A Model of Information Sampling using Visual Occlusion

by

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Abstract

Three stages of research were carried out to investigate the use of the self-paced visual occlusion technique, and to model visual information sampling.

Stage 1. A low-fidelity driving simulator study was carried out to investigate the effect of glance duration, a key parameter of the self-paced occlusion technique, on occlusion times. Results from this experiment, paired with analysis of data available from an on-road driving study, found an asymptotic relationship between the two variables. This finding has practical implications for establishing the appropriate glance duration in experimental studies that use self-paced visual occlusion.

Stage 2. A model of visual information sampling was proposed, which incorporates elements of uncertainty development, subjective thresholds, and an awareness of past and current states of the system during occlusion. Using this modelling framework, average information sampling behaviour in occlusion studies can be analysed via mean occlusion times, and moment-by-moment responses to system output can be analysed via individual occlusion times. Analysis using the on-road driving data found that experienced drivers demonstrated a more complex and dynamic sampling strategy than inexperienced drivers.
Stage 3. Findings from Stage 2 led to a simple monitoring experiment that investigated whether human operators are in fact capable of predicting system output when temporarily occluded. The platform was designed such that the dynamics of the system naturally facilitated predictions without making the monitoring task trivial. Results showed that participants were able to take predictive information into account in their sampling decisions, in addition to using the content of the information they observed from each visual sample.
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1 Introduction

1.1 Motivation

Central to human factors research is the need to understand the relationship between humans and the complex, dynamic systems they interact with. This was true when early efforts were focused on studying pilot performance using manual controls, and it remains true after computers and automation have put human operators in supervisory roles across all kinds of systems. In particular, how human operators obtain and use information remains an area of high interest, with practical implications for the design of better human-computer interactions and more appropriate use of automation.

While humans perceive information via multiple senses, the present work focuses on visual information processing, our primary means for gathering information about the world. In particular, this work is concerned with how human operators manage uncertainty in processing information. Due to limits in our sensory and cognitive functions, to the vast amount of information present in our environment, and to the highly dynamic nature of most systems, uncertainty is nearly always present in situations where human operators have to make critical decisions. This is true not only for such specialized areas as aviation and power plant operations, where the stakes are high, but also for everyday tasks such as driving an automobile. In spite of this uncertainty, trained operators can monitor multiple displays in a process control plant, skilled surgeons can operate successfully on patients in a highly dynamic surgical environment and experienced drivers can attend to all sorts of in-vehicle devices and drive safely at the same time. In other words, trained operators in complex domains appear to tolerate some amount of uncertainty about their environment. To understand such skilled work, it is crucial to study to what extent human operators can tolerate uncertainty, beyond which they can no longer perform normally. These are the questions that underlie the present research.

1.2 Using Visual Occlusion to Model Information Sampling

Having observed that a driver’s attention to the road is not continuous but intermittent (an extreme case being the acceptance of windshield wipers to provide temporary views of the roadway during heavy rain), Senders et al. (1967) proposed an analytical model of how uncertainty about the roadway-vehicle system grows when vision is interrupted and is resolved when vision is regained (see Figure 1-1).
Figure 1-1: Depiction of how uncertainty develops during visual occlusion and is resolved during visual sampling. (Adapted from Senders et al., 1967)

The model proposes that a driver’s uncertainty during such occlusion intervals comes from two sources: uncertainty about the road due to a loss of relevant information; and uncertainty about the position of the vehicle due to random disturbances. In the first case, uncertainty represents the information that has been lost since the beginning of occlusion, and hence rises asymptotically to the maximum amount of information that was available at the beginning of occlusion. In the latter case, uncertainty rises without bound as the vehicle’s response to disturbances accumulates over time during occlusion.

The model further postulates that drivers will allow their uncertainty to grow only up to a certain acceptable level, or threshold ($U_c$), whereupon they will feel compelled to request a new sample of the roadway. Mathematically, uncertainty during the occlusion interval, $U(t)$, was proposed to follow the formula:

$$U(t) = H \cdot D \left[1 - e^{-(V/D+1/F)t}\right] + K_n V^2(t)^{3/2} \leq U_c$$

where:

- $U(t)$ = uncertainty during the occlusion interval;
- $H$ = information density of the road, in bits per unit distance;
- $V$ = velocity of vehicle;
- $F$ = ‘forgetting rate’ parameter;
- $D$, $K_n$ = weighting constants;

The first term describes an exponential rise (to a maximum value $H \cdot D$) whose rate of increase varies directly with the velocity of the vehicle and inversely with the rate of forgetting. The second term is
modelled to reflect the expected value of the lateral displacement of the vehicle. Following the Senders et al. model, the driver will decide to request a new visual sample at a time $T_d$, such that:

$$U(T_d) \leq U_e$$

To study this model in the context of automobile driving, Senders et al. introduced the method of artificially occluding vision by equipping drivers with a mechanical visor that blocked their vision. They identified and carried out two experimental paradigms:

1) constant frequency of glances, with the driver controlling only the vehicle’s speed; and

2) constant speed, with the driver controlling when (and thus how often) to look.

Data resulting from the first paradigm in their original report lent support to the analytical model, particularly with regards to the quantifiable relationship between occlusion intervals and speed. The model was not applied to data collected from Senders et al.’s investigations using the second paradigm (hereafter referred to as “self-paced visual occlusion”) due to limitations in time and cost. However, simple comparisons were made between data collected using the two paradigms and showed that self-paced occlusion times appeared to be shorter than the fixed occlusion times corresponding to the same speed.

Another important observation made regarding the self-paced occlusion paradigm was the evident variability in the occlusion times observed, suggesting that drivers actually perceived the roadway as possessing a variable amount of information, as opposed to the constant information density, $H$, assumed in the model. This led them to propose that the self-paced occlusion technique would be a useful paradigm for evaluating the attentional demands associated with different traffic situations or vehicles.

For both of Senders’ experimental paradigms it is important to note that emphasis is not to be placed on risk taking; rather, the reason for occluding an operator’s vision is to compel him to carry out a well-known task, with no reductions in performance, while making use of a subjectively comfortable minimal amount of visual information.

Senders’ self-paced visual occlusion research was followed up by Milgram, Blaauw, and Godthelp in the 1980’s, resulting in the development of a multivariate time series monitoring model (Milgram et al, 1982), a supervisory driver model (Blaauw et al., 1984), and a time to line crossing model (Godthelp et al, 1984). All three models extended Senders’ theory about uncertainty, by quantifying its development using the growing error associated with the driver’s estimate of the state of vehicle. The differences lay in the approaches each took in modelling the estimates of variables such as lateral position. Milgram et al.
characterised the estimating process mathematically by using time series analysis, in which uncertainty was represented by the forecast error of the time series predictions. Godthelp et al. carried out a similar analysis, but took into account drivers’ steering control signals. Blaauw et al., on the other hand, applied the optimal control model, using Kalman filtering to estimate the variables of interest.

Despite their differences, these three models are all top-down in their approach, and share the assumption that well trained human operators controlling a system are aware of the probabilistic characteristics of the system, allowing them to keep track of the system without observing it continuously. Predictions or estimates of the current system state while under occlusion are therefore based on operators’ familiarity with the system and on prior observations. These models of uncertainty as forecast errors are in contrast to Senders’ more bottom-up analytical model, which focuses on identifying, and ultimately quantifying, the various factors that may influence the rate of uncertainty development.

1.3 Objectives

The occlusion technique proposed by Senders et al (1967) and followed up by Milgram et al (1982) has led to very interesting models. However, certain assumptions made in their models need to be addressed. For example, Senders et al noted in their work that treating the information density of the road as a constant may not be appropriate, as drivers were demonstrating variability in their self-paced occlusion times, possibly as a response to the varying rate of information present. In Milgram’s uncertainty model, using forecast errors to model uncertainty presumes that predicting exists. However, whether predicting was indeed taking place during occlusion was not explicitly demonstrated in their experimental study.

My dissertation aims to provide a more complete and unified theory of information sampling for tasks that do not require continuous visual input, for which application of the visual occlusion technique is thus meaningful. (This is in contrast to tasks for which any visual interruption may disrupt the operator’s performance.) The specific goal was to investigate the extent to which the self-paced visual occlusion technique, taken together with a quantitative approach to modelling information acquisition, may further develop Senders’ uncertainty model. As part of this goal, the dissertation also addresses the assumption that predicting does, or can, take place during occlusion by testing for such behaviour explicitly.

While simulated automobile driving was chosen for the sake of expediency as my original experimental platform, my dissertation research eventually led me to examine data collected from an extensive on-road driving study, which in turn led to an investigation involving a more general (although very simple) process monitoring task. An important takeaway message from this research trajectory is that, although the most obvious application of self-paced visual occlusion and the resulting model of information
sampling is to driving research – for example, towards understanding driver behaviour and designing driver support systems – my research should also prove useful for evaluating the attentional workload of other human monitoring tasks, such as the monitoring of cockpit displays by pilots. Monitoring of critical processes can also be encountered in environments as diverse as process control plants and medical workstations (for example, intensive care and anaesthesiology).

1.4 Roadmap

Chapter 2 provides a brief survey of background research of interest. The focus there is on models of monitoring, including some of the classic models of visual sampling, models of selective (visual) attention and the framework of situation awareness (SA).

The work presented in this dissertation was carried out in roughly three stages. Initial efforts (Stage I) centred on the uncertainty model, for which a low-fidelity driving simulator study was carried out (a) to test a proposed model of the effect of glance durations on occlusion times and (b) to replicate Milgram’s model of operator sampling to maintain relative uncertainty. Complemented by an analysis of existing data collected during an on-road study conducted in the 1980s, Chapter 3 describes the related findings. Chapter 4 presents a review of relative uncertainty theory and the analyses to test this theory with data collected from the driving simulator study.

In Stage II findings from the earlier stage led to a new hypothesis about a more dynamic sampling strategy making use of information from individual glances. Chapter 5 proposes a threshold model of information sampling, adding new components of active monitoring to the original notion of uncertainty. Recognising that operators, given their own expertise and the task at hand, may demonstrate a range of sampling behaviours, this model captures 5 progressive levels of sampling behaviour an operator may achieve. The chapter also presents a modelling framework, distinguishing the 5 levels captured, as an approach towards progressive analysis of visual occlusion data in accordance with the proposed model. In Chapter 6, an in-depth analysis of the same set of on-road data examined only superficially in Stage I demonstrates the use of this approach.

The final stage of my dissertation (Stage III) was an investigation of the active sampling behaviour prescribed by the proposed model. Specifically, a contrived experiment was carried out to investigate whether human operators would be able to demonstrate ‘predicting’ when the given visual occlusion task actually encourages them to do so. The idea is that, if predicting were made simple enough to achieve during occlusion such that it makes sense to do so, then not revealing such behaviour would contradict
much of the earlier hypotheses that rely on operators utilizing their internal models for the purpose of prediction. A summary of this experiment and findings is presented in Chapter 7.

Chapter 8 concludes by providing a summary of important findings in this dissertation. A list of the theoretical and practical contributions is provided, along with some suggestions for further work. The reader can find all supporting material for the experiments and detailed results of statistical analyses in the Appendices. Appendix E lists the acronyms and abbreviations used in this dissertation.

1.5 Summary of Analytical Techniques Used

This dissertation applied a number of analytical techniques in the modelling and analysis of data. While the techniques are explained in more detail later on when necessary, a brief summary is provided below to orient the reader to the general approaches taken in this work.

1.5.1 Analysis of Variance

Analysis of Variance, or ANOVA, was applied whenever the objective was to examine whether there are differences between group means that can be attributed to varying levels of one or more factors. Levels of a factor can be either categorical or ordinal, but not continuous.

1.5.2 Model Fitting

ANOVA allows us to determine differences between group means, which provides a solid foundation for further research. However, very often the objective of the research was to explore a more specific relationship, such as a linear function relating two or more variables. In such cases, a model fitting exercise was carried out, where data were fitted using a hypothesised mathematical model and the goodness of fit was examined. The mathematical models applied in this dissertation include a reciprocal function, a natural logarithmic function, and a power-law function. Justifications for the choice of model are given when the particular analysis is introduced.

To keep the analysis simple, transformations were carried out on variables to transform non-linear models into their linear counterparts. Following the transformation, linear mixed-effects models were fitted using the nlme package in R (Pinheiro, Bates, et al., 2013). This analysis approach allows for repeated measures on subjects to be accounted for as random effects, and both factors and continuous covariates can be specified as fixed effects. Evidence that a hypothesised relationship exists comes from finding a statistically significant ($p < 0.05$) estimate (regression slope) in the hypothesised direction.
For post-hoc analyses, the Multcomp package in R was used for testing simultaneous linear hypotheses and adjusted $p$-values using the single-step method (Hothorn, Bretz and Westfall, 2008).

1.5.3 Akaike’s Information Criterion for Model Selection.

In this dissertation, the approach to comparing the goodness of fit of models over a set of data was to use Akaike’s information criterion (AIC), defined as: $AIC = -2 \text{ (log likelihood)} + 2K$, where ‘$K$’ is the number of estimated parameters included in the model, and ‘log likelihood’ is of the model given the data and reflects the overall model fit (larger values indicate better fit) (Akaike, 1973 cited by Burnham and Anderson, 2002). Via its definition, the AIC accounts for the trade-off between goodness of fit and parsimony (i.e., based on the principle that less is better).\(^1\)

On its own, the AIC value of a particular model is not meaningful. It is a relative measure that becomes useful when two or more models, fitted for the same set of dependent measures, are being compared. In such cases, the “best model” among those compared is typically attributed to the one with the lowest AIC value. As a general rule of thumb, two models are indistinguishable by the AIC criterion if the difference in AIC values is less than 2. A difference greater than 10 is considered substantial (Burnham and Anderson, 2002).

It is important to note that AIC is not a test that provides ‘significance results’ – it is simply a criterion for selecting one out of a set of models. For more information about the use of AIC in model selection, see Burnham and Anderson (2002). In this dissertation, the AIC values associated with models constructed were readily available in statistical output produced by R (R Core Team, 2013).

1.5.4 Autoregressive time series

The investigation of uncertainty theory and predicting behaviour in this dissertation involved the modelling of an operator’s estimate of the state of the system. Following Milgram’s approach, autoregressive time series was used for modelling a driver’s estimates of the vehicle’s state with respect to the particular driving task in question.

An autoregressive (AR) model is in essence a (multiple) linear regression of the current value, $Y_t$, of the series against one or more prior values, $Y_{t-1}, Y_{t-2}, \ldots, Y_p$, of the series. It is defined as: $Y_t = c +$

\(^1\) Increasing the number of parameters in a model will improve the log likelihood estimate, but will also run the risk of over-fitting the data, resulting in a model that has little predictive power.
\[ \sum_{i=1}^{p} \varphi_i Y_{t-i} + \epsilon_t \], where \( \varphi_1, \varphi_2, \ldots, \varphi_p \) are the parameters of the model, \( c \) is a constant and \( \epsilon_t \) the white noise. An appropriate order, \( p \), is selected for the model using a recursive model fitting procedure based on the AIC.

The assumption in using this approach was that the predictions of system output attributed to a well trained operator, with (near) perfect knowledge of the system’s amplitude and temporal variations (bandwidth), can be modelled by means of the linear predictions provided by the autoregressive model of the system’s output. More specifically for the present work, records of lateral positions of the vehicle over the duration of lane keeping trials and the distance headway profiles found in car-following trials were treated as (univariate\(^2\)) time series, and an AR model was found for each of them. These models were then used to compute predictions of the output path at times of sampling requests to simulate what the driver may be estimating during occlusion.

The autoregressive models were also the basis of measuring relative uncertainty, as proposed by Milgram et al. (1982) using information theory. Growth of uncertainty during an occlusion period was modelled after the forecast errors associated with predictions over an occlusion period. Information redundancy, a measure of relative uncertainty, was defined as the log normalised ratio between the maximum variance and the forecast error variance at the time of sampling requests made.

The fitting of an autoregressive time series and the generation of predictions were achieved using the ‘stats’ package in R. Information redundancy values were computed following Milgram’s approach. A simplified derivation of the information redundancy using the \( p \)th order, univariate AR model is included in Appendix A. For the multivariate time series, see Milgram et al. (1983).

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\(^2\) Milgram’s 1982 work used multivariate time series to model an operator’s estimates of the state, to capture multiple concurrent variables describing a system output. In their application using on-road driving, lateral position and heading angle were taken and fitted using a bivariate AR model.
2 Literature Review

As early as the 1950s, when cockpits were developed with complicated panels of controls and displays that were often much too difficult for human operators to monitor and operate, the advent of instruments for measuring eye point of regard allowed for analysis of eye movements as pilots carried out different tasks (most notably described in Fitts et al., 1950 as cited in Moray, 1986). Since then, tracking of eye movements has remained a popular means to understand and consequently to model where and when the human operator looks in a controlled situation, otherwise known as selective visual attention.

In contrast to eye movement recordings, the visual occlusion approach does not provide a record of where the operator is looking; instead it focuses on the aspect of timing by indicating when new visual information is requested. In other words, the visual occlusion approach treats the entire environment or system (to be monitored) as a single source of information. The purpose of modelling sampling behaviour with this approach is, among other things, to provide a means to quantify the potential task load imposed by a system, the experience of which may vary with different operators. While this dissertation focuses on the timing of sampling behaviour as observed in the visual occlusion paradigm, eye movements necessarily play a large role in the processing of information perceived during visual samples.

It is also worthy to note that the present work pertains to one of the many forms of selective visual attention, namely that associated with supervisory control, where visual information is obtained from one or more sources to ensure that certain dynamic variables are within limits. Some useful distinctions are made by Wickens et al. (2012) about the different task types associated with selective visual attention. In addition to (1) supervisory control, there are (2) general orientation and scene scanning, when a visual space is first encountered; (3) noticing of unexpected events, (4) searching for specific targets, (5) reading, and (6) confirming that some control action has taken place.

Aside from models of visual sampling and selective attention, this literature review also surveys visual occlusion research in automobile driving to demonstrate its potential as a measure of workload associated with visual demands in driving, and the current relevance of this technique in the industry.

2.1 Early Models of Visual Sampling

The ability to record eye movements resulted in a number of analytical models of visual sampling behaviour in dynamic environments. The first attempt at quantitative modelling of selective attention in a
monitoring task has been widely attributed to Senders (1955, cited in Moray, 1986 and Kvålseth, 1978). That model assumes that the human observer behaves like a single channel device, attending to only one source of information at a time according to some rational sampling strategy, thereby enabling reconstruction of the time functions presented on each instrument. Senders proposed that: i) the mean sampling rate for a displayed signal should be proportional to its bandwidth, and ii) the sampling duration should be proportional to the rate at which the display or instrument generates information. These propositions were later supported empirically by the results of a series of validation studies (Senders 1964, 1983).

From the same perspective of directing eye gazes across multiple instruments, Carbonell (1966) and Smallwood (1967) both proposed probabilistic models of visual scanning processes. Carbonell’s model (1966) was based on queueing theory and, like Senders, Carbonell assumed that the human observer is a single channel processor, and the instruments being monitored wait in a queue to be processed. The queueing priority of each instrument depends on: i) the value of the signal (i.e. the signal content), ii) the time elapsed since its last observation, and iii) a cost-payoff relationship (i.e. utility of the information). The model supposes that the observer chooses the next instrument to sample by determining the probability of a signal exceeding a given threshold at any point in time given its last observed value and considering the cost of exceeding that threshold. Due to the complexity of the nonlinear decision process, Carbonell did not try to find an analytical solution to his mathematical constructs, but simulated the model digitally.

Smallwood (1967), on the other hand, asserted that the human operator tries to maintain and update some internal image or model of his environment and the system he is controlling. The dynamic nature of systems, assumed by Smallwood to be probabilistic, leads the operator to sample the different variables to maintain his internal representations accurately enough for decisions and actions.

In 1970, Sheridan adopted information value theory to describe how often a process supervisor or monitor should update his information about an input in order to maximise the expected return, which was considered to be some function of both the reference input and the control variable. Kvålseth (1978) also adopted an informational approach to modelling sampling behaviour, by formulating uncertainty, information gain and redundancy measures relevant to the sampling process and studying their characteristics by means of laboratory experiments. Both Kvålseth and Sheridan regarded the payoff matrix associated with observations and actions as the primary factor that controls monitoring.

For a more complete and detailed review on this topic, Moray’s review of monitoring behaviour and supervisory control (1986) remains an excellent reference. Most importantly, Moray summarised the
features that can contribute to sampling strategies of human operators. Table 2-1 groups these characteristics by their association with either the system or the human observer.

Table 2-1: Categorising, by the generating sources, features that appeared in Moray’s summary (1986) of what can influence the monitoring strategy of human observers

<table>
<thead>
<tr>
<th>System (processes)</th>
<th>Human Observer</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rate of uncertainty development due to the bandwidth and other statistical characteristics of the process and the presence of noise</td>
<td>Rate of uncertainty development due to human observer (such as forgetting)</td>
</tr>
<tr>
<td>Limits beyond which the process must not exceed</td>
<td>Inaccuracy in reading values¹</td>
</tr>
<tr>
<td>Causal relations or coupling between processes (information sources or signals)</td>
<td>Limits below which observer is indifferent</td>
</tr>
<tr>
<td></td>
<td>Subjective evaluation of the values and payoffs associated with the processes</td>
</tr>
</tbody>
</table>

2.2 Models of Visual Sampling using Visual Occlusion

As seen in Table 1, the rate of uncertainty development, stemming either from the system or the human observer, was recognised as an important factor in the earlier models of visual sampling. Senders’ (1967) introduction of the visual occlusion paradigms further attempted to model uncertainty directly as a method for analysing sampling behaviour by combining many of the features summarized in Table 1. Specifically, information density and vehicle velocity correspond to information bandwidth, and rate of forgetting is used to address the cognitive limitation (see Section 1.2). The criterion of an uncertainty threshold– that is, the maximum level of uncertainty that an operator is willing to accept prior to requesting a new visual sample – is then a combination of subjective evaluation of cost and values of the information, as well as the limit imposed by the system itself.

