTs for the different scenarios will be close to each other either because of the built-in scalability of safety margins (and thus, task-relevant event densities) across different road environments to account for the corresponding design speeds (FTA, 2013; TRB, 2003) or because the majority of drivers tend to select a comfortable speed for each road (TRB, 2003; Recarte & Nunes, 2002).

The best linear model for OD in the Suburban scenarios proved to be OD(x,suburban)=10.7-9.1*W, with R^2=.23. The impact of Winding in our model (H3 supported) can be explained by an effect observed by Lehtonen, Lappi, Kotkanen, and Summala (2013). Anticipatory look-ahead fixations to the winding road ahead seem to play a major role in visual information gathering in curve driving besides tracking the tangent point of the curve, as in the earlier driving models (e.g., Salvucci, 2006). The more the road is winding ahead, the higher the event density, that is, the more visual targets have to be processed in order to ensure a safe path of travel and to track the variable tangent point for steering.

The objective task-relevant event density is not however the only factor behind the preferred OD level. The current data indicates that OD varies systematically with a nearly constant individual factor for the same driver across driving scenarios (Figure 9, H2 supported). This finding gives support to the consistency of the subjective uncertainty acceptance threshold $Umax_k$ in our theoretical model and thus, for the generalizability of OD across driving scenarios. A driver's maximum level of tolerated uncertainty of the task-relevant event states is defined by psychological factors.

The more experienced drivers were able to achieve more accurate lane-keeping performance with similar ODs than the least experienced drivers. The road familiarity effect observed by Mourant and Rockwell (1970) provides an example of learning the task-relevant event rates for a particular driving scenario with enough repetition (expectancy calibration by Horrey, Wickens & Consalus, 2006; predictions of system output by Chen and Milgram, 2013). It is thought that novice drivers do not typically possess enough experience of different driving scenarios for proper evaluation of the situational event rates (Underwood et al., 2002; Wikman, Nieminen, & Summala, 1998).

However, unexpectedly the data did not support the idea of driving experience as a major factor on the preferred ODs. Better ability to evaluate the task-relevant event rate while occluded achieved with increasing driving experience can explain the improved lane-keeping accuracy with the same ODs, but it seems $Umax_k$ cannot be explained fully by the expectancy evaluation skill. If that was the case, there should have been a more visible difference in ODs between the least and the more experienced drivers according to previous research (e.g, Horrey et al., 2006). The findings suggest there might be individual differences in the level of uncertainty tolerated among both the least and the more experienced drivers.

Also the experienced high-OD drivers overestimated their capabilities if we assume that they tried to drive accurately: higher ODs led to lower lane keeping accuracy regardless of the level of experience (Figure 10). External motives and emotions, such as prizes for the most occluded drivers in our experiments, can push drivers towards risk-taking (Summala, 1988; Näätänen & Summala, 1974). Only about 10% of the participants were able to drive with median ODs of 30 meters comparable to J.W.S.' in Senders et al. (1967) in the Highway scenarios (Figures 1 and 8, Table 2). The study left the question of other relevant individual factors open for further research.

We claim that OD is a function of the subjectively experienced task-relevant event density of the driving environment. OD does not refer to distance to hazards or headway distance but varies with the inverse of the spatial density of expected task-relevant events requiring processing from the driver in order to achieve one's current goals of driving, in accordance with Wortelen et al. (2013). From the safety point of view, OD is related to the construct of safety margin (Summala, 1988), but there are also other events that can be relevant for achieving a subgoal in the driving task, such as noticing the correct exit in order to find the way to a destination.

To summarize, the individual task-relevant event density in space is determined in the interaction of both environmental factors as well as psychological factors through the level of uncertainty the driver experiences and tolerates. For any given driver k, our Suburban model can be written as $OD(x,suburban)_k=Umax_k*(10.7-9.1*W)$, where $Umax_k$ is a driver-specific constant that we interpret here as the subjective uncertainty acceptance threshold.

Our tentative model so far focuses on the effects of the environmental factor of road winding. Even if Winding together with the $Umax_k$-factor could perhaps explain the observed differences between the scenarios, these differed in many other aspects as well. Further research should be done on the effects of relevant environmental factors such as visibility, weather, signs, and proximity of traffic as well as on building a more accurate model for predicting ODs in other road environments than Finnish suburban roads.

A significant implication of our findings is that our theoretical model enables predictions. The median OD value of a given road environment can be predicted approximately, if its Winding is known. Even more importantly, it is possible to predict how an individual driver with a known uncertainty acceptance threshold $Umax_k$ will respond to the road environment, and in terms of speed selection, in particular.

The other advantage of OD relates to experimental design. Only one drive per driver with self-determined speeds and OTs is required for mapping the experienced event density of a road environment for the driver. With this information collected from a large driver sample, for example, the populations' 85^{th} percentile OTs for any speed on the road can be estimated.

This line of work can be utilized in the development of proactive distraction mitigation systems. The current findings indicate that because of the fairly static OT range across different driving scenarios, the general 2-second glance limit of acceptable in-vehicle glance duration (NHTSA, 2013) seems to make sense as the maximum limit for any situation. There seems to be also a correspondence to the risk limits of individual glance durations analyzed by Liang, Lee & Yekhshatyan (2012). However, for certain driving scenarios, such as intersections, two seconds can still be too much, depending on the speed of the car (Figure 6).

For a practical and acceptable proactive distraction warning application, we would want to define a warning threshold time (WT), that equals the time it takes to travel the longest distance the majority of drivers would choose to drive comfortably without vision when fully concentrating on the driving task in an occlusion experiment, that is, WT = OD / speed. To determine WT, we should use the 85th percentile margin that is a common design standard in traffic engineering (TRB, 2003). The median OD for the 85th percentile driver for the Suburban tracks was 14.4 meters. This corresponds to a WT of .86 seconds at 60 km/h. It is important to note that this WT applies only for the specific scenario used for the calculation (empty roads, speed limit 60 km/h) and the effect of Winding should be taken into account.

Besides alerting purposes, dynamic WTs could be utilized as appropriate individual in-car glance limits for any given driving scenario and a driver with a known uncertainty acceptance threshold $Umax_k$. These would enable general verification criteria for in-vehicle infotainment and telematics systems for distracted glancing behaviors with in-car tasks. Other uses can be found in the domain of human - automated vehicle interactions (Wortelen et al., 2013), as well as highway and speed design.

Time is not the only factor that matters when the driver travels eyes off the road. The severity of a two second off-road glance depends on the velocity of the vehicle and the task-relevant event density of the road environment.

Key points

- Occlusion distance seems to be an informative measure for assessing task-relevant event density in realistic traffic scenarios with self-controlled speed and occlusion time.
- There are systematic differences in the preferred occlusion distances between individual drivers and driving scenarios.
- The more experienced drivers were able to achieve more accurate lane-keeping performance than the least experienced drivers with similar ODs. However, driving experience does not seem to be a major factor on the preferred ODs.
- Occlusion distance can be utilized in the development of context-aware distraction mitigation systems, human - automated vehicle -interaction, road speed design, prediction of driver speed selection, and in the testing of visual in-vehicle user interfaces.

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Acknowledgements

This research was supported by DisGuard, an innovation and research project funded by TEKES (Finnish Funding Agency for Technology and Innovation) and University of Jyväskylä. Driving simulator software was developed and sponsored by Eepsoft Oy. We are thankful for Antti Vuorenmaa, Rebekah Rousi, Iida Jokinen, Jussi Jokinen, and Dario Salvucci as well as the anonymous reviewers for their invaluable feedback.

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