Milgram (1982), Blaauw (1984), and Godthelp (1984) extended the idea of sampling at a threshold of uncertainty by treating the driver-roadway system as a quantitative model, such that predictions and forecast errors can be generated to model uncertainty development.

¹Moray listed the inaccuracy in reading values as a standalone feature. However, this could be part of the uncertainty due to the human observer (inaccuracy generated by perceptual processes)
Milgram’s multivariate, autoregressive model captures temporal changes in system variables (in this case, measures of lane keeping performance using lane positions and heading angles), based on the assumption for experienced drivers of a perfect internal model. This allows for prediction of system variables commencing with the initiation of occlusion, based on previous observations. In addition to the simplicity of its implementation, the time series approach provides a natural representation of coupling between variables with its (bivariate) covariance matrix, thereby addressing the human observer’s internal model of the causal relations between such variables (Moray, 2004). (One potential limitation of Milgram’s model, however, is his assumption that the temporary occlusion does not significantly interfere with the overall driving performance.)

In terms of developing a sampling strategy, Milgram adopts an information theoretic approach that corresponds to Senders’ theory of sampling at the threshold of uncertainty. Milgram’s model postulates that the sampling threshold corresponds to drivers maintaining an approximately constant level of redundancy in their estimate of information related to the vehicle’s state. Information redundancy at the moment of sampling is derived from the level of forecast error reached relative to the overall variance of the system, which was postulated to represent the relative uncertainty that the particular driver was willing to accept.

Godthelp made an explicit distinction between open- and closed-loop strategies in driving, asserting that open loop control (without actively steering the vehicle) may occur temporarily during occlusion. In addition to the vehicle’s lane positions and heading angles, he took into account drivers’ steering control signals prior to occlusion to postulate a Time to Line Crossing (TLC) metric. TLC represents the time (since the beginning of occlusion) necessary for the vehicle to reach either side of the lane. Based on a self-paced visual occlusion driving study, Godthelp found evidence of a constant ratio, across different speeds, between the occlusion time and the TLC, which is the total available time to crossing during occlusion. This result is consistent with Milgram’s theory of drivers sample to maintain a constant level of redundancy.

Blaauw (1984) applied optimal control theory to a supervisory driver model. (Experienced) drivers, with leftover attentional resources, are expected to have “free time” in their vehicle control tasks, during which they sample information, much like the operators in the other models of visual sampling. This is consistent with Godthelp’s proposal of two modes in driving – error correction (control mode) in a visually closed loop and error-neglection during the open-loop (free times). A series of static and dynamic

---

2 The difference between TLC estimated and the self-paced occlusion time reveals a potential remaining time to line crossing at each sampling decision, analogous to the idea of information redundancy in Milgram’s model.
tests with an instrumented car were used to provide estimates for the display variables (lateral velocity, lateral position, yaw rate, heading angle, and steering angle) as part of the state space equations\(^3\). Importantly, these estimates included ‘preview’ of the road ahead, to enable the estimating of future lateral position via the present lateral speed cue.

According to Blaauw’s model, when occlusion occurs predicting is based on the cues that remain (previously perceived acceleration) and estimates of the state variables and the variances associated with those estimates are used to model drivers’ uncertainty, similar to Milgram’s use of forecast errors associated with the time series predictions. Control actions (assumed to take place only when drivers are looking) are initiated whenever it is predicted that the vehicle’s trajectory will deviate too much from an acceptable trajectory. Using optimal control modelling, one selects an observation noise level that corresponds to the standard deviation of lateral position observed during un-occluded vision. Occlusion times can then be predicted by choosing an infinite observation noise-to-signal ratio for the occluded display variables (lateral position and heading angle) while maintaining a finite observation noise-to-signal ratio for relevant non-occluded variables (acceleration cues) of the pre-occluded period. In other words, occlusion times are dependent on the lane keeping control asserted over the non-occluded period leading to the current occlusion period.

Blaauw’s validation of his supervisory driver model focused on predicting free (occlusion) times for experienced versus inexperienced drivers. According to the model, inexperienced drivers observe only lateral position during viewing periods, whereas experienced drivers use all possible information, including inclination angle, yaw rate, lateral and yaw accelerations. Data simulated using the model was compared to empirical data from an on-road, self-paced visual occlusion study with both experienced and inexperienced drivers. Means and standard deviations of occlusion times over trials and subjects were compared to the occlusion times predicted using the lateral position data obtained from corresponding trials\(^4\). In general, there was a better correspondence between predicted and measured occlusion times for the experienced drivers than for the inexperienced drivers, for whom the model predictions were underestimated.

\(^3\) Blaauw’s model makes other assumptions about the driving environment, such as absence of wind-gusts. Note that changing vehicles and/or the particular driving environment will need a new set of data on vehicle dynamics collected for that particular setup.

\(^4\) Conceivably occlusion time could be simulated for individual occlusion periods using Blaauw’s model. However, their analysis was limited to comparing mean occlusion times, with the simulated occlusion time based on overall lane keeping performance (standard deviation of lane positions) in a given trial.
Table 2-2 provides a summary of the approaches taken by the above three researchers. A main assumption underlying all three of the models is that experienced drivers have an essentially perfect internal model describing the behaviour of such parameters as velocity, lane position, and heading angle. We have seen that similar assumptions have been made, albeit not always as explicitly, in many of the earlier models for monitoring multiple instruments, such as those of Senders (1964), Carbonell (1966) and Sheridan (1970). More relevant is that Milgram’s, Blaauw’s and Godthelp’s models all postulate an active role of predicting by drivers when occluded, on the basis of his or her prior observations and knowledge about the system. Milgram and Blaauw further share the element of accounting for changes in variance of system parameters (as manifested by the standard deviation of lateral position).

Table 2-2: Summary of models proposed by Milgram et al (1982), Godthelp et al (1984), and Blaauw et al (1984). Note that these studies shared the same set of on-road driving data.

<table>
<thead>
<tr>
<th>Approach</th>
<th>Measure of Uncertainty</th>
<th>Experimental Finding</th>
</tr>
</thead>
<tbody>
<tr>
<td>Milgram et al (1982)</td>
<td>Used autoregressive time series to model lane keeping performance as a basis for estimations (predictions) during occlusion</td>
<td>Information redundancy at sampling instants based on forecast errors associated with time series predictions</td>
</tr>
<tr>
<td>Godthelp et al (1984)</td>
<td>Used steering control signals to estimate the time to line crossing (TLC) of the vehicle</td>
<td>Measure the ratio between occlusion time and TLC</td>
</tr>
<tr>
<td>Blaauw et al (1984)</td>
<td>Applied optimal control theory to model driving/lane keeping as a supervisory control task</td>
<td>Variances associated with the estimates of the state variables are used to model drivers’ uncertainty</td>
</tr>
</tbody>
</table>

2.3 Psychological Models of Selective Attention

Pew (1983) points out that from the control perspective, as seen in the classical models that prevailed until the 1980’s, there is a focus on the role of information processing to predict future responses. Furthermore, trained human operators, viewed as a function of the system, are expected to exhibit optimal or near optimal performance. In spite of the important influence of those classical top-down models, however, the research community has witnessed a number of changes in modelling approaches. Many of
The earlier quantitative models have given way to more qualitative psychological models which, rather than treating the human operator as an observational, control, or decision making element in a feedback loop, delve deeper into the cognitive processes of human behaviour. Those psychology-based bottom-up models tend to focus on the breakdown of behavioural activities to be performed, much like a task analysis.

Many of the psychological models are simple block diagrams, such as Stanton and Young’s psychological model of driving (2000), which attempts to map out all psychological functions relevant to the information processing involved in driving. Other models are descriptive in nature and serve more as a framework for studying the different cognitive processes involved in a particular activity. Many such models have formed the basis for computational models for simulating human cognitive processes involved in a particular task. Cognitive architectures, such as SOAR (Newell, 1990) and ACT-R (Anderson and Lebiere, 1998), are general frameworks for specifying computational models to simulate intelligent human behaviour, such as planning, reasoning, and learning. For example, Salvucci (2006) developed an integrated driving model in the framework of the cognitive architecture ACT-R, which contains three primary components of driving: control, monitoring and decision making. Especially of interest to the current topic is the monitoring component, which is responsible for awareness of traffic around the driver’s vehicle. The computational implementation of the monitoring component organizes the roadway into four areas for monitoring – left lane, right lane, forward and backward – and directs attention to one of the four areas, based on a random-sampling model that assumes equal likelihood for detection of any vehicles present. This model could be easily extended to monitoring of more than vehicles alone, and might also benefit from a more adaptive sampling model as developed by the present work.

Another notable psychological construct of selective attention is the SEEV model, proposed by Wickens and colleagues (2001). Combining both descriptive elements and computational functions, SEEV predicts the likelihood of attending to an area in a scanning process as a function of four parameters (the first letters of which form the acronym SEEV): salience of the information source; expectancy of receiving more information from the source; effort required to make an observation; and value of the source relative to others. The predictions made by the SEEV model were found to be fairly accurate in studies examining pilots’ performance (Wickens et al. 2007, cited in Wickens and McCarley, 2008) and in a driving application (Horrey et al, 2006). Furthermore, some of these parameters are not unfamiliar to us. For example, we have seen relative value described as cost-payoff in Carbonell’s (1966) queuing theory and in Sheridan’s cost-benefit matrix (1970).
Finally, the topic of situation awareness (SA) is included here not as a model of attention itself, but rather for the importance of selective attention within the context of SA. Endsley’s (1995) definition of SA is “the perception of the elements in the environment within a volume of time and space, the comprehension of their meaning, and the projection of their status in the near future.” The hierarchical nature of Endsley’s model allows for evaluation of different levels of expertise, in the sense that the model remains relevant for the more novice operators, who may not yet have achieved the highest level of SA.

2.4 Visual Occlusion Research in Automobile Driving

We have seen that the occlusion technique proposed by Senders (1967) has led to a number of very interesting models of sampling behaviour, particularly in automobile driving. For decades researchers have also used this technique to study the visual demands of driving under various conditions, sometimes on real roads and other times in simulators. Green and Tsimhoni (2001) presented a summary of methods adopted in visual occlusion experiments carried out to examine the visual demands of various driving situations (e.g. different lane curvatures, with and without traffic, real road versus simulated driving), using different variations of the occlusion method. A bibliographic overview of those studies can be found in Appendix B. For the most part, the *self-paced occlusion paradigm with fixed glance duration* has been chosen (e.g. Courage et al., 2000; Krammes et al., 1995; Tsimhoni and Green, 1999). On other occasions, however, *self-paced glance duration* has been adopted (e.g. Mourant and Ge, 1997; Godthelp and Kappler, 1988).

Tsimhoni and Green (1999) investigated the relationship, in a driving simulator, among visual demand, radius of curvature of the road, and curve length, and also as a function of driver’s age. Citing Shafer (1995), the visual demand of a given interval was determined by a simple equation of viewing time over occlusion time. The demand was reported to be sensitive to road geometry and to the driver’s age. Easa and Ganguly (2005) took a similar approach in using occlusion and viewing times to measure visual demands, but went beyond simple curves to study the effect of complex horizontal highway alignments, including simple, compound and complex reverse curves as well as tangents, in a driving simulator. Based on their findings, mathematical models were constructed for visual demand as a function of the type of curve element ahead. This work was also extended to include three-dimensional alignments, consisting of both horizontal and vertical alignments (Easa and He, 2006).

Tsimhoni (2003) later looked at issues of time sharing for performing visual in-vehicle tasks while driving. The technique of controlling both occlusion time and viewing time was used to test two hypotheses: (1) the driver can perform some post processing of what was just seen and plan ahead for the next glance, and (2) partitioning the in-vehicle task into small parts may tax the driver’s performance or
require more glances on the road. In the reported experiments, however, very little performance increase was observed in condition (1), and the cost of partitioning (2) was not significant either.

Over the last decade, we have observed a trend toward using fixed durations of occlusion and fixed glance times, with a shift in the goals of most studies away from the examining primary driving task and towards assessments of the visual demands associated with in-vehicle devices alone. For the sake of clarity, Figure 2-1 summarises the different experimental paradigms that can possibly be used in an occlusion study, in terms of combinations of interval of occlusion, interval of glance, and the dynamic of task. Highlighted in grey are the two most common forms: the fixed glance, variable occlusion paradigm found in the early studies of driving demands (Figure 2-1a) and the ‘involuntary’ technique, named after the lack of control on the participant’s part, using fixed occlusion, fixed glance and a discrete or static task (Figure 2-1b). The latter paradigm, as mentioned, has gained momentum in the automotive industry as a means to assess the static visual demand of in-vehicle devices.

Figure 2-1: Different possible paradigms for the visual occlusion technique. Highlighted in grey:
(a) focus of present research: self-paced occlusion with fixed interval of glance for a continuous task; (b) standard test for assessing in-vehicle devices: fixed intervals of occlusion and glance for a discrete task.

The involuntary occlusion technique has been prescribed as part of the standard procedure for approving new telematics devices in industry standards, such as the SAE recommended practice (J2364, 2004) and
ISO (16673:2007). In that context, the primary task is the use of an in-vehicle device via controlled glances, and occlusion periods represent the potential time a driver could spend looking at the road. Common performance measures for such assessments are the “total shutter open time (TSOT)” taken to complete a task using the in-vehicle device, and R, the ratio between TSOT and “total task time un-occluded” (the time it takes to complete a task without any occlusion). Both measure how interrupting the task with intermittent occlusion affects the overall performance of the task. In other words, they examine how difficult it is for one to resume the task of using the device in question, after a (surrogate) glance at the roadway.

The premise for evaluating in-vehicle devices based on aspects of task resumption is that tasks that are less affected by interruptions may also be less distracting to drivers, who are making continuous decisions about time-sharing between driving and other tasks (Noy et al., 2004). In a study of three in-vehicle tasks: scrolling visual search, static visual search and radio tuning, Noy et al. found differences in the resulting TSOT and R for the three tasks, making a case for using the occlusion paradigm to assess secondary tasks using in-vehicle devices.

In the same study, Noy et al. also found that the resulting total task times under (involuntary) occlusion were similar to those found in a simulated driving condition. Baumann et al (2004) compared the performance of a destination entry task (using an in-car navigation system) under the use of (involuntary) occlusion and during driving. Based on the accuracy of such performance, but not the total task time, they also found the use of occlusion to be adequate for simulating visual requirements of real traffic conditions.

More specifically associated with the visual demands of secondary tasks in driving, Pettitt et al. (2006) employed involuntary occlusion in driving tasks interacting with in-vehicle systems to compare results from an occlusion assessment and a road-based assessment based on static task time. The fixed occlusion

5 ISO 16673 uses the term vision interval interchangeably with the term shutter open time (SOT) for referring to the "discrete time during which the driver interface is visible when using an occlusion procedure." SAE Recommended Practice J2364 also uses the term SOT for "time interval during which the subject can see the visual display when using an occlusion technique." As both ISO 16673 and SAE J2364 pertain to assessing in-vehicle telematic devices using a particular occlusion procedure in the automotive industry, these definitions are specific to the corresponding paradigm (see Figure 2-1b) and are limited to the viewing of telematic devices being studied. In contrast, the term glance duration (GD) in an occlusion study, as used in the present dissertation, refers to the time duration of a visual sample, regardless of the chosen paradigm. In automobile driving self-paced occlusion studies, in other words, a glance is generally directed to the roadway, rather than some in-vehicle device.

Similarly, ISO 16673 and SAE J2364 apply the terms occlusion interval and shutter closed time to the discrete time the driver interface or device is not visible to the driver in their occlusion procedures. This dissertation uses the term occlusion time (OT) to refer to each occlusion period in our self-paced occlusion studies.
method was also concluded to be a valid technique in distinguishing tasks based on their level of visual demand.

For more information regarding the use of the involuntary occlusion technique for assessing the workload associated with in-vehicle devices, see Foley (2009) for a thorough description of the technique and a summary of literature.

2.5 Post-script

While we recognise the usefulness of other paradigms in visual occlusion, it is important to stress that my dissertation focuses on the paradigm of self-paced visual occlusion with fixed glance duration (Figure 2-1a). The use of self-paced occlusion compels the operator to monitor and/or control a process using a subjectively minimal amount of information about the environment. The underlying assumption is that the operator, following instructions provided by the study, will look ‘only when necessary’, but frequently enough to avoid a decrement in performance.

I also reiterate that, when carrying out a self-paced visual occlusion experiment, for which a typical instruction is along the lines of “look whenever you feel it is necessary, but make sure to carry out your task (e.g., to drive) normally”, the intention is not that participants partake in risk-taking, by waiting longer than would ordinarily be comfortable for them. The presumption is that monitoring of performance parameters both with and without occlusion should serve as an adequate means of ensuring that the instructions have indeed been followed correctly.

As a final remark, although the literature reviewed in this chapter on earlier investigations employing visual occlusion has focussed essentially exclusively on automobile driving, I reiterate my assertion that the technique has the potential to be equally as useful for evaluating any other tasks for which operators often are not entirely loaded and thus are able to perform adequately without needing to (overtly) observe their visual world continuously.
3 Investigation of the Effect of Glance Duration on Occlusion Times

3.1 Background

Following the lead of previous research in modelling self-paced occlusion behaviour, the present study continued to use automobile driving as its research platform. Driving provides a system, the roadway, to which attention must be paid on a continual basis, but not continuously. This is evident in the rich and ongoing research of driver inattention. While there are other examples of systems that require only intermittent attention, such as instrument sampling in a process control plant, two of the advantages of automobile driving lie in the ease of finding available participants who are experienced operators of the system (automobile drivers) and in the level of engagement the experiment may elicit from participants.

The first effort in the current work was directed towards investigating the effect of glance duration on occlusion times. Glance duration is a key parameter in self-paced visual occlusion studies\(^1\), but has received little attention in the literature. As mentioned in Chapter 2.4, Green and Tsimhoni (2001) provided a summary of studies that adopted the visual occlusion technique in various forms. (A bibliographic overview of those studies can be found in Appendix B.) Among the studies that adopted the self-paced occlusion paradigm, most employed a nominal standard of 0.5 seconds for the viewing time of each glance.

Beyond Green and Tsimhoni’s review, other researchers that have used a fixed 0.5 s glance time include Hoedemaeker and Kopf (2001) for their research on car-following, and Courage et al. (2000) in their investigation of straight and curve road driving in a low fidelity driving simulator. In spite of this prevalence, no empirical evidence was found in the literature to actually support this choice of 0.5 s, beyond the comment found in Senders’ (1967) seminal work regarding three initial considerations in determining the glance time (from among 0.25, 0.5, and 1 s): “based on preliminary experiments...the 0.50 sec viewing time was apparently long enough to provide nearly all the information needed to drive at any speed, and only a slight increase in velocity was expected to occur with a 1.0 sec viewing time.”

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\(^1\)Note that in the involuntary occlusion community, the term glance duration is commonly referred to as “shutter open time.”
For the purpose of investigating the relationship between glance duration and occlusion times, this chapter presents an experiment using a low fidelity driving simulator, systematically manipulating glance duration and speed. Complementing the results of this driving simulator study, an additional set of data collected from a real-road study was analysed.

### 3.2 Hypothesis

As previously mentioned (see Chapter 1.2 and Figure 1-1 in particular), the underlying modelling assumption about the visual occlusion technique in general, and the self-paced paradigm in particular, is that visual information about the system being monitored or controlled is gathered during a glance period. The longer the glance, the more information may be gathered, resulting in a lowered level of uncertainty at the end of this glance period (and consequently at the beginning of the subsequent occlusion interval). It therefore stands to reason that, if the occlusion interval commences with uncertainty at a minimum, the expected length of the following occlusion interval will on the average be at a maximum.

It is thus anticipated that, for any particular set of conditions, there is some glance duration for which the minimum level of uncertainty can be reached, such that, if the glance is made any longer, there will be no more uncertainty left to be resolved. In other words, for trials using the same experimental setup, it is hypothesised that the mean occlusion time will approach an upper limit as the glance duration is systematically increased. The value of glance duration for which the mean occlusion period reaches a specified proportion of its asymptotic limit (95% for example) can be deemed to be the maximum glance duration for ensuring consistent occlusion behaviour in the particular setup observed.

Furthermore, because the self-paced occlusion paradigm also assumes that the use of occlusion does not degrade primary task performance, the present hypothesis stipulates also that metrics such as lane-keeping performance remain about the same for trials both with and without occlusion.

The above reasoning is illustrated in the model presented in Figure 3-1, which, as an extension of Figure 1-1, shows a curve depicting the hypothetical rise and fall of uncertainty, in synchrony with a number of step functions representing the opening (grey portion, labelled as Glance Duration) and closing (white portion) of some visual occlusion device. The important element of the model is that for the shorter GD values shown in the middle of the figure, the relatively high uncertainty level still present at the end of the glance results in a relatively short subsequent occlusion interval.

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2 Note that this figure is intended only to illustrate the model hypothesis; for practical self-paced visual occlusion experiments it is most likely that only one fixed glance duration (the grey area) would be used.
In relation to the question at hand, the model predicts that, for trials with statistically unchanging conditions, the mean occlusion time (MOT) will be a direct function of the duration of the (fixed) GD. In particular, shorter GD values should result in correspondingly shorter MOT values. In the other direction, although we expect MOT to increase with increased GD, we also hypothesise that this value will not increase indefinitely. Rather, we expect MOT to approach an upper limit as the GD is systematically increased, due to the fact that, at some critical value of GD, the minimum level of certainty will already have been reached during the looking period, thereby affording no added value for longer GDs. This hypothetical situation is illustrated in the first and third GDs shown in Figure 1. Simply put, our main hypothesis is that, for unchanging conditions, as fixed glance duration is increased, we expect the resulting mean occlusion time to increase asymptotically.

The hypothesis can be further refined by speculating that a well-trained operator (e.g., an experienced driver), whose internal model about the system is relatively sophisticated, will be able to gather all necessary visual information relatively quickly during a glance, and thus arrive at his maximally useful glance duration (i.e. smaller minimum glance duration) sooner than an inexperienced operator. In other words, we expect the minimum GD value defined by the asymptotic MOT vs. GD curve to be shorter for experienced than for inexperienced operators.

Figure 3-1: Model depicting hypothetical increases and decreases of uncertainty versus time, as a function of different glance durations.
3.3 Driving Simulator Experiment

To investigate the hypothesized relationship between glance duration and mean occlusion times, a self-paced visual occlusion experiment was carried out using a low fidelity PC-based driving simulator. In addition to serving the purpose of investigating the glance duration (GD) parameter, the experiment was meant also for gathering data for modelling attentional demands associated with visual information processing. Therefore, an additional factor of speed was included as a dependent variable, to capture some variation in the task demands.

3.3.1 Method

3.3.1.1 Apparatus

The driving simulator software was developed by York Computer Technologies of Kingston, Ontario. It was run on a standard PC running Windows XP. As shown in Appendix C.1, the roadway scene was displayed on a large screen, using a commercial LCD projector (LitePro 620 from Infocus System Inc.). The input hardware was a Logitech G27 force feedback wheel and pedal set, a standard commercial game control device.

Self-paced visual occlusion was realised by means of a pair of liquid crystal PLATO goggles, provided by Translucent Technologies Inc. The goggles allowed participants to view the simulated environment only when a viewing request was made, by pressing a button attached to a tube-shaped device designed for ease of holding, in the participant’s preferred hand. Each button press allowed a glance time of a pre-specified fixed glance duration.

3.3.1.2 Participants

Twelve male participants were recruited for this study, all of whom were students (10 graduate and 2 undergraduate) from the Department of Mechanical and Industrial Engineering at the University of Toronto. They were all equipped with a valid Ontario G driving license or equivalent. By recruiting only relatively young male drivers, the study was designed to disregard any potential confounding effects of gender and age, and would thus have more power to detect any effects of the experimental factors.
3.3.1.3 Experimental Tasks

The experiment included two driving scenarios: lane-keeping and car-following. The lane-keeping task has traditionally been popular, as it provides a simple, straightforward means for examining fundamental driving behaviour. In addition to having a lane centre that a participant could nominally aim to follow, the two sides of the lane provide a convenient boundary, while still allowing some slack in performance. The task is also natural for an experienced driver to understand and perform. Measures of a lane-keeping task are also simple and consistent, with the lane position data available in most driving simulators.

As lane-keeping has already been investigated in earlier visual occlusion studies, it was decided also to study an additional, more challenging car-following task, which requires longitudinal control by forcing the driver to maintain a specified headway from a lead vehicle. However, rather than asking participants to perform lane-keeping and car-following at the same time, the experiment separated the two tasks by disabling the use of the gas pedal in the lane-keeping task and by disabling steering in the car-following scenario. This results in a lane keeping task that requires only steering wheel control (speed was fixed by the simulator), and a car-following task that requires only gas pedal control (lateral position was fixed in the centre of the lane). This isolation of input was intended to ensure that the tasks investigated were in their simplest and purest form.³

Care was taken also to ensure that the tasks imposed a ‘minimal yet adequate’ workload on participants, such that they would need to sample the road continually, but not continuously, in order to maintain nominal levels of task performance. During pilot studies, it was discovered that it was possible for participants to find a particular position of the input device (gas pedal or steering wheel) that would allow satisfactory task performance almost without any visual sampling at all. For this reason, a small amount of simulated wind was introduced at random intervals during the trials (for both tasks) to prevent this problem.

In the car-following scenario, a lead vehicle (LV) of constant speed was built into the simulation. Participants had to follow the LV safely, at their own subjective level of comfort. To maintain the necessary amount of workload, participants were asked to follow the LV within 3 seconds of time.

³ It is also important to keep in mind that the visual occlusion technique is intended to be used to evaluate information processing for tasks that do not require continuous sampling of new information. It therefore would not make sense to try and apply it for evaluating a situation that has a priori been deemed to be highly loading.
headway$^4$. To help them maintain the required headway (such that their workload was not overly high), a predictor display appeared on the screen, in the form of an arrow on the ground to show where their own vehicle would be 3 seconds in the future. Participants were told to use the predictor display as an indicator of range instead of a single point to be pursued. The idea was to allow some slack in their task, to maintain a relatively low level of demand, analogous to the clear boundary and slack that the two sides of a lane provided them in the lane-keeping scenario. The choice of 3 seconds was based on preliminary runs, which examined a range of speeds and time headways. For ‘reasonable’ speeds of 40 or 60 km/h in this simulator, 2 seconds was deemed to provide too small a headway (too much workload) and at 4 seconds the size of the LV and the displayed predictor became too small to be easily perceived on the projected screen.

Screenshots of the simulator setup and a typical scene for each scenario during the simulation are attached in Appendix C.1.

### 3.3.1.4 Experiment Design

The study followed a repeated measures design with three within-subject factors: task (2 levels: car-following and lane-keeping), speed (2 levels), and glance duration (5 levels). Table 1 lists the values of all factors. Ten driving conditions (5 glance durations x 2 speeds) were repeated back-to-back, for a total of two trials for each of the two tasks. The trials were partitioned into 2 sessions with respect to the two tasks, and carried out on 2 successive days. Baseline trials with no occlusion were run in the beginning of each session for both speeds. In total, the study comprised 44 trials, each lasting 2 minutes. The order of sessions was counterbalanced across all participants to eliminate carryover effects of task type, and the order of presentation of trials within each session was randomized between subjects.

<table>
<thead>
<tr>
<th>Task</th>
<th>Car-following (steering disabled)</th>
<th>Lane-keeping (pedals disabled)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Speed</td>
<td>40 km/h, 60 km/h</td>
<td>20 km/h, 40 km/h</td>
</tr>
<tr>
<td>GD</td>
<td>Baseline (no occlusion), 0.5, 1.0, 1.5, 2.0, and 4 seconds</td>
<td></td>
</tr>
</tbody>
</table>

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$^4$ *Time headway*, as per draft SAE Recommend Practice J2944 (2013), refers to the time interval between two vehicles, measured from the same common feature of both vehicles, in this case their respective front bumpers. *Distance headway* is equal to time headway multiplied by the speed of the following vehicle.
3.3.1.5 Procedure

Participants received written and verbal instructions prior to the experiment regarding the experimental task and setup. Participants also signed a consent form and filled out a questionnaire prior to beginning any trials. These documents can be found in Appendix C.2.

The experiment began by familiarising the participants with the simulator and with the use of visual occlusion goggles while driving. For each scenario, the participant underwent a baseline trial without any occlusion. The participant then underwent training trials using occlusion. The training was concluded when the participant felt comfortable with the task, and achieved a level of task performance using occlusion that was comparable to their baseline performance with no occlusion (based on the graphical output of their performance, and as judged by the experimenter). The entire experiment of 2 sessions lasted 3.5 to 4 hours in total. Each participant was paid $40 upon completion of both sessions. They were informed, prior to the experiment, of their right to withdraw from the experiment at any time, and be compensated at a rate of $10 per hour up to the point of withdrawal. However, all 12 participants completed the entire experiment of two sessions.

During training for the car-following task, participants were advised to avoid driving too closely to the LV or too closely to the 3 second required headway, as either may compel them to look more frequently than necessary. A 2 second headway was recommended, but not required, as ideal. However, it was up to the participants to determine where the 2 second headway was on screen, or more precisely, what headway they considered ideal.

Overall, participants were instructed to perform the task as well as in the baseline trial (without any occlusion), with the difference being that they were told to view the road only when they felt that it was necessary. In both sessions, it was emphasized to the participants that this was not an experiment in risk taking; their primary task was to ‘drive safely’ at all times.

3.3.1.6 Measures

Every trial run resulted in two separate sets of data: occlusion data, which were a record of button press times that were synced to the computer system time, and performance data collected by the driving simulation software, at a sampling rate of 25 Hz. Only the second minute of every trial was used in the analysis, to discount the initial efforts of the participants to orient themselves with the glance time and to achieve a steady state level of driving performance.
Task Performance

The measures of task performance were lane positions in the case of lane keeping, and time headways maintained in the case of car following. The time headway, at any given time, was calculated from the instantaneous distance to lead vehicle and the speed of the following vehicle at that instant of time. In both lane keeping and car following scenarios, trial means and standard deviations of their respective measures were computed. There was also a record of the percentage of time the vehicle spent outside of the boundary (i.e. when the vehicle went outside either side of the lane or when the vehicle exceeded the 3s headway required) to ensure that participants were conducting the task as instructed.

Occlusion Data

The button presses of each trial were translated into a set of occlusion times, by calculating the times between successive button presses. For the \( i \)th button press,

\[
\text{Occlusion Time}_i = (\text{Button Press Time}_i - \text{Button Press Time}_{i-1}) - \text{Glance Duration}
\]

A mean occlusion time (MOT) was computed across the two replicated trials for each combination of Task x Speed x Glance Duration (GD).

3.3.2 Results

3.3.2.1 Analysis of Task Performance

The objective in analysing task performance data was to determine whether the factors investigated affected the driving task performance of participants. This was apart from the hypothetical asymptotic effect of glance duration on MOT.

Four sets of repeated measures ANOVA tests were carried out on the mean and standard deviation (STD) of time headway across the car-following trials, and on the mean and standard deviation of lane position for the lane keeping trials, using the nlme package in R (Pinheiro, Bates, et al., 2013). Speed (2 levels) and GD (6 levels) were treated as factors, and the repeated measures of subjects were treated as a random effect. The conditional F tests were obtained using marginal sums of squares.

As can be seen in Figure 3-2, GD did not have a significant effect \((p > 0.05)\) on any of the task performance measures, except for the STD of lane positions \((F(5,240)=5.50, p=.000)\), for which the STDs were significantly different between each of the 5 glance durations and the baseline (See Appendix D.1 for detailed statistics). On average, the STDs of lane positions found at each of the 5 levels were about 0.1m above that of the baseline (see Table 3-2). For practical considerations, this is a reasonably small
value despite the statistical significance, as the lane is 3.35m wide in this simulator. Furthermore, in only 13 out of the 240 lane-keeping trials did the participants sway outside of their lane at any given time, and of these 13 trials, only an average of 5% of the trial duration was spent outside the lane.

In summary, this analysis showed that participants for the most part succeeded in matching their control performance under the occlusion conditions to about the same levels of performance as during the non-occlusion trials. In other words, they were following the experiment’s instructions in driving safely and relatively normally.

Figure 3-2: Estimated means and 95% confidence intervals for task performance measures:
(Top) lane keeping - mean and standard deviation of lane position
(Bottom) car following - mean and standard deviation of distance headway
Table 3-2: Post-hoc analysis for comparing STD-LP between each GD and the baseline condition

<table>
<thead>
<tr>
<th>Simultaneous Linear Hypothesis</th>
<th>t-statistics</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.5s - baseline</td>
<td>Δ=0.152, t(241)=4.71, p&lt;.001</td>
</tr>
<tr>
<td>1s - baseline</td>
<td>Δ=0.120 , t(241)=3.70, p&lt;.001</td>
</tr>
<tr>
<td>1.5s - baseline</td>
<td>Δ=0.129, t(241)=3.99, p&lt;.001</td>
</tr>
<tr>
<td>2s - baseline</td>
<td>Δ=0.073, t(241)=2.27, p=0.024</td>
</tr>
<tr>
<td>4s - baseline</td>
<td>Δ=0.112, t(241)=3.47, p&lt;.001</td>
</tr>
</tbody>
</table>

3.3.2.2 Analysis of Visual Sampling Behaviour

There are many mathematical models that depict the kind of horizontally asymptotic function hypothesised – i.e., one that represents a function that increases but is limited by some maximum level. One such function has the form \( y = (ax + b)/(1 + cx) \); another is the exponential recovery function \( y = a - bc^x \). For the sake of simplicity, however, the function \( y = a - b/x \) was chosen for investigating the relationship between MOT GD. Another important advantage of this function is that, by transforming the independent measure GD into its own inverse, i.e. \( z = 1/GD \), the nonlinear regression is further reduced to a linear equation of the form: \( y = a - bz \), where \( y \) is the dependent measure of mean occluded times (MOT). This function can then be easily tested using standard statistical tools. More specifically, the resulting \( y \)-intercept, \( a \), would represent the asymptotic limit, or maximum MOT for the resulting function and \( b \), the regression slope, would determine how quickly the asymptotic function grows, if it exists at all.

A linear mixed analysis was carried out for both sets of tasks. The continuous measure of MOT was analysed separately for the two tasks using the nlme package in R. The factor Speed\(^5\) (2 levels) and the continuous variable of 1/GD were specified as fixed effects, and the repeated measures on subjects were taken as a random effect. Initial analyses including the factors by subject interactions as random effects did not improve the model fit. They were thus removed from the models to avoid exhausting the data (Kutner et al., 2004). Figure 3-3 shows the final fitted functions together with the raw data. In the figure, the independent variables have been transformed back from 1/GD to GD, in order to illustrate how well the data fit the hypothesised asymptote model.

\(^5\) Note that speed, as a factor, was examined for its effect on the intercept of the linear regression. In other words, the analysis examined how changes in the level of speed may shift the entire function upward or downward. Speed may also have an impact on the size of the regression slope (estimate for 1/GD) if an interaction effect exists between speed and 1/GD.
Figure 3-3: Asymptotical model fit of the mean occlusion times (MOT) as a function of glance duration (GD) for: (Left) lane keeping trials and (Right) car following trials.

There was no significant interaction between GD and Speed in either model, and they were thus removed from the final models. Speed and 1/GD were both found to be significant in the analysis of lane keeping trials (Speed: $F(1,222)=5.28$, $p=0.023$; 1/GD: $F(1,222)=12.57$, $p=0.001$). Analysis of car following trials also found speed and 1/GD to be significant (Speed: $F(1,221)=5.10$, $p=0.025$; 1/GD: $F(1,221)=0.24$, $p=0.003$).

Referring to the $y = a - b/x$ function above, the resulting model for the lane keeping trials can be expressed as:

$$MOT = 2.29 - 0.20 \cdot S - 0.20/GD, \quad where \quad S = \begin{cases} 1, & \text{if speed = 40 km/hr} \\ 0, & \text{if speed = 20 km/hr} \end{cases}$$

The final model for the car following trials can be expressed as:

$$MOT = 2.34 + 0.31 \cdot S - 0.26/GD, \quad where \quad S = \begin{cases} 1, & \text{if speed = 60 km/hr} \\ 0, & \text{if speed = 40 km/hr} \end{cases}$$

A complete summary of statistics associated with the resulting models can be found in Appendix D.2.

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6In the car-following task, higher speed resulted in higher MOT values, whereas higher speed in the lane-keeping task resulted in lower MOT values.
3.4 On-Road Driving Study

3.4.1 Background

Courtesy of my thesis advisor, Professor Paul Milgram, a second set of data was made available for investigating the glance duration parameter. These data came from a large study comprising three on-road, self-paced visual occlusion experiments carried out in the early 1980’s on a straight stretch of new but empty highway in the Netherlands. The objective of all three experiments was to examine the visual demands of driving at different speeds. Driving a specially instrumented car, participants focussed on lane keeping while driving at constant speed. (The speed was held constant by means of a servo-controlled gas pedal designed specifically for that purpose.) Visual occlusion was realised by means of a special helmet-mounted electrically controlled visor. In all conditions, participants were asked to “drive safely but look only when you feel it necessary, by pressing the horn button, which will raise your visor for a fixed period of time.”

Data employed by this dissertation came from the second (II) and third (III) experiments of that study, where together with different speeds, a range of (fixed) glance durations were investigated. Experiment II involved experienced drivers, whereas participants in Experiment III were relatively inexperienced. More details of the conditions can be found in Milgram et al (1982) and Godthelp (1984). It is important to note however that the analysis presented here of the effect of glance duration on occlusion times was not previously carried out using this set of data.

3.4.2 Method

As outlined, two lane-keeping experiments were conducted using self-paced visual occlusion. Both followed a repeated measures design with two within-subject factors: 3 speeds {20, 60, 100 km/hr} and 5 glance durations {.25, .5, 1, 2, 4 s}. All conditions were run twice, totalling 30 trials per participant. The order of trials was randomized between subjects and counter-balanced across all participants. The first experiment (Expt. II) involved 6 experienced male drivers with at least 3 years and 30,000 Km driving experience. The second experiment (Expt. III) recruited 6 inexperienced (newly licensed) male drivers.

3.4.3 Results

7 Experiment I in that series investigated a larger number of driving speeds, but employed only a single glance duration, 0.5s.
The same mixed model analysis was carried out for both sets of experiments. The continuous measure of MOT was analysed using the NLME package in R. Speed, a factor of 3 levels, and the inverse of glance duration, a continuous variable, were specified as fixed effects and the repeated measures on subjects were taken as a random effect. Figure 4 shows the final fitted functions together with the raw data for both a) the experienced drivers and b) the inexperienced drivers. In the two plots, the independent variables have been transformed back from 1/GD to GD to show the asymptotic behaviour of the function.

![Graph showing MOT analysis results](image)

**Figure 3-4: Asymptotic model fit of the on-road driving study: a) (Left) experienced drivers and b) (Right) inexperienced drivers**

### 3.4.3.1 Experienced Drivers

Interaction between Speed and 1/GD was significant \( F(2,167)=9.00, p=0.0002 \), along with significant main effects (Speed: \( F(2,167)=180, p<0.0001 \) and 1/GD: \( F(1,167)=60.0, p<0.0001 \)). Post-hoc analysis found that the regression slope of 1/GD parameter was significant at all three levels of speed (20 km/hr: slope = -0.46, \( p<0.0001 \); 60 km/hr, slope = -0.16, \( p = 0.023 \); 100 km/hr: slope = -0.15, \( p = 0.035 \)). More importantly, the estimated coefficient of 1/GD (i.e. the slope of the regression line) was negative at all three levels of speed, as hypothesized.

Increasing speed was found to lower the MOT (from 20 to 60km/hr: \( \Delta \text{Estimate}=-2.38, p=.000 \); from 60 to 100km/hr: \( \Delta \text{Estimate} = -0.73, p=.000 \)). The slope at 60 km/hr was also found to be significantly smaller than that at 20 km/hr (\( \Delta \text{slope} = 0.30, p =.001 \)), but not significantly different from the slope at 100 km/hr. These findings suggest that the effect of glance duration is more prominent when the speed is lower.
Mathematically, the model derived from the analysis is expressed as:

\[ MOT = 6.33 - 2.38 S_1 - 3.11 S_2 - 0.46/GD + 0.30 S_1/GD + 0.31 S_2/GD \]

where \( S_1 = \begin{cases} 1, & \text{if speed } = 20 \text{ km/hr} \\ 0, & \text{otherwise} \end{cases} \); \( S_2 = \begin{cases} 1, & \text{if speed } = 60 \text{ km/hr} \\ 0, & \text{otherwise} \end{cases} \)

### 3.4.3.2 Inexperienced drivers

With inexperienced drivers as participants, both speed and inverse GD were again significant (Speed: \( F(2, 169) = 136.61, p < .0001 \); 1/GD: \( F(1, 169) = 7.15, p = .0082 \)), but without a significant interaction. The interaction term was therefore removed from the final model. The estimated coefficient of 1/GD is negative as hypothesized and increasing speed was also found to lower the maximum MOT achieved (shifting the MOT function downward). An increase from 20 to 60 km/hr resulted in a decrease of maximum MOT by 1.34 s (\( p = .000 \)). From 60 to 100 km/hr, the maximum MOT was lowered by 0.57 s (\( p < .0001 \)).

As the analyses were carried out separately for the experienced and inexperienced drivers, statistical interpretations are not available for comparing the MOT functions fitted for the two groups of participants. However, Figure 3-4 suggests that experienced drivers achieved higher maximum occlusion times (the asymptotic upper bound), and their fitted asymptotic function grows more quickly than the corresponding ones for the inexperienced drivers.

The fitted model for the inexperienced drivers can be expressed as:

\[ MOT = 4.41 - 1.34 S_1 - 1.91 S_2 - 0.28/GD \]

where \( S_1 = \begin{cases} 1, & \text{if speed } = 60 \text{ km/hr} \\ 0, & \text{otherwise} \end{cases} \); \( S_2 = \begin{cases} 1, & \text{if speed } = 100 \text{ km/hr} \\ 0, & \text{otherwise} \end{cases} \)

Appendix D.4 contains a summary of all parameter estimates and their statistics of the final models fitted for the experienced drivers and the inexperienced drivers.

### 3.5 Discussion

For the simulated driving task, mean occlusion times and driving performance have been recorded and analysed for five different glance durations, using two different tasks and two different speeds. Another set of data collected from a real road driving experiment provided additional mean occlusion times in a lane-keeping task using 3 different speeds and 5 different glance times.
As hypothesised, the length of time that participants chose to stay occluded increased with increases in glance duration, but only up until a certain level, after which there appeared to be no obvious gain from a longer preceding glance. This asymptotic relationship was demonstrated in both the driving simulator experiment and the on-road driving experiment. However, the on-road driving revealed a set of much higher MOTs, which shows, in other words, that participants in the on-road driving study sampled their visual environment less frequently on average. The lower level of MOTs found in the simulator study is likely due to the low fidelity of the driving simulator. The lack of motion feedback through sound and vibration in the rudimentary fixed-base simulator used was likely hindering the participants’ perception of speed, which was important for maintaining time headway from the lead vehicle in the car-following task. In the lane keeping scenario, many participants found the steering wheel to be overly sensitive and rather difficult to control, which was likely influencing how long they were willing to steer without visual input.

It was also evident that the experienced drivers were able to remain occluded for longer periods of time (higher maximum MOT) than the inexperienced drivers in the real-road study, given the same speed and glance duration (see Figure 3-4). Not surprisingly, larger estimates of the regression slope for 1/GD were found also in the analysis for experienced drivers, as demonstrated in Figure 3-4 by a more obvious asymptotic growth of MOT. In other words, the inexperienced drivers did not benefit as much from the increase in GD overall. As suggested earlier, an inexperienced driver may be more limited in his ability to make use of information acquired during a preceding glance, which in turn is likely to have a more limited impact on his occlusion behaviour.

For either set of models (simulated or real on-road driving), the maximum values of the asymptotic functions identified appear to shift upward or downward depending on the speed at which the task was performed. The fact that speed has an impact on how long a driver chooses to stay occluded has long been documented (e.g. Senders et al, 1967; Mourant and Ge, 1997; Courage et al., 2000). In other words, it is well accepted in the literature that driving at a higher speed demands more visual attention and thus should result in lower occluded times. The on-road driving data demonstrates this relationship very well. From the standpoint of uncertainty modelling, at higher speeds the uncertainty during occlusion will increase more rapidly due to a smaller time constant, or faster system response (in the sense that a greater road segment is traversed per unit of time). This should thus cause one’s uncertainty threshold to be reached sooner, resulting in a more frequent need to look, manifested as shorter mean occlusion intervals.

3.5.1 Limitations of Experiment

In light of these expectations, it is perhaps surprising to find that the lower speed in the car-following task yielded lower occlusion times. This may be a result of the largely simplified road scene, for which there
were minimal changes in the scenery and no traffic other than the lead vehicle. Any increase in speed therefore did not result in a noticeable increase in the dynamic properties of the visual scene, i.e. the road. Given that the lead vehicle and the predictor display were the primary focus of attention in their visual information processing, a plausible explanation may lie with the participant’s perception of distance headway. Participants might have found that, given that they were asked to remain within 3 seconds of time headway from the LV, the lower speed condition corresponded to a shorter distance headway to maintain. It was possible that participants were less comfortable driving with a smaller distance headway, since it would have been perceptually more difficult, rather than less difficult, to monitor whether they were successfully remaining within the prescribed headway. Several participants indeed made such comments during the experiment. This explanation may further be supported by the observed significant difference in mean time headways kept by the participants for the two speeds, for which participants kept a significantly larger time headway in the lower speed condition relative to the higher speed condition (see Figure 3-2).

Some participants also commented that it would be simpler if the predictor had pointed out where they should be, rather than continuously showing a 3s prediction, which was a limit for how much they could fall behind the LV. It was originally thought that providing a limit would give the participants some slack in their task, whereas providing a single point would require more attention. However, by suggesting to the participants that 2 seconds of headway was ideal, the experimental results suggest that additional workload was imposed on the participants.

It is also unknown to what extent the low fidelity of the simulator affected the participants’ perception of time and distance headway. In real-road driving, it is conceivable that an experienced driver would be comfortable maintaining a relatively short time headway to a lead vehicle due to their own low speed. Perhaps with only visual feedback, as with this simulator setup, distance to the lead vehicle became an even more dominant factor in one’s sense of speed. There is relatively little literature documenting visual occlusion behaviour in car-following scenarios. Hoedemaeker and Kopf (2001) ran a car-following experiment using visual occlusion, but with only one (constant) lead speed of 80 km/h.

Higher MOTs were also found in the car-following task than in the lane-keeping task. However, this finding should not lead to any generalisation regarding lateral versus longitudinal control. It is likely that this result pertains only to this particular setup of steering wheel and pedal set, the limitations of which were discussed earlier. Perhaps the difficulty associated with controlling the hypersensitive steering wheel imposed too much workload, such that the participants were unable to rely on an internal model that includes dynamic responses of the vehicle for governing their sampling decisions. In this case, the
participants might have needed extra viewing time to learn the consequences of their own steering actions.

On the other hand, this issue may be strictly one of training. It is important in this experimental paradigm to have the participant drive safely and (relatively) normally, even when they are occluded. This requirement was satisfied for the most part. Baseline performance in both car-following and lane-keeping tasks was compared to the occluded performance. The lane-keeping task revealed that the SD of the lane position maintained was greater in the occluded trials than in the baseline trials. However, as mentioned in 3.3.1, participants very rarely swayed outside the lane boundary. Nevertheless, none of the other performance measures found any significant difference between the baseline and occluded trials.

Due to the observed issues with the lane-keeping task, lane-keeping using this particular setup should be avoided in future experiments. If future experimenters wish to use this particular experimental setup for a steering-related task, they should ensure that extensive training is done to warrant that participants are indeed comfortable with controlling the simulated vehicle.

3.5.2 Practical Implications

The results of this experiment have important implications for future self-paced visual occlusion studies (including those that do not involve automobile driving). Based on the analyses performed here, it is likely that similar asymptotic MOT vs. glance duration function fits will be obtained – if future researchers take the trouble to carry out such experiments. The importance of carrying out this ‘calibration step’ is that it should enable one to select an objectively appropriate value for glance duration for any future self-paced visual occlusion study. In other words, carrying out a preliminary study in which GD is varied systematically should ensure that an arguably optimal value of GD is selected for each study, which in turn would increase the likelihood that fair comparisons are made across experimental conditions.

A particular GD decision might be made by estimating the value of GD that results in MOT reaching a predetermined criterion – say 95% of its asymptotic limit. Referring to Figure 3-4, this leads us to the fortuitous observation that the GD of 0.5 s so often found in the literature is actually a reasonable value. On the other hand, from Figure 3-3 we might conclude that, for tasks using, for example, low fidelity driving simulators similar to the one we used, a fixed GD value of 1 to 1.5 s might be more appropriate.
3.5.3 Remarks on Glance Duration for Research using Involuntary Occlusion Paradigm

The hypothesised model and findings regarding the choice of glance duration is for the *self-paced* visual occlusion technique, which is only one of the many visual occlusion paradigms possible (summarised in Figure 1-2). As mentioned earlier, the automotive industry has recently taken an interest in applying the ‘involuntary’ occlusion technique to assess the visual demands of in-vehicle devices, essentially swapping the primary task of interest from driving to any other task that involves visual attention outside of the roadway. In this context, (fixed) occlusion intervals represent the potential time a driver could spend looking at the road, rather than the time *not* looking at the road.

A common purpose of that experimental paradigm is to measure the ‘interruptibility’ of a task using an in-vehicle device. The sum of all glances needed to perform a task using the involuntary occlusion technique is compared with the time it takes to complete a task without any occlusion (Foley, 2009). Although the International Organization for Standardization (ISO) and the Japanese Automobile Manufacturer Association (JAMA) have published procedures (ISO 16673, 2007 and JAMA guideline V3.0, 2003) for using the involuntary occlusion technique to assess in-vehicle devices, the values for occlusion and glance durations are not always consistent across them. The ISO has prescribed the use of 1.5 seconds of occlusion time and 1.5 seconds of viewing time (following recommendations proposed by Pettitt et al., 2006), whereas JAMA guidelines suggest 1.0 seconds of occlusion time with 1.5 seconds of viewing time.

The inconsistency of occlusion durations in the involuntary paradigm suggests that, like the self-paced paradigm, there is a lack of empirical research in this regard. This concern has also been raised by researchers such as Lansdown et al. (2004) and Brook-Carter et al. (2009). Karlsson and Fichtenberg (2001), for example, tested the effect of four (fixed) occlusion times (1,3,4, 6s) on the total time (of glances) needed to perform a task and found no significant differences. Using yet another paradigm, Weir et al. (2003) found that participants performing a data-entry task using a touch screen while driving in a simulator, at their own level of comfort, were making back and forth glances of 1.5 seconds or longer between the road and the touch screen, without sacrificing performance in either the driving or the data-entry task. The present study has implications for both voluntary and involuntary techniques.

While it is beyond the scope of this dissertation, it is nonetheless interesting to consider the following: given the purpose of examining driver safety in assessing in-vehicle devices, to what extent does occlusion simulate the need to ‘look at the road’ as depicted in the involuntary paradigm? In summary, whether it is with the self-paced paradigm or the involuntary occlusion technique, more empirical
investigations of the appropriate parameters are in need. The work presented in this chapter hope to serve as a reminder that choices of such parameters may have significant implications based on their theoretical origin.
4 Investigation of Relative Uncertainty Theory

4.1 Background

While the first experiment was designed to investigate the relationship between glance duration (GD) and occlusion times, the data collected were also meant for contributing to the modelling aspect of this thesis. In particular, the data were used to investigate the theory of visual sampling to maintain relative uncertainty, put forth by Milgram (1982) and Milgram et al. (1983).

Extending from Senders’ uncertainty model, Milgram quantitatively modelled uncertainty development using autoregressive (AR) time series modelling of the process being monitored. Using this approach, a particular time series model is able not only to predict future values of a process based on previous samples, but also to provide estimates of increases in the forecast errors associated with those predictions. If allowed to continue indefinitely, all predictions will eventually approach the system’s mean output, and the forecast error will asymptotically approach its maximum value, equal to the variance of the system output. (It is thus clear that the reliability of predictions decrease with time, with the most reliable estimates being those for which the prediction horizon is short.)

Applying this approach to visual occlusion assumes a well trained human operator who has acquired a perfect internal model of the probabilistic characteristics of the system. That internal model can be instantiated in a variety of ways, one of which is through autoregressive time series modelling. Using such a model, the operator is able to extrapolate observations of previous system outputs to predict the future course of the system during visual occlusion.

Just after a visual sample has been taken (and just before occlusion commences) it is assumed that the operator’s uncertainty about the system output is zero. Following the transition from observing to occlusion, the operator starts predicting the system output, and that prediction is accompanied by a growth over time of the forecast error. Needless to say, the model presumes that a rational operator will request a new sample while his or her prediction is still relatively reliable – that is, well before the

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1 Other potential modelling approaches include moving average models, autoregressive moving average models, and Kalman filtering.

2 Referring to the results of Experiment 1, whether this assumption is valid will depend on whether the glance duration is sufficiently long.
theoretical maximum forecast error. According to Milgram’s model, that level is determined by the
relative uncertainty.

Mathematically, the relative uncertainty, or information redundancy, is defined as the log normalised ratio
between the maximum variance and the instantaneous forecast error variance. What this means in terms
of the sampling model is that the relative uncertainty is an estimate of the amount of uncertainty resolved
during a glance relative to the maximum uncertainty that would be resolved if the forecast error were
allowed to reach its maximum value. Clearly information redundancy will decrease as occlusion time
increases. In other words, if the driver is willing to wait a long time before sampling, that means that s/he
is willing to accept more uncertainty; hence the information redundancy at the time of sampling should be
very low. Conversely, a driver that elects to sample very soon after a previous glance, s/he will acquire
relatively little new information, which corresponds to the information redundancy being very high.

Using the redundancy measure to represent relative uncertainty, Milgram proposed that operators adapt
their self-paced sampling behaviour to maintain a constant degree of relative uncertainty. In other words,
whereas it is not surprising to obtain different mean occlusion times for different experimental conditions,
such as driving at different speeds, the model postulates that, when analysed in terms of relative
uncertainty, it is possible to show that a single criterion might have generated those different occlusion
times – constant information redundancy. Using the data collected with experienced drivers in the on-
road study as seen in Chapter 3, Milgram et al. showed that these drivers appeared to sample at a constant
level of redundancy across different speeds, in their estimates of the vehicle's lateral position and heading
angle.

This chapter presents analyses using the driving simulator study described in Chapter 3 to investigate
further Milgram’s theory about relative uncertainty.

### 4.2 Analysis of Mean Redundancy

Following Milgram’s lead, separate autoregressive time series models were fitted to the lane deviation
data (lane positions minus the trial mean) for the lane keeping trials, and distance headway\(^3\) data for the
car following trials, as described in Section 1.5. These models were then used post hoc to compute
predictions and the associated forecast errors over the duration of each occlusion period within the trials

\(^3\) Although participants were asked to maintain time headway in this study, distance headway was used for
modelling purposes since it is a more concrete measure. Recall that participants were following a lead vehicle of
constant speed (either 40 or 60 km/h) during each run, hence the instructions about maintaining time headway would
result in a consistent profile of distance headway.
for which the models were fitted. Information redundancy values at every instant of visual sampling (button presses) were also computed. (See Appendix A for an explanation of how they were computed.)

To test the theory that human operators sample at a constant level of information redundancy, regardless of conditions, the means of the information redundancy values computed for each sampling decision were analysed against the parameters investigated: in this case speed (2 levels) and GD (5 levels). The hypothesis was that participants would maintain constant redundancy across different speeds for each fixed glance duration (GD).

In Chapter 3 it is shown that a sufficient duration of glance is necessary to reduce uncertainty to a minimum level prior to the subsequent occlusion period. Hypothetically then, GD should not affect the relative uncertainty at which operators need to look, since the threshold of uncertainty is expected to remain constant. However, in the present analysis, forecast error function used to compute redundancy, or relative uncertainty, starts at zero whenever occlusion is initiated, regardless of GD. Therefore, the residual uncertainty level from insufficient GD is not accounted for, and may thus affect the hypothesis of sampling at constant redundancy across different GDs.

### 4.2.1 Results

Using the nlme package in R, linear mixed model analyses were carried out to examine the effects of speed and GD, as factors, on the continuous measure of mean redundancy computed for the sampling instants, for the lane keeping task and the car following task respectively. In both analyses, the repeated measures on subjects were treated as a random effect. To control for Type 1 error rate, a post-hoc analysis examined pair-wise comparisons only on the effects that were significant. Using the ‘multcomp’ package in R, Tukey’s contrasts were chosen and the adjusted p-values are reported.

Speed, GD, and their interaction term had no significant effect ($p>0.05$) on the mean redundancy sampled from the lane keeping trials (see Figure 4-1a). The analysis on the car following data found that GD was significant ($F(4,186)=2.59, p=0.038$), but speed and interaction were not significant ($p>0.05$) (see Figure 4-1b). The study had a 0.8 power to detect an effect size of 0.135 or greater in mean redundancy.
Following up with the only significant factor, GD in car following trials, pair-wise comparisons did not find any significant differences among the levels of GD at the alpha level of 0.05. However, there was a borderline significant difference between GDs of 1s and 2s conditions ($\Delta=0.354$, $p=0.08$). In light of the hypothesis that insufficient GD may affect mean redundancy differently from a very long GD, a 5-level factor GD was re-coded to compare “sufficient” versus “insufficient” durations. Based on the findings of the investigation in Chapter 3 on the effect of GD on MOT, 0.5 and 1s GDs were combined to constitute the “low” condition (potentially insufficient duration), and 1.5, 2, and 4s GDs were combined to form the “high” condition (sufficient duration). The new, higher level of GD was found to significantly reduce the mean redundancy ($\Delta=-0.213$, $t(192)=-2.14$, $p=0.034$).

4.2.2 Discussion

Consistent with Milgram’s theory, participants in the simulator study did not show signs of varying their modelled threshold level of relative uncertainty across different speeds. Sufficient GD was hypothesized to be necessary for maintaining constant redundancy. However, this was demonstrated only in the car-following trials. It is unclear whether GD’s lack of significant effect on mean redundancy sampled in the lane keeping task indicates that 0.5 and 1s GDs were actually sufficient for participants to resolve their uncertainty completely. Given the inconsistent results about the GD factor in the two tasks, along with the inherent difficulty in proving a null hypothesis, it is difficult to validate Milgram’s theory of relative uncertainty sampling.
4.3 Analysis of Prediction Error

Milgram’s approach to analysing redundancy is based on the assumption that the uncertainty function (modelled in this case by the prediction error\(^4\) function of an autoregressive time series) existed and was adopted by the drivers to determine when their threshold was reached. In other words, the constant redundancy was expected to be a result of prediction error at visual sampling instants varying with changes in the system variance, rather than the result of random sampling that is independent of the dynamics and performance of the system.

Therefore, the prediction error at visual sampling instants was hypothesized to vary with the variance of task performance in that particular trial. Standard deviations of the lane positions were used for the lane keeping task, and standard deviations of distance headway maintained were used for the car following task. Speed and GD were included again to determine whether they have any additional impact on the mean prediction error sampled.

4.3.1 Results

Prediction errors were analysed by the mixed model analysis using R’s nlme package. Standard deviations of the task measure (lane position for the lane keeping task, and distance headway for the car following task) were included as a continuous fixed effect. Speed and GD were once again included as factors, and the repeated measures on subjects were treated as the random effect.

For the lane keeping task, a significant interaction between GD and STD-LP was present (F(4, 187) = 2.95, p = 0.021), along with a significant main effect of STD-LP (F(1,187)=79.5, p < .0001). There were no other significant effects. Collapsing over speed found the regression estimate (slope) of STD-LP to be positive and significant at all 5 levels of glances (see Figure 4-2).

Consistent results were found in the car following trials. A significant interaction between GD and STD-Headway was present (F(4, 181) = 3.14, p = 0.016), along with a significant main effect of STD-Headway (F(1,181)=11.6, p =0.001). There were no other significant effects. Averaging over the two levels of speed, regression slopes of STD-Headway were positive and significant at all 5 levels of glances (see Figure 4-3).

\(^4\)Note that the terms prediction and prediction error being used here are frequently referred to as forecast and forecast error in the literature.
4.3.2 Discussion

It was evident from both lane keeping and car following tasks that participants were sampling at a prediction error relative to the variance of task performance. The hypothesised positive relationship between mean prediction error sampled and standard deviations of performance measure was demonstrated at all levels of GD. The assumption that drivers used an uncertainty function was met and thus made findings about constant redundancy across different speeds more promising.

Figure 4-2: Mean prediction error vs. standard deviation of lane position for the lane keeping trials. Each point represents a trial average of the corresponding variables over all of the samples from that particular trial. Separate linear fits for the 5 glance durations are included.
4.4 Analysis of Mean Occlusion Times

The rate of information flow perceived by the observer during visual samples no doubt determines how quickly the uncertainty function grows. For example, in automobile driving the mean occlusion time (MOT) is expected to vary with speed, which has direct impact on the rate of change of the roadway-vehicle system. This was discussed in Chapter 3, as part of the analysis on the effect of GD on mean occlusion times (MOT).

On the other hand, when system parameters such as speed are fixed, we would expect one particular function describing growth of uncertainty with respect to time, leaving only the variance of the system process to be accounted for, according to the relative uncertainty theory. Therefore, in the present study where drivers were assumed to perform as well as they could, lower performance (i.e. larger variations in driving performance over a trial) was likely to be associated with a lower uncertainty threshold adopted.
by the driver, and as a result shorter occlusion times. Using deviations of the lane positions or distance headways as a measure of their performance, MOT was hypothesized to be an inverse function of the variance of task measures, in addition to the effect of speed and GD.

4.4.1 Results

Analyses were carried out on MOT, specifying three fixed effects: speed (2 levels), GD (5 levels), and the continuous variable of the standard deviations of either lane positions (STD-LP, for the lane keeping task) or distance headways (STD-Headway, for the car-following task). None of the fixed effects and their interactions was significant for the lane keeping task at the alpha level of 0.05, but STD-LP was almost significant ($p = 0.058$). Upon removing the interaction term, all three main effects were significant (Speed: $F(1,219)=9.42$, $p=.002$; GD: $F(4,219)=4.66$, $p=.001$; STD-LP: $F(1,219)=11.6$, $p=.001$). More importantly for this analysis, STD-LP was found with a negative coefficient (slope = -1.84, t(219)= -3.41, $p=0.001$).

There were no significant main or interaction effects found in the fully specified model for the car-following data. Removing interaction terms also found all three fixed effects significant(Speed: $F(1,218)=4.87$, $p=0.028$; GD: $F(4,218)=5.77$, $p=0.002$; STD-Headway: $F(1,218)=4.50$, $p=0.035$), but the regression estimate for STD-Headway was positive (slope = 0.044, t(218)= 2.12, $p=0.035$).

The complete $F$-statistics for both the fully specified model and the simplified model for both tasks are included in Appendix D.3.

4.4.2 Discussion

The hypothesis that MOT was an inverse function of task performance was demonstrated only in the lane keeping task. In the car following trials, not only was the effect of standard deviations not significant before removing interaction terms, but the estimate of the regression slope was positive. However, given the near zero slope estimated at 0.044, it is doubtful that an actual positive relationship exists between the STD of headway vs. MOT. Overall, evidence for this hypothesis was not completely satisfactory. There thus remains a concern about the validity of the assumption that drivers were maintaining their performance. The obvious complication is the difficulty in assessing goodness of driving using standard deviation of lane position or headway as a continuous metric. Evaluation of driving performance is not a unitary concept, and furthermore driving strategies may vary significantly across individuals.
4.5 General Discussion

4.5.1 Present analyses

Findings from the analysis of redundancy computed across conditions did not contradict Milgram’s theory of relative uncertainty. However, given that the null hypothesis cannot be proven by showing the absence of significant findings, and given that the effect size associated with a 0.8 power was not particularly small, results were not conclusive about drivers sampling to maintain constant redundancy.

One way to generate more insights about the relative uncertainty theory is to examine the underlying assumptions. It was interesting to find that the mean prediction error associated with sampling decisions varied with the standard deviations of the task performance measures, implying that the assumed fixed ratio between overall variance and the sampled error variance did exist. This finding thus lends support to the constant redundancy hypothesis, and provides a new perspective in assessing redundancy values as such.

On the other hand, the hypothesis that drivers were sampling at higher redundancy, or a lower uncertainty threshold, when the task was harder to perform was not thoroughly supported by the analysis of MOT vs. driving performance, as described in section 4.4. This suggests that the standard deviations of task measures (lane position and distance headway, respectively) may not have reflected the goodness of driving performance, in the sense that any consistent behaviour within limits may be deemed satisfactory by the driver.

It is also possible that the specific system parameters (speed in this case) already captured the difficulty level of the task, and hence no additional insights could be provided by the variation in task performance. Finally, if MOT varies with the standard deviations of task performance, as hinted by the small but positive slope of STD-Headway found in car following trials, then the case of drivers actually permitting themselves to drive in a more relax manner, by lowering their threshold of uncertainty, would need to be investigated further. Again, this is tied to the issue of measuring goodness of performance in automobile driving, and the difference in risk-taking behaviour across drivers.
4.5.2 Moving forward with the uncertainty model

Re-examining the uncertainty model in light of present findings, it was curious to note that predictions did not take a more explicit role in the uncertainty model. The ability to predict the course of system output during occlusion, based on the operator’s internal model, seems implied in the uncertainty model. In other words, there would be no need for uncertainty if there were no predictions to be made.

Consider an experienced driver driving safely on the road under intermittent occlusion. Her decisions to look are, according to the model, based on the growth of uncertainty surrounding her on-going predictions of the vehicle-roadway situation. It seems hardly plausible that she would not be influenced by her predictions of the situation. For example, if she predicts, with low uncertainty (i.e. high certainty), that she is currently driving near the edge of the road, would she not be compelled to look sooner, rather than later?

Furthermore, what is the role of information obtained from a glance? Besides resolving uncertainty build up, new information observed also helps keep our driver’s internal model of the system updated. It is also the only form of feedback for how ‘safely’ she is driving under her current sampling strategy. It is questionable then, that each visual sample of the roadway would serve only to resolve global uncertainty, without affecting her next sampling decision.

To explore further the above notions, predictions about the system under occlusion and information observed during glances were investigated as part of the uncertainty model. What the two elements share in common is that their potential impacts on sampling decisions are not with respect to the average rate of sampling. Instead, they both point to a more dynamic, moment-to-moment sampling behaviour during occlusion. From the perspective of data analysis, they contribute to variability from one occlusion duration to another within the same trial or condition.
5 Proposed Model

Following Milgram’s autoregressive modelling approach for analysing information redundancy, results from the driving simulator study reported in Chapter 4 were inconclusive about the hypothesis that drivers sample to maintain a constant level of relative uncertainty. On the other hand, the variability observed in occlusion data within trials led to new hypotheses about how a human operator may use information obtained from glances to determine their sampling decisions.

It is thus hypothesised that information available during a glance can be used in two ways. First, the human operator may interpret the information observed in a straightforward way, and take this into account during the subsequent occlusion period. For example, the operator is likely to wait longer if the observed sample is well within the safe zone and is likely to sample much sooner if the observed sample is close to the limit. Second, the operator may use the observed information also to predict the system output when occluded, based on what he or she has observed. This anticipation may then play a role in the subsequent decision to sample. It is important to point out that these two uses of information obtained during a glance are not intended to be mutually exclusive, since it is clear that in order to predict system output during occlusion (the second alternative) it is necessary to make use of the information gathered during a glance (the first alternative).

This new hypothesis about using glance information is to be distinguished from the model discussed in Chapter 4, which attempted to explain mean sampling behaviour, in terms of the global course of increasing uncertainty while an operator is occluded. The model presented in this chapter includes the more dynamic aspects of monitoring a system intermittently, by accounting for the variability observed in occlusion times. This variability has been largely neglected in past models associated with visual occlusion, which have focused on estimating the average rate of sampling for any particular trial, rather than analysing the moment to moment glance request decisions.

Bringing forward the new hypothesis, a new model of information sampling based on the original uncertainty model is proposed, as depicted in Figure 5-1. The new model relates to a visual information processing task that demands continuous monitoring, but not necessarily the human operator’s full attention the entire time. Visual occlusion of the task environment may occur naturally, as in the case of an operator attending to a separate task simultaneously, or in a contrived fashion, such as in an experimental setting where an occlusion apparatus is employed.
5.1 Major components of the model

Need to Look Processor. In general, while the term uncertainty implies that the operator is under pressure from not knowing, the term ‘need to look’ goes beyond this to include other influencing factors, such as the pressure an operator may experience as a consequence of previously obtained information (such as having approached the system’s limits). The Need to Look Processor therefore represents an aggregation of factors that contribute to an operator’s need to acquire new information during an occlusion period.

Input to Need to Look Processor. Five sources of need to look have been identified in this model. As depicted in Figure 5-1, noise, task parameters, and error estimation due to bandwidth and amplitude are always present, independent of any information gathered from visual samples of the system output. These model components are explained below, in sections 5.2.2, 5.2.3, and 5.2.4. They are represented here as a sort of non time-varying input (c.f. dc voltage) to the need to look processor, contributing to the mean sampling rate an operator may achieve in a given task. The remaining two sources are represented as variable inputs (c.f. ac voltage) that depend on information obtained from visual samples of the external input.

Sampled Visual Information. As previously described, sampled visual information informs sampling decisions in two ways: by providing updates about the system being monitored, and by providing information as a basis for predicting the course of system output during occlusion. This feedback loop of
using sampled visual information allows the model to capture a more dynamic sampling strategy of an operator in response to changes in system output over time.

*Threshold sampling.* Threshold sampling is depicted as a comparator in Figure 5-1. The model shows that the operator’s need to look feed into the comparator continuously. Each time a threshold is reached in the comparator, the model generates a sampling request, which is depicted as a switch that leads into the opening and closing of the visual occlusion device. At the same time, this signal resets the ‘need to look processor’ and enables the operator to receive new external input.

It is important to note that the threshold is likely to differ for individuals, hence the inclusion of a “psychological function” as a factor contributing to the determination of the threshold. The psychological function accounts for an individual operator’s motivation, risk taking behaviour, confidence, etc. (It is also possible to use this variable to incorporate related factors, such as rate of forgetting, one of the variables proposed in the original Senders et al (1967) model.)

### 5.2 A model that captures the development of expertise

While Figure 5-1 shows a comprehensive model of how expert human operators may arrive at sampling decisions, it allows for a large range of sampling strategies. Simply put, the model proposes a hierarchy of sampling behaviours, ranging from a rather simple strategy for determining when to sample during visual occlusion up to a much more sophisticated strategy that involves optimal use of sampled information and knowledge of the system. Using subsets of the model as depicted in Figure 5-1, the following subsections illustrate the hierarchy of sampling strategies supported by this model.

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1 This representation was inspired by, and is analogous to, a similar threshold model, called the integral pulse frequency modulation (IPFM) model, often used to describe how neural spikes are produced (Bayly, 1968). The IPFM model stipulates that a nerve fires when the stimulus signal reaches a particular threshold within the comparator.
5.2.1 Level 0 – Null model

![Figure 5-2: Proposed Level 0 Behaviour - Null model](image)

For the sake of completeness, the model acknowledges the possibility that an operator could begin with little or no understanding of the system and thus have no basis for when to sample its output. In this (unlikely) case, the operator may both ignore the system’s dynamic behaviour and disregard whatever information is available from the individual visual samples, and continue obliviously to sample at irregular intervals, independently of how the system is behaving. This is depicted in Figure 5-2 as a simple open-loop process with noise being the only input to the Need to Look Processor.

5.2.2 Level 1 – Passive monitoring

![Figure 5-3: Proposed Level 1 Behaviour - Passive Monitoring](image)
The next alternative to Level 0 involves the human operator possessing some knowledge about the system’s general dynamic conditions. Such knowledge would logically support a simple strategy of quasi-periodic sampling, but with the magnitude of the mean sampling frequency sensitive to parameters that reflect global conditions of system operation. As passive monitoring behaviour, visual samples at this level provide verification that the system is conforming to those global conditions (see Figure 5-3). For example, one would expect more frequent sampling under conditions of higher speed, adverse road conditions, etc. In general, a relatively slowly changing (low bandwidth) system would be expected to result in a relatively low mean sampling rate, and vice versa—in accordance with the kind of sampling behaviour prescribed in Senders’ (1964) model of instrument sampling.

5.2.3 Level 2 – Static sampling at threshold of uncertainty

![Figure 5-4: Proposed Level 2 Behaviour - Static Sampling at threshold of uncertainty](image)

Level 2 behaviour would exhibit a sampling pattern that is similar to Level 1, in the sense that the human operator would again be expected to adopt a quasi-periodic sampling strategy defined by system parameters. However, while both Level 1 and Level 2 strategies are intended to describe mean sampling behaviour, there is a subtle but important difference that underlies Level 2 behaviour: the operator is now operating on knowledge about dynamic changes in the system’s output, and consequently monitoring it with an internal model of how often a look should be necessary to ensure the normal functioning. For example, if the operator is aware that the system being monitored has a tendency to oscillate relatively rapidly and/or to exhibit relatively large changes, it stands to reason that s/he will decide that sampling relatively more often would be a wise strategy. This is essentially a response to how quickly prediction...
error may increase during occlusion and is illustrated in Figure 5-4 with the additional block of *error estimation due to bandwidth and amplitude*. This input determines the amount of uncertainty present at any given instant during an occlusion period and therefore contributes to the operator's need to look.

This level of sampling behaviour corresponds to the notion of uncertainty development in Senders’ model about automobile driving, where uncertainty development is a function of predetermined parameters such as velocity and information density of the road (1967). Milgram’s (1982), Blaauw’s (1984), and Godthelp’s (1984) estimates of uncertainty growth accompanying predictions of system behaviour also correspond to the present level—but for which variations in the precise timing of samples have not yet been explored.

### 5.2.4 Level 3 – Active Monitoring

![Figure 5-5: Proposed Level 3 Behaviour - Active Monitoring](image)

The proposed Level 2 strategy recognizes that sampling of a system is more likely to be based on important system parameters and global system output rather than be completely random. However, because it is a model of *average* performance, that strategy necessarily does not take into account moment by moment changes in system output, independent of the latest information that is available to an operator
during a sample. To address this, Level 3 (depicted in Figure 5-5) describes a more active monitoring behaviour by including the feedback loop from the visual sample to the need to look processor. More specifically, it is proposed that a particular sampling decision depends on information obtained and integrated during the most recent observation. Using their internal model about the system, operators can assess the meaning and significance of what they saw prior to an occlusion period, thereby adopting a strategy that is sensitive to not only system parameters, but also to the visual updates they perceive. A straightforward example of such behaviour would be a tendency to sample sooner following an observation that showed the system to be approaching the prescribed limits of system operation … and vice versa.

Note that availability of information does not necessarily mean the operator can perceive and make use of such information, since it stands to reason that the ability to absorb new information will depend also on the amount of time available for doing so. In particular, a longer glance means more information can be obtained. Therefore, sufficient glance duration is a condition for Level 3 to take place. In Chapter 3, the actual relationship between glance duration and OT was shown, through experimentation, to be an asymptotic relationship.

5.2.5 Level 4 – Active Monitoring Enhanced with Predicting

Having achieved all the earlier levels, according to which the human operator has a good internal model of the system’s dynamics and statistical variability and is able to comprehend information obtained previously, expert operators are postulated to be able to further predict the response of the system during
occlusion. Because such predictions are based on previous system output, predicting is also part of the feedback loop using the sampled visual information. Figure 5-6 illustrates and distinguishes how sampled visual input informs the sampling decisions at Level 3 (Active monitoring) and Level 4 (Predicting) in a lane keeping scenario.

As depicted by the complete Level 4 model in Figure 5-1, continuous predictions about the system during an occlusion period add to the instantaneous sampling decisions. This complexity of balancing between managing uncertainty and expectation makes this level the most dynamic and comprehensive strategy an operator could undertake.

Figure 5-6: Illustration of Level 3 and Level 4 sampling decisions using identical lane keeping scenarios. The vehicle's travelled path (top-down view) is shown as a blue solid line, with grey and white blocks representing respectively portions of travel done during occlusion and without occlusion. Green dotted lines represent the driver's predictions during occlusion.
5.3 Framework for analysing visual occlusion data using proposed model

An advantage of visual occlusion over other techniques, such as eye movement tracking, is the simplicity of its measurement – a simple record of when glance requests are made. This section presents a framework for analysing visual occlusion data in a way that is consistent with the proposed model’s nested structure of levels of sampling behaviour.

As shown in Figure 5-7, the framework suggests a series of questions to formulate testable hypotheses, which are then used to determine which level of sampling behaviour the operators are demonstrating. The analysis moves from one level to the next only if the hypothesis associated with that level has been supported. The framework is therefore progressive, in the sense that support for Level 4 presupposes the presence of Level 3, support for Level 3 depends on Level 2, and so forth.

The dependent measure, mean occlusion time (MOT), is proposed for Level 0 to Level 2 analyses, where the focus is on mean sampling rate. However, analyses for Levels 3 and 4 must examine each glance request individually to capture the respective relationship between the instantaneous glance decision and the information observed (Level 3) or the information predicted (Level 4).
Figure 5-7: A framework for analysing visual occlusion data
6  An Application of the Modelling Framework

This chapter presents an application of the model analysis framework proposed in Chapter 5 (see Figure 5-7), using data from the on-road driving study examined earlier. To reiterate, that self-paced visual occlusion study investigated sampling decisions for straight road driving, using a range of fixed glance durations (GDs), a number of constant speeds, for both experienced and inexperienced drivers. The twin goals of this application of the framework are:

- to understand better the self-paced visual occlusion paradigm in terms of the information processing that may occur during occlusion that leads to decisions to acquire new samples of the visual environment;

- to analyse actual occlusion data, to determine how the particular variables manipulated – speed and GD – may affect the sampling behaviour of experienced and inexperienced drivers.

6.1 Measures and Explanatory Variables

The dependent measure of this analysis is the occlusion times, in the forms of trial means (at Level 1 and Level 2) and individual samples (at Level 3 and Level 4). Changes in system dynamics were manipulated via speed, which has been consistently found to affect the mean sampling frequency in self-paced visual occlusion studies in the automobile driving domain (Senders et al, 1967; Courage et al., 2000; van der Horst, 2004). For depicting the kind of visual input drivers may observe about the system, lateral position of the vehicle with respect to the lane was taken as a continuous covariate in this analysis. This variable has also been a common measure of the roadway-vehicle system behaviour in the earlier occlusion studies (Milgram et al, 1982; Blaauw et al, 1984; Godthelp et al, 1984).

Considering the lateral position of the vehicle, any uncertainty growth, if it exists, will depend on the human operator's mental model of how the vehicle deviates with respect to (the centre of) the lane. Operators may also observe the latest lane deviation during a visual sample (a glance), and may or may not use such information to maintain and update their mental model. Operators may also use their observation about lane deviation in a more direct manner. As illustrated in Figure 5-6, imagine a driver who, during her most recent visual sample, saw her vehicle driving near the edge of the road. In that case she would likely look again sooner than she would if she had seen herself driving at the centre of the road. This would be an example of Level 3 behaviour. She may also continuously predict the current lane deviation while she is occluded, and look sooner when she expects her vehicle to be near the edge of the
road – an example of Level 4 behaviour. Therefore, lane deviation (LD) can both capture the performance of the driver as well as represent the information to be actively monitored.

6.2 Analytical Approach

The analytical approach following the framework calls for testing the hypotheses associated with each level in an incremental order. Using the abovementioned variables, Table 6-1 lists the hypotheses to be tested at each level for the lane keeping scenario specific to this study. It is important to note that parameters characterising the system and the kind of information that can be observed during glances are specific to the task environment. There are also other parameters associated with lane keeping that may be applicable for this framework. However, the present ones are the most representative and accessible parameters to be evaluated in the particular experimental platform.

<table>
<thead>
<tr>
<th>Level Reached</th>
<th>Hypotheses associated with individual level</th>
<th>Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 – Passive Monitoring</td>
<td>H₀: no relationship between average occlusion time (OT) and speed, Hₐ: significant relationship between average OT and speed</td>
<td>Mean OT = g(Speed)</td>
</tr>
<tr>
<td>2 – Sampling at Uncertainty Threshold</td>
<td>H₀: no relationship between average OT and lane keeping performance, Hₐ: mean occlusion time is inverse function of lane keeping performance</td>
<td>Mean OT = g(Speed, std(Lane Position))</td>
</tr>
<tr>
<td>3 – Active Monitoring</td>
<td>H₀: no relationship between OT and lane deviation (LD) observed at end of the previous sample, Hₐ: significant relationship between OT and LD observed at end of the previous sample</td>
<td>OT = f(Previous Observation) + g(Speed)</td>
</tr>
<tr>
<td>4 – Active Monitoring, enhanced with predicting</td>
<td>H₀: no relationship between OT and predicted LD based on preceding visual sample, Hₐ: significant relationship between OT and predicted LD based on preceding visual sample.</td>
<td>OT = f(Previous Observation, Predicted Observation) + g(Speed)</td>
</tr>
</tbody>
</table>
6.3 Hypothesised Relationship at Level 3 and Level 4

As shown in Table 6-2, the level 3 analysis was to investigate OT as a function of lane deviation (LD) observed at the end of the previous glance period, in addition to speed and GD. The basic premise is that maximum occlusion time for any particular set of conditions (e.g. speed) can occur whenever a LD of zero from the centre is observed preceding an occlusion period. Thereafter, shorter occlusion times are expected to follow larger deviations. A negative exponential function: \( y = ae^{-bx} \), was proposed to describe this relationship, as depicted in Figure 6-1, due to its simplicity and the fact that it is decreasing for increasing \( x \), but does not go below zero.

Figure 6-1: Negative exponential relationship proposed between OT and the observed/predicted deviation from the centre of the lane

Referring to Figure 6-1 and the function being fitted: \( y = ae^{-bx} \), the dependent measure \( y \) represents the occlusion time between two consecutive visual samples, the constant \( a \) represents the maximum occlusion time (as \( y \)-intercept in Figure 6-1), and the variable \( x \) is the LD perceived by the driver at the end of the previous visual sample. (Note that the occurrence of a value of \( y=0 \) simply means that the driver chose to request a new visual sample immediately following the previous one.) Assuming that deviations towards either side of the lane have equal significance, lane deviation is treated as an absolute value, thereby eliminating consideration of direction and ensuring a maximum at (0, a).

A similar negative exponential relationship (Figure 6-1) was hypothesised for OT vs. LD predicted, based on the premise that drivers would tend to request subsequent GDs sooner if they predicted that they were deviating farther from the centre of the lane. One of the challenges facing Level 4 hypothesis testing is to generate a set of (hypothetical) predictions that the driver could reasonably be making. Predictions for
this study were previously generated using Milgram’s autoregressive time series approach, which has been demonstrated to model real lane keeping performance well.

6.4 Hypotheses for Effects of Factors Investigated on Sampling Behaviour at Various Levels

For the particular on-road driving study, hypotheses were made about how the factors investigated (speed, GD, and population of drivers) may affect the findings of different levels of behaviour proposed. To begin with, the first and essential hypothesis about this study was that experienced drivers would demonstrate predicting behaviour (Level 4) in their sampling decisions. This means that predicted lane deviations would affect OT, and that the addition of this variable would provide the best fit among models formed for different levels. Inexperienced drivers, without the knowledge and experience to support a good mental model of their driving situation, were hypothesised as not likely to demonstrate predicting behaviour (Level 4).

Hypotheses regarding the effects of GD and speed on different levels of sampling behaviour mostly centre on Level 3 and Level 4. As an overview, Figure 6-2 provides a set of simple sketches to illustrate the hypothesised effects of the two factors on OT vs. LD observed (left) and OT vs. LD predicted (right).

![Figure 6-2: Hypothesised effects of speed and GD on the (assumingly present) relationship between occlusion time and LD observed (Left) and that between occlusion time and LD Predicted (Right).](image)

*Speed* was hypothesized to play a consistent role at all levels of the model, in the sense that decreasing speed should increase the mean occlusion times of models at Level 1 and 2, and increase the mean maximum occlusion time of models at Level 3 and 4 (see Figure 6-2: note the shift in y-intercept in both
plots). Beyond such, speed was not expected to have an effect on the presence of a relationship between OT and previously observed or predicted lane deviations. At very high speeds, however, it is conceivable that predicting behaviour associated with Level 4 may disappear, due to the fact that the driving task now takes up almost all of the drivers’ attentional capacity, such that there is little time (and mental capacity) for drivers to form predictions during occlusion.

In line with the analysis in Chapter 3, *glance duration* was hypothesized to have an asymptotically increasing effect on mean occlusion times due to the need to resolve uncertainty completely during a visual sample, suggesting that it affects sampling behaviour at Level 2. Similarly, level 4 behaviour requires drivers to maintain a good mental model of the driving performance in order that predictions can be made. As shown in Figure 6-2(b), increasing GD would increase the rate of decay of the hypothesised function. However, when GD is already sufficient to resolve uncertainty and to maintain their mental model, increasing the GD further will not facilitate the hypothesised relationship any further. Level 3 behaviour, on the other hand, is manifested through the use of information observed at the very end of a glance. Therefore, as long as drivers are able to perceive the road via a glance, the glance duration should not affect the hypothesised relationship between OT and LD observed (see Figure 6-2(a): increasing GD does not vary the reference line).

6.5 Summary of Results - Experienced Drivers

The statistical analysis proceeded by forming a model for each level to test the hypothesis associated with that level. Due to the nested nature of the proposed model, explanatory variables found significant at one level continue to be included in the next level. For example, if Level 1 finds speed to be significant, Level 2 analysis will continue to include speed as a factor. For further evidence that the drivers achieved certain level of behaviour, comparisons are made to determine whether moving to a higher level improves the model fit. Mixed-effects models were used to account for the repeated measures on drivers and the inclusion of continuous explanatory variables (e.g. lane deviations observed). As described in Section 1.5, models were fitted using the nlme package in R (Pinheiro, Bates, et al., 2013) and the Akaike’s information criterion (AIC) computed by the package were used to compare the goodness of fit of the models.

6.5.1 Level 1 and Level 2 models analysing trial means of occlusion times

At Level 1 and Level 2, the analysis targets the constant component of occlusion times, and thus uses trial means of occlusion times (MOT) as the dependent measure of the model. The Level 1 model tests MOT as a function of speed (3 levels) only. While GD was manipulated in the study, it was not hypothesised as
part of Level 1 sampling behaviour. As expected, speed was found to be a significant factor (F(2,170)=202, p<.0001).

Moving on to analyse Level 2 behaviour, in addition to speed, two new variables were included: GD\(^1\) was included for its hypothesised role in resolving uncertainty, and the standard deviation (std.) of lane positions was included as a measure of the overall lane keeping performance. The three main effects were all borderline significant at \(p=0.05\). Since none of the interaction terms were significant, they were removed for a more parsimonious model. Interestingly, the std. of lane position was no longer significant \((p> 0.05)\) in this model, suggesting the lack of an effect on the part of lane keeping performance. In fact, removing the std. of lane positions (referred to as ‘Level 2 Reduced’) found a model fit that was on a par with the original Level 2 model (see AIC values associated with models at Level 2 and Level 2 Reduced in Table 6-2: Experienced drivers - AIC values found for models fitted using MOT, providing further evidence that adding the lane keeping performance measure did not help explain the variation in MOT. On the other hand, Level 2 models demonstrated a better fit of the data than Level 1 (\(\Delta\text{AIC} = -37\), see Table 6-2: Experienced drivers - AIC values found for models fitted using MOT).

With the reduced model at Level 2, Speed, GD and their interaction were all found significant(Speed: F(2, 158) = 32.7, \(p<.0001\); GD:F(4, 158) = 18.1, \(p<.0001\); Speed x GD: F(8, 158) = 2.91, \(p=.005\)). The interaction effect of speed and GD has been discussed in the analysis of asymptotic effects on OT in Chapter 3 and is therefore not discussed further here. More details about the statistical analyses using mean occlusion times can be found in Appendix D.3.

**Table 6-2: Experienced drivers - AIC values found for models fitted using MOT**

<table>
<thead>
<tr>
<th>Level</th>
<th>Mixed Effects Model</th>
<th>AIC</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Mean OT = g{Speed}</td>
<td>427</td>
</tr>
<tr>
<td>2– Reduced</td>
<td>Mean OT = g{Speed, GD}</td>
<td>390</td>
</tr>
<tr>
<td>2</td>
<td>Mean OT = g{Speed, GD, std(Lane Position)}</td>
<td>391</td>
</tr>
</tbody>
</table>

6.5.2 Level 3 model analysing individual occlusion times

\(^1\)In Chapter 3, MOT was also analysed as a function of Speed and GD, using the same data set. However, GD was included as a continuous variable (and inversely transformed) to explore the asymptotic relationship between MOT and GD. The present analysis treats GD as a factor to examine the effect of GD on the presence of sampling behaviour hypothesised for different levels.
As shown in Table 6-1, beyond level 2, analyses were carried out on individual sampling decisions, in the form of individual OTs, instead of mean OTs (MOT) across trials.

The level 3 analysis investigated OT as a function of lane deviation (LD) observed at the end of the previous glance period, in addition to speed and GD. As described earlier, a negative exponential function was hypothesised to capture the relationship between OT and LD observed (as depicted in Figure 6-1). By taking the natural log of both sides of the equation, $y = ae^{-bx}$, the analysis becomes one of testing a simple linear regression of the form: $\ln y = \ln a - bx$. The mixed effects model was therefore specified, with $\ln(\text{OT})$ as a function of the fixed effects, Speed, GD, and LD observed, and the random effect of repeated measures on subjects. The intercept found via this mixed-effects model, $c = \ln a$, would require back-transformation, $e^{\ln a}$, to determine $a$, the maximum OT, on average. The estimate of regression slope $b$, if significant and negative, would determine the rate of decay of OT as a function of LD observed.

A significant three-way interaction was found among the three fixed effects, as well as a significant interaction between Speed and GD. (See Appendix D.3 for a summary of $F$-statistics for this model.) Given the known interaction between speed and GD on OT, it may be the case that LD observed was significant at a certain combination of speed and GD only. Regression slopes of the LD observed variable were thus determined at all 15 combinations of speed and GD. Figure 6-2 presents the separately fitted function on occlusion data for all 15 combinations. The slope estimates and their associate p-values are summarised in Table 6-3. Equations of these fitted models are presented in Table 6-4.
Figure 6-3: Experienced Drivers - Level 3 models of OT vs. LD observed at 15 combinations of speed and GD
Further analyses were carried out using subsets of data to analyse the effect of GD on the hypothesised relationship between OT and LD observed (regression slope, or coefficient estimated for LD observed) at the three different speeds. For speeds of 20km/hr and 60km/hr, GD was found to affect the y-intercept of the negative exponential function but not the rate of exponential decay (regression slope associated with LD observed). At 100km/hr, a significant interaction between GD and LD observed was found ($F(4,734)=3.10, p=0.015$) with a non-significant coefficient for LD observed. Evident in Figure 6-3 and in the estimates presented in Table 6-2, it is clear that the hypothesised Level 3 relationship was not present in most of the levels of GD at 100km/hr.

Similarly, analyses were carried out using subsets of data to analyse the effect of speed on the regression slope at the five different GDs. There was no significant interaction effect between speed and LD observed for any of the five GDs, supporting the hypothesis that speed does not affect the rate of exponential decay found in the Level 3 model. (See Appendix D.3 for a complete list of $F$-test results from these analyses.)

Further to finding that the regression estimate of LD observed was significant and negative at many of the conditions, mostly for trials with lower speed and lower GD (see Table 6-3), Level 3 was also found to have a better fit than the Level 1 model, when individual OTs were specified as a function of GD and Speed only ($\Delta AIC=-145.73$).

<table>
<thead>
<tr>
<th>GD</th>
<th>20 km/hr</th>
<th>p-value</th>
<th>60 km/hr</th>
<th>p-value</th>
<th>100 km/hr</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.25s</td>
<td>0.207</td>
<td>0.022</td>
<td>0.269</td>
<td>0.048</td>
<td>0.218</td>
<td>n.s.</td>
</tr>
<tr>
<td>0.55s</td>
<td>0.321</td>
<td>0.003</td>
<td>0.257</td>
<td>n.s.</td>
<td>0.552</td>
<td>&lt;.0001</td>
</tr>
<tr>
<td>1s</td>
<td>0.312</td>
<td>0.045</td>
<td>0.431</td>
<td>0.001</td>
<td>0.006</td>
<td>n.s.</td>
</tr>
<tr>
<td>2s</td>
<td>0.224</td>
<td>n.s.</td>
<td>0.098</td>
<td>n.s.</td>
<td>0.163</td>
<td>n.s.</td>
</tr>
<tr>
<td>GD 4s</td>
<td>0.455</td>
<td>n.s.</td>
<td>0.496</td>
<td>0.019</td>
<td>0.226</td>
<td>n.s.</td>
</tr>
</tbody>
</table>

$^2$Alpha level was modified to control for Type I error associated with analysing a subset of data. When speed (3 levels) was used to subset data, the new alpha level was 0.017 (0.05 divided by 3). When GD (5 levels) was used to subset data, the resulting alpha level was 0.01 (0.05 divided by 5). The only case where this adjustment of alpha level showed a difference was with respect to the analysis on 4s GD. Interaction between Speed and LD observed had a p-value of 0.025 ($F(1,259)=9.47$), which would have been significant at the alpha level of 0.05, but was deemed not significant given the new level of 0.01.

$^3$This was a different model from the original Level 1 model, which was fitted using MOT, not individual OT. However, it was not possible to compare models of different dependent measures, hence reconstructing a Level 1 model using individual OTs was necessary for the sake of model fit comparisons.
Table 6-4: Experienced Drivers – Level 3 Models separately fitted to equation $y = ae^{-bx}$, for combinations of speed and GD. ($y = OT$ and $x = LD$ observed)

<table>
<thead>
<tr>
<th>Glance</th>
<th>Speed 20 km/hr</th>
<th>Speed 60 km/hr</th>
<th>Speed 100 km/hr</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.25s</td>
<td>$y = 1.57e^{-0.314x}$</td>
<td>$y = 1.26e^{-0.370x}$</td>
<td>$y = 1.00e^{-0.154x}$</td>
</tr>
<tr>
<td>0.5s</td>
<td>$y = 1.66e^{-0.304x}$</td>
<td>$y = 1.32e^{-0.313x}$</td>
<td>$y = 1.10e^{-0.453x}$</td>
</tr>
<tr>
<td>1s</td>
<td>$y = 1.75e^{-0.293x}$</td>
<td>$y = 1.38e^{-0.441x}$</td>
<td>$y = 1.08e^{-0.046x}$</td>
</tr>
<tr>
<td>2s</td>
<td>$y = 1.86e^{-0.329x}$</td>
<td>$y = 1.35e^{-0.194x}$</td>
<td>$y = 1.18e^{-0.183x}$</td>
</tr>
<tr>
<td>4s</td>
<td>$y = 1.90e^{-0.484x}$</td>
<td>$y = 1.43e^{-0.474x}$</td>
<td>$y = 1.18e^{-0.118x}$</td>
</tr>
</tbody>
</table>

6.5.3 Level 4 model analysing individual occlusion times

For the level 4 analysis, in addition to using observed LD, the model included what was postulated as the drivers’ predicted lane deviation at the end of each occlusion interval. The prediction values were derived from the autoregressive modelling approach described in Section 1.5. Given that OT was at this level a function of two continuous variables (both hypothesised to have a respective negative exponential relationship with OT), the hypothesised model became three-dimensional: $OT = ae^{-bx-cy}$, where $x$ represents LD observed and $y$ represents LD predicted. Taking the natural log of both sides yields the multiple linear regression model of $\ln(OT) = \ln(a) - bx - cy$. The regression estimates of $b$ and $c$ were expected to be negative, such that $a$ remains the maximum OT on average.

Specifying Speed, GD, LD observed and LD predicted as fixed effects resulted in a significant 4-way interaction and many other significant interaction terms. Interactions involving LD-observed and LD-predicted, both being continuous, made it especially difficult to interpret the model further. However, the model did provide a better fit over the Level 3 model ($\Delta AIC = -67.52$), supporting the presence of Level 4 behaviour.

A simplified Level 4 model excluded the variable of previously observed LD to allow for further investigations of the relationship between OT and predicted LD, and the effects of speed and GD on this relationship. In this model, individual OTs were fitted as a function of speed, GD and predicted LD. No significant three way interaction was found and was thus removed from the model. The remaining model was significant for all main effects and two way interactions. The F-statistics associated with both the original model and the simplified model for Level 4 are included in Appendix D.3.

With the simplified model for Level 4, the significant two-way interactions between predicted LD and GD and Speed, respectively, already suggest that both GD and speed have an impact on the hypothesised relationship between OT and predicted LD ($OT = ae^{-b(LD\,predicted)}$). However, as can be seen in Figure
6-4, which presents the separately fitted function on occlusion data for all 15 combinations, the negative exponential relationship was clearly a poor fit of data for all conditions with 2s and 4s GD. Trials using these two values of GD were therefore excluded from further analysis. Table 6-5 presents the estimates of the regression slope at the 15 conditions and their associate p-values. Equations of these fitted models are presented in Table 6-6.
Figure 6-4: Experienced Drivers - Level 4 models of OT vs. LD predicted at 15 combinations of speed and GD.
Post-hoc contrasts found that increasing speed from 20 to 60 km/hr actually increased the rate of exponential decay (yielded a more negative regression slope) for GDs of 0.5s (Δ slope = -0.176, \( p=0.041 \)) and 1s (Δ slope = -0.219, \( p=0.007 \)). Increasing speed otherwise had no effect on the rate of decay.

Increasing GD from 0.25 to 0.5 sec also increased the rate of exponential decay at all three speeds (20 km/hr: Δ slope = -0.214, \( p=0.012 \); 60 km/hr: Δ slope = -0.268, \( p=0.003 \); 100 km/hr: Δ slope = -0.264, \( p=0.005 \)). Increasing from 0.55 to 1s GD did not have an impact on the regression slope at any of the speeds.

### Table 6-5: Experienced drivers - regression slopes of OT vs. LD predicted at all 15 combinations of speed and GD.

<table>
<thead>
<tr>
<th>GD</th>
<th>20 km/hr Slope estimate</th>
<th>20 km/hr p-value</th>
<th>60 km/hr Slope estimate</th>
<th>60 km/hr p-value</th>
<th>100 km/hr Slope estimate</th>
<th>100 km/hr p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.25s</td>
<td>-0.388</td>
<td>&lt;.0001</td>
<td>-0.510</td>
<td>&lt;.0001</td>
<td>-0.639</td>
<td>&lt;.0001</td>
</tr>
<tr>
<td>0.55s</td>
<td>-0.602</td>
<td>&lt;.0001</td>
<td>-0.724</td>
<td>&lt;.0001</td>
<td>-0.853</td>
<td>&lt;.0001</td>
</tr>
<tr>
<td>1s</td>
<td>-0.464</td>
<td>&lt;.0001</td>
<td>-0.586</td>
<td>&lt;.0001</td>
<td>-0.715</td>
<td>&lt;.0001</td>
</tr>
<tr>
<td>2s</td>
<td>-0.060</td>
<td>n.s.</td>
<td>-0.182</td>
<td>n.s.</td>
<td>-0.311</td>
<td>n.s.</td>
</tr>
<tr>
<td>4s</td>
<td>0.208</td>
<td>0.014</td>
<td>0.086</td>
<td>n.s.</td>
<td>-0.042</td>
<td>n.s.</td>
</tr>
</tbody>
</table>

### Table 6-6: Experienced Drivers – (Simplified) Level 4 Models separately fitted to equation \( y = ae^{-bx} \) for combinations of speed and GD. Note that \( y = OT \) and \( x = LD \) predicted.

<table>
<thead>
<tr>
<th>Glance</th>
<th>Speed</th>
<th>20 km/hr</th>
<th>60 km/hr</th>
<th>100 km/hr</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.25s</td>
<td>( y = 1.62e^{-0.557x} )</td>
<td>( y = 1.29e^{-0.541x} )</td>
<td>( y = 1.05e^{-0.596x} )</td>
<td></td>
</tr>
<tr>
<td>0.5s</td>
<td>( y = 1.72e^{-0.607x} )</td>
<td>( y = 1.36e^{-0.693x} )</td>
<td>( y = 1.15e^{-0.830x} )</td>
<td></td>
</tr>
<tr>
<td>1s</td>
<td>( y = 1.76e^{-0.351x} )</td>
<td>( y = 1.41e^{-0.769x} )</td>
<td>( y = 1.17e^{-0.758x} )</td>
<td></td>
</tr>
<tr>
<td>2s</td>
<td>( y = 1.83e^{-0.117x} )</td>
<td>( y = 1.37e^{-0.321x} )</td>
<td>( y = 1.21e^{-0.576x} )</td>
<td></td>
</tr>
<tr>
<td>4s</td>
<td>( y = 1.81e^{-0.044x} )</td>
<td>( y = 1.26e^{0.652x} )</td>
<td>( y = 1.15e^{0.116x} )</td>
<td></td>
</tr>
</tbody>
</table>
6.6 Summary of Results – Inexperienced Drivers

A similar set of analyses was carried out using the data collected from inexperienced drivers. Using mean occlusion time (MOT) as the dependent measure, the Level 1 model was constructed with only speed, which was found significant \((F(2,172)=131, p<.0001)\). The Level 2 model was constructed with speed, GD, and the standard deviation (std.) of lane positions. None of the effects were found significant in this model, and the model, with an AIC value of 395, was a worse fit than the Level 1 model, with an AIC value of 390. Furthermore, when MOT was analysed as a function of speed and GD (analogous to the reduced Level 2 model in the analysis for data pertaining to experienced drivers), only speed was significant \((F(2,169)=11.8, p=.000)\). A summary of the fitted models is included in Appendix D.3.

Given that only speed was found significant in the analysis of MOT, it was unlikely that the inexperienced drivers were accounting for anything beyond speed. However, an attempt was made to examine potential use of information obtained from look. A Level 3 analysis was carried out using individual occlusion times, including speed, GD and LD previously observed as fixed effects. The three-way and two-way interaction terms were all significant. The main effects of speed and GD were significant, but LD observed was not significant. As seen in Figure 6-6, the OT vs. LD observed relationship was not apparent, even when the function was separately fitted for the 15 combinations of speed and GD. In fact, only 1 out of the 15 combinations found a significant and negative regression slopes hypothesized. Table 6-7 presents the equations associated with the 15 fits, as seen in Figure 6-5. F-statistics and results from the post-hoc analysis at Level 3 can be found in Appendix D.3. In summary, there was a lack of evidence to support the hypothesis that LD observed was in use, and the Level 4 model was consequently not tested. (The nested nature of the framework requires a significant Level 3 behaviour before continuing to test at Level 4.)
Figure 6-5: Inexperienced drivers - Level 3 models of OT vs. LD observed at 15 combinations of speed and GD
Table 6-7: Inexperienced Drivers – Level 3 Models separately fitted for combinations of speed and GD. (y = OT and x = LD observed)

<table>
<thead>
<tr>
<th>Glance</th>
<th>Speed</th>
<th>20 km/hr</th>
<th>60 km/hr</th>
<th>100 km/hr</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.25s</td>
<td>$y = 1.29e^{0.036x}$</td>
<td>$y = 0.95e^{0.140x}$</td>
<td>$y = 0.84e^{-0.295x}$</td>
<td></td>
</tr>
<tr>
<td>0.5s</td>
<td>$y = 1.41e^{-0.221x}$</td>
<td>$y = 1.01e^{-0.0076x}$</td>
<td>$y = 0.78e^{-0.014x}$</td>
<td></td>
</tr>
<tr>
<td>1s</td>
<td>$y = 1.46e^{-0.020x}$</td>
<td>$y = 1.09e^{-0.236}$</td>
<td>$y = 0.84e^{-0.030x}$</td>
<td></td>
</tr>
<tr>
<td>2s</td>
<td>$y = 1.43e^{-0.071x}$</td>
<td>$y = 1.06e^{0.085x}$</td>
<td>$y = 0.83e^{-0.002}$</td>
<td></td>
</tr>
<tr>
<td>4s</td>
<td>$y = 1.54e^{-0.112x}$</td>
<td>$y = 1.08e^{0.139x}$</td>
<td>$y = 0.91e^{-0.377x}$</td>
<td></td>
</tr>
</tbody>
</table>

6.7 Discussion

Results from model fit comparisons and the significant parameter estimates provided support for the modelling framework (depicted in Figure 5-7), which calls for analysing sampling behaviour at four different levels. We saw that the experienced drivers in the study were demonstrating Level 4 behaviour, according to which they appeared to use the proposed predicted lane deviations in their decisions to sample. Results from the inexperienced drivers, as hypothesised, did not support the presence of a more active sampling strategy. However, it was still possible that within these inexperienced drivers, a few of them might exhibit a higher level of sampling behaviour than the rest.

Given that inexperienced drivers were not demonstrating a more active sampling strategy, the following discussion of Level 3 and Level 4 sampling behaviour concentrates on the findings from the experienced drivers.

We can see from Figure 6-3 that the hypothesised negative exponential model was a poor fit for trials of the highest speed, 100 km/hr, in general. On the other hand, at Level 4, it was the highest GDs, 2 and 4 sec trials that demonstrated a visibly worse fit of the data (evident in Figure 6-4). That at 100 km/hr, experienced drivers were still demonstrating predicting behaviour suggests that straight-road driving at 100km/hr (without any other traffic) was not taking up all of their attentional capacity and they were able to ‘optimise’ their sampling behaviour.

The lack of evidence for supporting Level 3 behaviour at 100km/hr may be the result of a significant interaction between predicted information and observed information found in this case. It may be that the use of predicted information diminished the importance of information observed, especially when the
predicted deviations were, to a certain extent, based on actual recent deviations. This effect may be magnified when sampling was done at higher frequencies (often the case for high speeds), in which case predictions would closely follow observations.

Another contributing factor may come from limitations in the data available for this study. Because complete raw data were not available, the values used for LD observed were in fact observed at the beginning of the previous glance period, rather than at the end of the glance period as intended. Therefore, at higher speeds and for longer GDs, what would have been observed at the end of a look could conceivably have been considerably different from what was observed at the beginning. It is also worth noting that, given the fixed trial time (2 minutes each), considerably fewer sampling decisions were recorded for trials using GDs of 2s and 4s (evident in Figure 6-3 and Figure 6-4).

Apart from the cases discussed above, the rest of the data appeared to behave as expected. At level 4, the significant interaction between previously observed LD and predicted LD presented difficulties in interpreting their combined effect on OT, but significant main effects were found with negative estimates, as hypothesised for both variables, making for a convincing case that their effect on OT was as expected. Furthermore, the model fit at level 4 showed improvement over the one for level 3. This is also evident from comparing the plots in Figure 6-3 to the plots in Figure 6-4.

### 6.7.1 Effect of GD on different levels of behaviour

Evidence was also found to support the hypotheses regarding how speed and GD may affect the parameters of the proposed negative exponential function. (See Figure 6-2 for an illustrated summary of such hypotheses.) A few observations were made:

**Speed**

- Speed as a parameter characterizing the task continued to affect the mean sampling frequency at all levels, providing evidence that the hierarchy of sampling behaviours was progressive, rather than distinct.

- As discussed earlier, the relationship between OT and LD observed was more apparent for a lower speed.

- Speed did not appear to affect the presence of an apparent relationship between OT and LD predicted. (In other words, predicting as prescribed by Level 4 was found for all levels of speed.)
• Speed appeared to have some effect on the relationship between OT and LD predicted. Increasing speed from 60 and 100 km/hr showed an increase in the estimated rate of decay at 0.55 and 1s GD. This means that drivers were more sensitive to smaller deviations from the centre at higher speeds, possibly a reaction to the fact that higher speeds result in more rapid changes in roadway information and vehicle response.

Glance Duration (GD)

• There was no evidence to suggest that GD had any influence on the relationship between LD observed and OT (Level 3).

• Increasing GD from 0.25 to 0.5 sec appeared to amplify the relationship between LD predicted and OT, but not for increasing from 0.5 to 1s. This was consistent at all three speeds, and may be another piece of evidence for the need to have sufficiently long GD to maintain drivers’ mental model of the current situation.

6.7.2 Modelling of Individual Behaviours

It is also possible to examine individual drivers’ visual sampling behaviour by analysing their data separately. As an example, Figure 6-6 presents separately fitted models for data collected from three subjects in the condition: 1s GD and 60 km/hr. OT was fitted to previously observed LD (on the top) and to predicted LD (on the bottom) for each of the three subjects. Subj1 clearly exhibits an excellent fit using the negative exponential model, especially for predicted LD. Subj6 shows a mediocre fit, and a barely significant relationship between LDs and OT (both fixed effects are at p=0.06). Finally Subj 4 reveals a poor fit to the model, in which LD values appear to be scattered randomly across the range of occlusion times. Conceivably Subj1 may be said to have achieved level 4 sampling behaviour, whereas Subj4 may be considered to have remained at a level 0 or 1 behaviour, depending on whether he or she was sensitive to the varying levels of speed.
Limitations of the on-road driving study

Part of the limitations for this study came from data availability, such as the problem already mentioned of not having actual data on observed LD at the end of each look, as well as the limited number of samples available for larger GDs.

It could be argued that there are also limitations inherent from the choice of system/task. Each driver in the study likely had his or her own driving style and interpretation of what driving safely meant, even though they were driving normally and safely as instructed, but with natural variations in the manner in which each of them kept their vehicle within the lane. Furthermore, for some drivers the emphasis on driving normally and safely could mean a lower acceptable threshold of uncertainty, and consequently more samples and a smaller range of variability in the resulting occlusion times. In light of this, the finding that mean occlusion times increased with increasing lane deviations may not be surprising from a cause and effect point of view, since it is possible that drivers who were more likely to have wider deviation within the lane could be those who felt more comfortable with longer occlusion times.

Furthermore, for the analysis presented here, driving behaviour was assumed to be open-loop, in the sense that drivers' steering performance was consistent and not affected by the presence or lack of visual input. Therefore, relying on lane keeping was possibly not ideal for measuring driving performance to reflect the
changes from level 1 to level 2. The earlier hypothesis testing about the asymptotic relationship between MOT and GD was likely a stronger piece of evidence that drivers were developing and resolving uncertainty throughout the trial.

Another important observation is that most of the data tested were concentrated at the crossover region of small LD and low OT (see for example Figures 6-3 and 6-5), reflecting the premise that drivers were sampling often to maintain good performance. This is especially true for the inexperienced drivers. This distribution of samples made it difficult to determine the hypothesized negative exponential relationship, and consequently less knowledge could be gained about the variability in occlusion times. Ideally, a more evenly and widely spread range of information observed/predicted would have allowed for a better model to be fitted.

In conclusion, the analysis reported here on the on-road driving study did find evidence for a more active component in monitoring behaviour in visual occlusion. However, due to limitations in data availability, the necessary assumptions about automobile driving, and the complexity of interactions present, it was difficult to draw very solid conclusions about whether predicting during visual occlusion really takes place, apart from observations during visual samples, and to what extent human operators can use such predictions in their sampling decisions. Therefore, the next phase in my dissertation focuses on investigating predicting behaviour in visual sampling processes, by means of a new experimental study.
7 Simple Monitoring Experiment – an investigation of predicting behaviour during occlusion

7.1 Introduction

Some of the findings from the previous study using on-road driving data were somewhat ambiguous. It was unclear whether the drivers, during occlusion, were relying on information they acquired during preceding glances or on predictions of their own vehicle's trajectory. To strengthen the hypothesis of the prediction portion of the proposed model, there is a need to show that human operators fundamentally are in fact able to predict when the situation allows them to. This chapter presents a directed investigation of the existence of predicting behaviour during visual occlusion.

7.2 Procedure

A self-paced visual occlusion experiment was carried out to seek evidence for the two higher levels of sampling behaviour associated with active monitoring in the proposed model (see Figure 5-1). This experiment moved away from automobile driving to a contrived monitoring experiment, independent of application domain. The rationale was that a more controlled and straightforward perceptual task, unrelated to automobile driving, may eliminate assumptions one might otherwise have to make about the automobile driving environment. Furthermore, by creating an experiment in which rational advantages for predicting during occlusion are built into the experiment, the straightforward goal is to confirm that prediction occurs. In this case, failure to detect prediction behaviour would thus also be considered a noteworthy outcome.

7.2.1 Experimental Setup

On a computer screen, participants observe a simple two dimensional representation of a ball inside a swinging basin, represented by an arc (see Figure 7-1). The ball sits at the bottom of the basin, which oscillates back and forth, driven by a quasi-random forcing function. Visual occlusion is achieved by blacking out the screen, as the default state, while the ball-in-basin system continues to oscillate. The participant’s task is to monitor this system while viewing it intermittently. Whenever he feels a need to observe the system output, the participant presses the spacebar, which initiates a glance of fixed duration.
Figure 7-1: Illustration of what participants observe on screen. The ball sits at the bottom of the basin as it oscillates back and forth (middle). However, when the basin swings too far to one side (left/right), the ball may drop off the side of the basin.

The motivation for monitoring the system is that sometimes the basin swings too far to one side, and the ball can drop off the edge of the basin. By ignoring friction, the ball remains in the same location relative to the screen, but not to the basin … except when a drop-event occurs. After a drop-event, the ball is immediately replaced by another ball at the location where it dropped off. The participant’s overall goal is to report, via a key press, whenever the ball drops off. Because the ball is replaced on the basin immediately after dropping off, it is thus important to sample the system whenever it is likely that the ball will be in the vicinity of the edge, where it is very possible to not detect an event if sampling is not carried out (i.e. a miss). Similarly, because approaching the edge does not necessarily mean that a drop-off is imminent, it is also important not to report a drop-off when in fact none occurred (i.e. a false alarm).

The experiment was conducted using a PC with a VGA monitor. The program displaying the ball-in-basin system was written in the Processing language (Processing Foundation, n.d.), which allows for some interactions via a keyboard.

The parallel between the present experimental paradigm and the notion of intermittently monitoring an automobile that may approach a lane boundary, outside of which it may or may not stray, was intentional. However, the experiment was designed to address some of the limitations of the experiments previously reported, while maintaining the basic nature of the tasks for which the visual occlusion sample model is intended. In particular:

1) Because the ball is not always near the edge, the ball-in-basin system is meant to simulate a visual information processing task that requires on-going monitoring but not continuous full attention.

2) The process to be monitored is random in nature, such that the human operator cannot have a definite knowledge of the precise state of the process during occlusion. On the other hand, because it is driven by a well defined forcing function, the operator should be able to (relatively quickly) learn the
statistical properties of the system output, which thus can form a basis for predictions. To this end, by swinging back and forth, the output of the ball-in-basin system was defined as a zero-mean low-pass random process, analogous to the lane keeping dynamics of automobile driving.

3) The monitoring task is intentionally free of controlling actions on the part of the operator. This eliminates the need to require “normal control performance” during task execution with occlusion, as was the case with the closed loop automobile driving tasks examined thus far. In the experiment, participants report ball-drop events by pressing the spacebar, but this action does not have any effect on system output. As long as participants are reporting all ball-drop events, as they are instructed to, there will be no variation in how well they achieve their monitoring objective.

4) The ball-in-basin system provides straightforward variables that may be used to investigate Level 3 and Level 4 behaviours independently. For Level 3 – related to the possibility of using information available during a glance – the operator can use the ball’s observed distance with respect to the edge to determine whether the system output was near the boundary during the previous glance, and factor that information into their decision of when next to look. If the operator exploits the information available during glances further and anticipates where, and potentially also how quickly, the ball is headed given the motion information he has just observed, the operator would be demonstrating Level 4 behaviour – predicting. With this in mind, the (low-pass) driving function was designed explicitly, as explained below, to be dominated by relatively low frequencies, in order to facilitate perception of rate of change (velocity) information during glances.

5) An additional advantage about this platform is that people can achieve expert behaviour very quickly due to the simplicity of the task.

To maximize the likelihood of success, experimental parameters and the dynamics of the system were carefully determined. One such parameter was the forcing function that drives the motion of the swinging basin. In driving studies, participants were asked to drive ‘safely and normally’, which was a rather subjective guideline for performance. This resulted in many participants sampling frequently (likely more often than necessary) to achieve very little deviation in their lane keeping task. Consequently, the resulting occlusion times were often closely packed to a low mean value, making it difficult to study the variability. Having taken away control of system performance from the operators in this experiment, the forcing function was designed such that the system approaches its limits as well as its safest spot (the zero mean point) on a regular basis. This allowed for investigation of whether people respond to the variability in system performance by varying their occlusion times.
The applied forcing function driving the angular rotation of the swinging basin, $\theta(t)$, was defined as the sum of three sinusoidal functions of different amplitudes, frequencies and phases, as follows:

$$\theta(t) = A_1 \sin(\omega_1 t + \alpha_1) + A_2 \sin(\omega_2 t + \alpha_2) + A_3 \sin(\omega_3 t + \alpha_3)$$

Eq. 7-1

where:

$$A_1 = 0.275 \quad \omega_1 = 0.200 \quad \alpha_1 = \pi/3$$

$$A_2 = 0.055 \quad \omega_2 = 0.160 \quad \alpha_2 = -\pi/2$$

$$A_3 = 0.495 \quad \omega_3 = 0.300 \quad \alpha_3 = -\pi$$

These particular amplitudes, frequencies and phases were chosen to ensure that the system did not go off limits (where the ball would fall off) for too long and that the limits were approached without actually going over frequently enough to motivate the operator to look ‘at reasonable intervals’. In other words, the system needed to provide enough workload to cause the operator to have to look fairly frequently, such that the monitoring task does not become a vigilance task. On the other hand, the workload must not be so high that it would cause the operator to look too frequently.

7.2.2 Experimental Factor

The only experimental factor manipulated was the length of glance durations (GDs). For monitoring to occur, the glance must allow at least sufficient time for the observer to visually perceive elements of the system during the glance. Clearly a minimum threshold for such perception depends on a wide array of elements, ranging from luminance, size and features of the object being perceived, to the perceptual acuity of individual subjects. Dainton (2010), citing various research, provided a brief summary of the minimum duration for a visual stimulus to reach consciousness: 50-80 msec for basic sensations to be perceived (Pockett, 2002; Efron, 1967), 250 msec for an object to be properly recognized (Koch 2004:260), and up to 500 msec for a more comprehensive judgements about the data (Libet, 1993 and 2004).

Pilot studies of the particular experimental setup explored a range of values for GD. At 50 msec, participants of the pilot studies were having difficulty with the monitoring task, such that they were requesting visual samples nearly continuously. At 100 msec, participants were able to perform the monitoring task but reported that they were not able to perceive velocity information of the ball with respect to the basin. Therefore, 100msec was chosen to be the lowest value of GD for this study.

At the other end of the range of GD, it was also important to have one or more levels of GD long enough to allow participants to perceive how quickly the ball was moving away from or towards the edge. In light of the investigation in Chapter 3 on the asymptotic behaviour of the effect of GD on OT, we are already
aware that the benefits of increasing GD should trail off after reaching a certain value, after which there is no more additional benefit. In fact, it would not be ideal to have glances lasting so long that the observer may see too large a portion of the swing dynamics. Looking at our forcing function, the average time a ball would travel from one end to another (half a period) is about 8 seconds, hence allowing a 2 or 4 second glance means that the operator would be able to observe almost an entire ‘going toward the edge’ event. If that were the case, there would be very little meaning attached to the occlusion times collected. In addition, such longer glance times would significantly reduce the number of data collected within a trial of fixed length.

In summary, a range of glance duration (GD) values was presented. The largest GD value was designed to be long enough to ensure that participants could perceive both position and rate of change during a glance, and thereby maximise the likelihood of prediction taking place. The shortest GD value was designed to be short enough to allow perception of position but not rate of change, and thereby provide the possibility to conclude that, if prediction is not observed, the length of the glance would be the likely reason. Three values, including an intermediate value, were thus chosen: 100, 300, and 500 msec.

7.2.3 Participants

Twelve male participants between the ages of 21 and 40, all with corrected to normal vision, were recruited for this experiment. The majority of the participants were graduate students from the Mechanical and Industrial Engineering department at the University of Toronto. By recruiting only male participants, the study was designed to avoid any potential confounding effects of gender.

7.2.4 Experimental Design

The study followed a within subjects design with only one factor: GD. A baseline, non-occluded trial was followed by three conditions of different GDs {100, 300, and 500msec}, repeated twice, for all 12 participants. There were a total of 7 trials, each lasting 2 minutes. The order of presentation was counterbalanced across all participants. Prior to commencing the experimental task, participants first read a set of instructions (see Appendix C.3) that explained the purpose and the task and then signed an informed consent form. Participants then engaged in training trials, with the experimenter on the side providing explanations. Participants were instructed to perform the task as well as they would have done without any occlusion, which was equivalent to never missing any ball-drop events, but they were also told to request a look only when they felt that it was necessary. It was emphasized that this was not an experiment in risk taking: their primary task was to report all ball-drop events.
The study was carefully designed to ensure that participants were engaged in ‘normal’ performance using a subjectively minimal amount of visual information. For example, a reward for performance was deliberately not implemented. While participants may be motivated by cash reward or other incentives to perform well in the detection task, they may also look more frequently than they really need to. Similarly, if additional incentives were provided for requesting as few glances as possible, participants may be enticed to take risks in their detection performance. Therefore, participants were compensated with $15 for completion of the study, which lasted approximately one hour.

7.3 Measures and Hypotheses

Similar to the previous studies, the dependent measure was the occlusion times (OTs). Each glance request produced a single measure of OT, defined as the duration of occlusion since the end of the previous glance.

7.3.1 Measure for Level 3 Sampling Behaviour

To investigate whether participants were making use of the information that was available during glances in their sampling decisions, a new measure was introduced: the absolute distance to the nearer of the two edges preceding each occlusion period (refer to as ‘distance observed’ hereafter). The basic premise was that greater occlusion times would occur whenever participants observed, at the end of a glance, the ball to be further away from the edge (towards the centre of the basin). Conversely, it was presumed that participants would look much sooner if the ball was observed nearer to the edge of the basin, with a limit of zero occlusion time at the edge. Therefore, larger occlusion times were hypothesised to follow larger observed distances, as a manifestation of Level 3 sampling behaviour.

The logistic function was originally considered for describing the said relationship between distance observed and occlusion time (see Figure 7-2a). OT increases slowly initially (hovering near zero when the ball is near the edge), then gradually increases at a more and more rapid rate but levels off as the distance continues to increase. However, it is difficult to fit data to such a function because, unlike the previous model fitting exercises using the asymptotic function and the natural logarithmic function, a simple transformation of variables to turn the non-linear logistic function into a linear function is not possible.
Instead, the power function \( y = kx^c \) was chosen\(^1\) to approximate the relationship between OT and distance observed. With \( c < 1 \), the power function (see Figure 7-2b) provides a monotonically increasing function with decreasing slope. For small values of \( x \) (in this case the observed distance to the edge has the limited range of \([0, \pi/4]\)), and this function provides a decent approximation of the behaviour we are interested in. That is, a zero OT corresponds to a zero observed distance to the edge, and the rate of increase of OT slows down as observed distance to the edge increases. By taking the natural log of both sides of the equation, the analysis tests a simple linear regression of the form: \( \ln y = \ln k + c \ln x \).

\[ \text{Figure 7-2: Proposed relationship between OT and the observed distance from the ball to the nearer edge, ideally using (a) a logistic function (Left); and more practically, using (b) a power-law relationship (Right)} \]

7.3.2 Measures for Level 4 Sampling Behaviour

Level 4 of the sampling model entails a sampling strategy that is based on predictions about the system output. However, similar to the on-road driving study, there is no means for determining what the participant's actual predictions are, if any. Estimates of such predictions were thus necessary for the analysis to be carried out. Given the emphasis on predicting behaviour in this study, three different approaches (termed Level 4A, 4B and 4C), ranging from crude to perfect estimates of predictions, were investigated.

\(^1\) An exponential function in the form of \( y=[a-be]^{\hat{y}}\) was also considered for approximating the logistic function. It has similar properties as the power function chosen, and would have been more consistent with earlier analysis. However, a simple transformation to achieve linear analysis was not available for this model, due to the additional constant term, \( a \), in the equation.
7.3.2.1 Predictions at Level 4A - Direction

As the simplest demonstration of Level 4 predicting behaviour, participants were hypothesized to complement their use of distance information with the direction of movement of the ball, either approaching or moving away from an edge. In particular, given the same absolute distance to the nearest edge, the case of the ball moving away should pose much less of a concern than one that is heading toward the edge. More formally, the hypothesis with this measure is that, for any given distance observation, OTs are likely to be smaller when movement is towards the edge than when it is away.

7.3.2.2 Predictions at Level 4B - Estimated Time-to-Drop-off

A somewhat more sophisticated manifestation of Level 4 prediction was hypothesised to be the continuously updated estimates of time-to-drop-off (TTD), based on simple first order predictions (assuming constant speed) of how long it would take from its present location for the ball to reach the edge, a potential drop-off event. TTD estimated at the end of a visual sample is thus formulated as:

\[ \text{TTD} = \frac{\text{Distance to Edge (in the direction of travel)}}{\text{Instantaneous Speed}} \]

Participants would thus observe not only the distance information as in Level 3, but also the velocity (speed and direction) of the ball with respect to the swinging basin. Formally, the hypothesis is that occlusion times will vary directly with the continuous variable of TTD – i.e., smaller OTs for smaller TTD values, and vice versa. Mathematically, the same power function proposed to capture OT versus Distance Observed (see Figure 7-2b) was hypothesised to capture the relationship OT versus TTD.

7.3.2.3 Predictions at Level 4C - Distance to Edge Predicted

A third model of Level 4 prediction, distance to edge predicted, is analogous to the predicted lane deviations used in the analysis of the on-road automobile driving data reported in Chapter 6. In that analysis, OT was hypothesized to vary inversely with predicted deviation from the lane centre at the time of sampling. In the present case, the predicted distance to edge during occlusion was computed by means of the actual forcing function used to drive the experiment, given in Equation 7-1. Although the analytical approaches to computing the predicted distances are very similar, two important distinctions should be noted here:

- In analysing the on-road driving data, the assumption was made that predictions made by the (well-trained) drivers during occlusion could best be approximated by using an appropriate optimal prediction algorithm. For that particular research, autoregressive time series modelling
was used for this purpose, as explained in section 1.5. To generate those models, the actual time-
sampled vehicle data from the associated experimental trials were used. A similar approach
could have been used in the present experiment – by sampling the actual oscillations of the
simulated basin and then using those samples to create an autoregressive time series model to
describe those variations. Such an approach was deemed to be unnecessary, however, because, in
contrast to the earlier driving experiment, in which the system output was generated by the
participants in the experiment, the system output in the present case was generated by the
experimenter. In other words, rather than best fitting an optimal model to the data, we used a
perfect model – the actual forcing function.

- Although the “predictions” used for the present analysis correspond to the actual
distances between the ball and the edge of the basin, which are thus perfect in terms of accuracy, our
analysis does not presume that the participants themselves were perfect predictors.²(If they were
indeed perfect, they would never have to sample the system at all, except just prior to all ball-
drop events, whose occurrences they would automatically know.)

The power function $y = kx^c$, where $c < 1$, was proposed for the relationship between OT and predicted
distances. Larger OTs were hypothesized to associate with larger predicted distances, but to a lesser effect
(i.e. smaller increase in OT) as predicted distance increases (see Figure 7-2b).

### 7.3.3 Hypotheses about the Experimental Study

Based on the abovementioned measures developed for level 3 and level 4 behaviours, specific hypotheses
were made regarding the parameters investigated in this experiment:

- Level 3 behaviour was expected to be demonstrated for all three GDs tested. In other words, all
three GD levels were hypothesized to be sufficiently long for OT to be a power function (with a
positive power that is less than one) of the ball’s absolute distance to the nearer edge.

- In addition to the absolute distance, occlusion time was hypothesized to be a function also of the
direction of the ball, with shorter OT values for cases in which the ball was approaching the edge

---

² The present approach presents an interesting departure from most instances of normative modelling, for which it is
customary to assign a perfect internal model of the system to a presumed rational human monitor / controller, and
for which any deviations from perfect performance are attributed to errors in the model. In the present case we are
still assigning a perfect internal model to the human, but here any deviations from perfect performance are attributed
to the human, rather than to the model.
and longer times for moving away from the edge. Such behaviour would support a Level 4 manifestation of predicting, and was expected to be found in larger values of GD, namely 300 and 500 msec, but not for 100ms. It was hypothesised that at 100ms, there was insufficient time for participants to perceive the ball's direction of motion.

- Predicting behaviour using estimated time-to-drop-off (TTD) was hypothesized to have an impact on occlusion time achieved, in the form of shorter OT values for smaller TTD values. This relationship was expected to be evident for the larger values of GD, namely 300 and 500ms, but not for 100ms.

- Predicting distance (to edge) based on a perfect model of system output variations was hypothesized to have an impact on occlusion time achieved, in the form of shorter OT values for smaller predicted distance from the edge at the end of the occlusion interval. This relationship was also expected to be evident in the larger values of GD, i.e. in 300 and 500ms, but not 100ms.

7.4 Summary of Results

Participants had little difficulty in performing the monitoring task and, as anticipated, did not miss any of the ball-drop events. Detection performance was thus not analysed further.

For the analysis of sampling behaviour using individual occlusion times,

Table 7-1 lists the parameters involved in the mixed-effects models fitted for Levels 3, 4A, 4B and 4C. Given the progressive nature of the sampling model, Level 4 models retained the “observed distance” variable from level 3, in addition to the variable introduced for estimating predictions specific to that level of strategy. As mentioned earlier, OT, observed/predicted distance, and time-to-drop-off (TTD) were all transformed by the natural log function in order to test the power law relationship as hypothesised. GD (3 levels) and direction (2 levels), on the other hand, were included as factors to explore their respective
effect on the power law relationship being tested. The repeated measures on subjects were accounted for as a random effect.

### Table 7-1: Parameters included in models tested for different levels of sampling behaviour

<table>
<thead>
<tr>
<th>Level</th>
<th>Model Parameters</th>
</tr>
</thead>
<tbody>
<tr>
<td>3</td>
<td>$OT = f{\text{Observed Distance}} + g{GD}$</td>
</tr>
<tr>
<td>4A</td>
<td>$OT = f{\text{Observed Distance}} + g{GD} + h{\text{Direction}}$</td>
</tr>
<tr>
<td>4B</td>
<td>$OT = f{\text{Observed Distance, Estimated Time-to-Drop-Off}} + g{GD}$</td>
</tr>
<tr>
<td>4C</td>
<td>$OT = f{\text{Observed Distance, Predicted Distance-to-Edge}} + g{GD}$</td>
</tr>
</tbody>
</table>

#### 7.4.1 Level 3 Sampling Behaviour

Figure 7-3 shows that Level 3 behaviour, hypothesised as a linear relationship between $\ln(OT)$ and $\ln(\text{distance observed})$ was found in all three GDs tested ($p = .000$). The asymptotic power law relationship was evident since the regression slopes were all positive and less than one.
Figure 7-3: log-log plot showing the model fits between ln(OT) and ln(distance observed) at the three levels of GD

More specifically, the overall mixed-effects model found a significant interaction ($F(2, 3224) = 5.09, p = .006$) between GD and distance observed, while both main effects of GD and distance observed were also significant (GD: $F(2, 3224) = 16.4, p = .000$; distance observed: $F(1, 3224) = 707, p = .000$). Furthermore, the post-hoc analysis revealed that the effect of distance (regression slope) was significantly larger in the 500msec condition than in the 300msec condition ($\Delta = 0.084, p = 0.015$). The complete results of the post-hoc analysis and the $F$-statistics of the specified model can be found in Appendix D.4.

To demonstrate the power law relationship found at level 3, Figure 7-4 shows the back-transformed fits of the model plotted over the original data. A larger regression slope in Figure 7-3 corresponds to a power law function that grows more quickly in Figure 7-4.
Figure 7-4: Back-transformed model fits of OT vs. Distance Observed for the original data for all three glance durations

The back-transformed models (as seen in Figure 7-4) can be expressed as the following:

\[
OT = \begin{cases} 
2.92x^{0.490}, & \text{for } GD = 100\text{msec} \\
3.44x^{0.496}, & \text{for } GD = 300\text{msec} \\
3.96x^{0.580}, & \text{for } GD = 500\text{msec}
\end{cases}
\]

where x = Distance (to edge) Observed

7.4.2 Level 4A Sampling Behaviour - Predicting with Direction

The model specified for Level 3 was extended to include direction as a factor for the Level 4A analysis. A significant three way interaction was present \((F(2, 3218)=4.08, p = 0.017)\), suggesting that there was a two-way interaction that varied across levels of a third variable. Therefore, post-hoc analyses were carried out to examine the two-way interaction effect between distance and direction at the three levels of GD; and the two-way interaction effect between distance and GD at the two levels of direction.
To summarise the post-hoc results, Figure 7-5 shows that for all three levels of GD, shorter OT values were found for cases in which the ball was approaching the edge and longer times for moving away from the edge. As evident in Figure 7-5, direction also has an effect on the regression slope fitted. A steeper relationship between ln(OT) and ln(distance) was found whenever the ball was approaching, instead of moving away from, the edge. See Appendix D.4 for results of the post-hoc analyses and $F$-statistics of the specified model.

**Figure 7-5: log-log plot of OT vs. Distance Observed, for (Left) when the ball was moving **away from the edge** and (Right) when the ball was moving **toward** the edge**

Linear equations of the fitted models using log-transformed variables (as seen in Figure 7-5) can be expressed as the following equations, where $y = \ln(OT)$ and $x = \ln(\text{Distance Observed})$:

For the direction of travelling **away from edge**:  
$$y = \begin{cases} 1.294 + 0.359x, & \text{if } GD = 100\text{msec} \\ 1.466 + 0.303x, & \text{if } GD = 300\text{msec} \\ 1.582 + 0.383x, & \text{if } GD = 500\text{msec} \end{cases}$$

For the direction of travelling **toward edge**:  
$$y = \begin{cases} 0.867 + 0.544x, & \text{if } GD = 100\text{msec} \\ 1.039 + 0.599x, & \text{if } GD = 300\text{msec} \\ 1.223 + 0.764x, & \text{if } GD = 500\text{msec} \end{cases}$$
7.4.3 Level 4B Predicting Behaviour – Estimated Time to Drop-off

At Level 4B, the predicting behaviour was estimated by time-to-drop-off (TTD), computed using Equation 7-2. Analysis to include the TTD variable was carried out only for data pertaining to moments when the ball was approaching the edge, for the reason that whenever a ball was moving away from the edge, participants may have had a different criterion for estimating the distance to be travelled before a look is necessary. For example, some may have considered distance all the way to the other edge, while some may have considered reaching the middle of the basin as a point to look again.

As explained earlier, the relationship between OT and TTD was also hypothesised to resemble a power law relationship. The model fitting at this level included the fixed effects of two continuous variables, distance observed and TTD, in addition to the GD factor. Interpretation of the resulting model was particularly difficult as significant interaction effects of the two continuous variables (in both three-way and two-way terms) were present. (See Appendix D.4 for detailed results.)

A piecewise analysis was thus carried out to further investigate the effect of TTD at different levels of distance, by categorizing distance in terms of how close the ball was to the edge: “near”, “mid-range”, or “far”. Each level covers roughly 1/3 of the distance between the edge and the middle of the basin.

Separately plotted for each level of GD, Figure 7-6 shows ln(OT) as a function of ln(TTD) for the three levels of distance specified. The linear relationship hypothesised between ln(OT) and ln(TTD) were present in most cases, except for the cases of mid-range and furthest distances in the 100msec condition.
Evident from Figure 7-6, significant interactions are present among ln(TTD), distance (as a factor), and GD. (See Appendix D.4 for the F-statistics.) The linear fits appeared steeper for higher values of GD, and within each level of GD, the steepest slope was consistently found for "near the edge" level of distance.

The reader is referred to Appendix D.4 for a detailed post-hoc analysis that examined (1) a two-way interaction effect between TTD and distance at the three levels of GD separately; and (2) a two-way interaction effect between TTD and GD at the three levels of distance separately.

Finally, the fitted linear models using log-transformed variables (as seen in Figure 7-6) can be expressed as the following equations, where $y = \ln(OT)$ and $x = \ln(Distance\ Observed)$:

$$\ln(OT) = \beta_0 + \beta_1 \ln(Distance\ Observed) + \beta_2 \ln(TTD) + \beta_3 \text{GD} + \beta_4 \text{Distance\ Observed} \times \text{GD} + \epsilon$$
At Level 4C, the predicting behaviour was estimated by the system’s actual forcing function, providing a perfect predictor of the distance (to the nearer edge) at the times sampled. To enable comparison with results from Level 4B, the present analysis of Level 4C was also carried out only for data pertaining to moments when the ball was approaching the edge.

Similar to the model for 4B, this model, using ln(OT) as the dependent variable, specified GD, ln(distance observed) and ln(distance predicted) as fixed effects. Once again, significant interactions, especially those involving the two continuous variables of observed distance and predicted distance, made it difficult to interpret the results. (See Appendix D.4 for this model's summary statistics.) A piecewise analysis was thus carried out, treating distance as a three level factor rather than a continuous covariate.

Figure 7-7 shows that the hypothesised linear relationship between ln(OT) and ln(distance predicted) were present in all but for the cases when the ball was furthest away from the edge. Note that in the cases where the hypothesised relationship was found, the slope was positive and less than one, revealing that the increase of OT was bounded as expected.

The complete post-hoc analysis for this piecewise analysis is included in Appendix D.4. Similar to level 4B analysis, the post-hoc analysis examined (1) a two-way interaction effect between distance predicted and observed distance (as a factor) at the three levels of GD separately; and (2) a two-way interaction effect between distance predicted and GD at the three levels of distance separately.
Fitted models (see Figure 7-7) are as followed, where $y = \ln(OT)$ and $x = \ln(\text{Distance Predicted})$:

For glance duration of 100msec:
$$y = \begin{cases} 
0.224 + 0.268x, & \text{if ball was 'near edge'} \\
0.524 + 0.186x, & \text{if ball was 'mid range'} \\
0.574 - 0.134x, & \text{if ball was 'furthest away'}
\end{cases}$$

For glance duration of 300msec:
$$y = \begin{cases} 
0.525 + 0.345x, & \text{if ball was 'near edge'} \\
0.825 + 0.569x, & \text{if ball was 'mid range'} \\
0.875 + 0.122x, & \text{if ball was 'furthest away'}
\end{cases}$$

For glance duration of 100msec:
$$y = \begin{cases} 
1.140 + 0.600x, & \text{if ball was 'near edge'} \\
1.440 + 0.632x, & \text{if ball was 'mid range'} \\
1.740 + 0.014x, & \text{if ball was 'furthest away'}
\end{cases}$$
7.4.5 Comparison of model fits for different sampling strategies

Compared to the mixed-effects model specified for Level 3, Level 4A, with an additional factor of direction, showed an improved fit of the occlusion data ($\Delta$AIC = -1160).

Since models for the Level 4B and 4C predicting behaviour were fitted for only a subset of data, comparisons between 4A and 4B/C required that 4A be reanalyzed using the same subset of data. However, this subset of data, pertaining only to moments when the ball was approaching the edge, was one of the two levels of the direction factor in Level 4A. Therefore, the re-fitted model of Level 4A (referred to as 4A-R) was in fact equivalent to the data and model fit presented under the title 'Toward Edge' in Figure 7-5. Summary statistics of this model is included in Appendix D.4 for reference.

The Level 4B model provided the best fit of data among the three Level 4 models. It was an improved fit over the Level 4A-R model ($\Delta$AIC = -419) and over Level 4C model ($\Delta$AIC = -134). While Level 4C model was not as good a fit as Level 4B, it was still a better fit than the Level 4A-R model ($\Delta$AIC = -295).

7.5 Discussion

A sampling strategy corresponding to Level 3 of the proposed model was evident in all three levels of GD. Participants were found to vary their occlusion times with the observed distance to the nearer of the two edges at the end of a look. In particular, occlusion times were more sensitive to changes in the observed distance in the 500msec GD condition, whereas no difference was found between the 100 and 300msec conditions.

Predicting behaviour, corresponding to Level 4A in the proposed model, was demonstrated as participants took into account the direction of the ball: either approaching the edge or moving away from the edge. Furthermore, the inclusion of the direction factor improved the model fit of occlusion data from Level 3, lending more support to the hypothesis that participants had achieved Level 4. As hypothesised, occlusion times were longer when the ball was moving away from the edge. On the other hand, contrary to the hypothesis that Level 4A would be found in 300 and 500msec only, the effect of direction was significant at all three levels of GD. This suggests that participants were mostly able to perceive the direction of the ball’s movement even for a brief look of 100msec.

An effort was thus made to determine whether participants were likely to perceive direction during glance durations of 100msec. In other words, a psychophysical threshold of motion detection that takes into account geometry of the experimental setup was sought. An analysis was carried out following an
approach outlined in Green (2013)\(^3\) for this purpose. At a maximum angular speed of 0.2 radian/sec, the ball in the basin could cover 4mm of distance on the screen during 100 ms. Using a small angle approximation, the corresponding expansion of retinal image size was estimated to be 0.006 radians\(^4\), based on an assumed distance from the monitor of 700 mm. This increase in retinal image size was above the 0.0005 radian expansion possible, based on a detection threshold\(^5\) of 0.005 radian/sec for 100msec. In fact, the median speed of the system, at 0.02 radian/sec, would result in 0.0006 radians of retinal image expansion, which was just over the detection threshold. According to these calculations, it would thus seem reasonable that participants were sometimes (but not always) able to perceive and use direction information.

Participants were also more sensitive to changes in observed distance when the ball was approaching the edge, as demonstrated by the steeper slopes found in \(\ln(OT)\) vs. \(\ln(\text{observed distance})\). For data pertaining to moments when the ball was approaching the edge, the 500msec condition demonstrated a particularly steep slope. This suggests that the increase from 300 to 500msec in GD provided extra benefits for participants to obtain and make more effective use of the information available during a glance. This seems to be in line with the earlier references summarized by Dainton (2010) regarding how long it takes visual stimuli to reach consciousness: while as little as 50 msec may provide basic sensations and 250 msec facilitates proper recognition of an object, it may require 500 msec when some complicated judgements are being made concerning the object being perceived.

When the ball was moving away from the edge, no difference was observed in the regression slope across levels of GD, suggesting that once the ball had entered the perceived ‘safer’ zone, participants were less sensitive to the value of distance observed.

Beyond simply recognizing the direction of the ball, two other measures of predicting behaviour were investigated. A more sophisticated level of predicting (Level 4B) was demonstrated by the participants as OT also varied with the estimated time-to-drop-off (TTD) when the ball was approaching the edge.

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\(^3\) This approach described in Green (2013) is intended for determining the distance at which looming motion may be detectable in driving, as related to rear-end collisions. The approach calls for computing the perceived expansion rate of an object at a distance with respect to changes in distance. In the present experiment, distance between the participant and the monitor is fixed at 700 mm. Therefore, the analysis was modified to compute expansion rate as a direct function of changes in viewing angle (distance travelled by the ball on screen) at a fixed distance from the participant.

\(^4\) Using the small angle approximation, the changes in retinal image angle was calculated as the displacement of the ball on screen (4mm) over distance between participant and the monitor (700mm), which was 0.0057(4/700).

\(^5\) What Green (2013) suggested was a range between 0.004 to 0.008 radian/second. For ease of interpretation, the value 0.005 was selected to represent a value within this range.
Contrary to expectations, results showed such predicting occurred even when glance duration was only 100ms, albeit only when the ball was observed to be near an edge at the end of last look\(^6\). While this suggests that participants were potentially capable of predicting even when the glance duration was as low as 100ms, they appeared to make a larger effort to predict when the situation was deemed critical (such as the case where the ball was near and approaching the edge).

This kind of interaction between TTD and the observed distance was evident for all three levels of GD, suggesting that the extent of predicting behaviour may have been adaptive to the dynamic situation. When the ball was furthest from the edge, there was less pressure for participants to predict the future precisely. On the other hand, when the ball was closer to the edge, participants were likely investing more effort in attempting to predict well.

On the other hand, the effect of TTD on OT was more pronounced for higher glance durations. For the 500msec condition, participants were demonstrating Level 4B sampling strategy even when the ball was furthest away from the edge. This may be an indication that predicting happens more naturally when visual samples are long enough.

Considering finally the Level 4C analysis, the distance (to edge) predicted, using the actual distance whenever a glance was requested, was defined to be the ‘perfect estimate’ of potential prediction. In other words, this level of analysis investigated whether participants might have been employing an extremely accurate internal model of the system dynamics. There was evidence that OT did vary with the distance predicted, in a manner similar to the Level 4A and 4B analyses of observed distance and estimated time-to-drop-off. This relationship was, once again, most apparent when the ball was approaching ‘near the edge’, and not evident for distances furthest away from the edge.

Given that the Level 4B model fit the occlusion data better than the 4C model, participants were found more likely to predict based on estimated time information using previous samples than to predict more accurately by having a perfect model of how the basin was swinging back and forth. In fact, it was not surprising that the participants did not exhibit behaviour consistent with the most sophisticated mode of predicting, given that the experiment was specifically designed to be difficult to predict perfectly.

In conclusion, the study achieved its objective in providing evidence that humans, when given a chance, are able to predict. Furthermore, the multiple approaches to estimating predictions demonstrate that when

\(^6\) Recall that in the piecewise analysis for Level 4B model, distance observed was turned into a factor of three levels (near, mid-range, and furthest from the edge).
humans predict, they do so in a relatively simple manner, such as extrapolating information from what they observed during a visual sample, rather than optimally predicting using a perfect internal model of the system behaviour.
8 Conclusions

8.1 Summary

The goal of this research was to develop a model of information sampling using (self-paced) visual occlusion, an experimental paradigm that forces participants to carry out tasks using a subjectively minimal amount of information, by “looking whenever necessary”, without compromising performance and without taking risks. The dissertation comprises a series of investigations motivated by the model of uncertainty development and resolution originally proposed by Senders et al. in the 1960s. The research not only investigated the issue of rate of sampling for resolving uncertainty during occlusion, but also endeavoured to determine how human observers may adjust their sampling strategy in response to the dynamic environment or process that they are monitoring.

One of the principal results of this dissertation is a model of information sampling that incorporates elements of uncertainty development, subjective thresholds, and an awareness of current and future states of the system (as seen in Figure 5-1). The model development begins with a null model of open-loop sampling behaviour that essentially disregards all characteristics of the system, and progressively builds toward a highly engaged model of strategic sampling. More specifically, multiple nested levels of models of sampling have been proposed, as follows (with each number given representing the corresponding level of inquiry of the framework):

0. A null model of sampling that ignores system characteristics and performance. Sampling can be random (modelled as noise) or effectively continual (choosing to look all the time).

1. A static sampling strategy based on only global system characteristics. Quasi-periodic sampling is observed, at a rate that is sensitive to changes in system parameters.

2. Static sampling at a threshold of uncertainty, at a rate that is expected also to be quasi-periodic, but dependent on overall system behaviour.

3. A dynamic sampling strategy in which information obtained from each glance contributes to the sampling decision in the subsequent occlusion period. Rate of sampling depends on the system parameters, but variability from one glance to another is observed, in response to the content of the observed information.
4. A dynamic sampling strategy in which on-going predicting of the system output during occlusion influences the sampling decision. Rate of sampling depends on the system parameters, but variability from one glance to another is observed in response to predictions.

An analysis framework, based on the notion of having multiple levels of sampling behaviour, was proposed for the analysis of data collected from occlusion experiments. Following this framework, evidence supporting the proposed model was found using data collected from two self-paced occlusion studies – one involving a low fidelity driving simulator and the other an on-road driving study. One major result was that, depending on the particular task being examined, there appears to be an ‘optimal’ duration during which new visual information can reasonably be sampled. Another major result was that variability in occlusion times demonstrated a dynamic sampling strategy on the part of the drivers that went beyond merely responding to changes in speed.

The use of a simple perceptual experiment (detailed in Chapter 7) further addresses the assumption that human operators are able to predict the state of the system under conditions of visual occlusion. By contriving a situation where human observers can easily understand the dynamics of the system and thus should easily be able to make predictions, participants demonstrated an ability to take predictive information into account in their sampling decisions. This provides proof that humans are able to predict when temporarily occluded, whenever the system’s output can be predicted. This predicting behaviour is not to be confused with simply responding to the content of observations made at each sampling interval.

However, there is an important distinction between the predicting behaviour investigated in driving (and simulated driving) experiments and that investigated in the present simple perceptual experiment, namely the difference in viewpoints. Drivers naturally have an egocentric view of the world, and thus can sample only the present, as well as some first derivative information. For drivers to carry out predictions in the occlusion experiments, they have to sample enough information (position, velocity, etc.) during a glance to be able to use that for predicting the future\(^1\). As such, it is inherently difficult for predicting to take place. On the other hand, the operators’ view of the system is exocentric in the simple perceptual experiment, affording them the opportunity to extrapolate information from the past. However, this advantage is somewhat reduced under visual occlusion, as the past information is not immediately evident, especially not for very short glance durations.

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\(^1\) The alternative is that the human operator recalls the observations that were made over several previous samples, to extrapolate into the future. This is highly unlikely, since it would require maintaining a mental image spanning several samples over many seconds. (Especially given the finding that drivers in the on-road study were able to remain occluded for over 5s, and with glance durations of 2s or more.)
With the emphasis on dynamic monitoring in the present work, it is important to note that uncertainty remains a significant component of the present model. Empirical findings from the driving studies, both on-road and using a driving simulator, do not contradict Senders et al’s (1967) original concept of how uncertainty develops and becomes resolved.

8.2 Major Contributions

The proposed model of information sampling (see Figure 5-1) is based on Senders’ notion of sampling to resolve uncertainty. It differs from earlier models in its identification of “threshold sampling”, for which threshold refers to a tolerance of uncertainty alone. The present model, in associating the notion of a threshold with “the need to look,” is inclusive of the concurrent contribution of growing uncertainty and predictions of the present state of the system. Furthermore, the model suggests progressive levels of sampling strategy, considering potential differences in an operator’s psychological function and level of expertise. It is therefore more flexible than the classical visual sampling models, which assume a well-trained operator with a perfect knowledge of system functioning. The model presented in this dissertation is thus a synthesis of past theories of visual sampling behaviour, making efforts to bridge the gap between quantitative models and the more contemporary psychologically-based models, and answering the call for predictive models in current research (Moray, 2004).

Furthermore, the dissertation makes a contribution to research in the modelling of human information processing through its exploration of the feasibility of humans’ ability to predict future system outputs – and, for the particular case of visual occlusion, present system outputs – based on (past and present) observations and knowledge of system characteristics. Many human performance models have in the past assumed such ability, but very few have endeavoured to demonstrate that, given appropriate conditions, adequate information, and a suitable viewpoint for making observations, this is indeed an obtainable human operator capability.

The dissertation also presents a novel approach to analysing visual occlusion data by proposing a modelling framework, which entails fitting data with a new but progressively more complicated statistical model at each level of the framework (see Figure 5-7). At lower levels of the framework, the focus is on modelling average sampling behaviour – how operators vary their sampling frequency in response to system characteristics and overall output of a system. At higher levels of the framework, the analysis using individual occlusion times acknowledges both the need to respond to system characteristics and the dynamic output of the system.
The modelling framework also allows for comparisons to be made between the goodness of fit of models at different levels. This approach then provides a means to measure a particular population with respect to their level of expertise or cognitive capacity via their sampling strategies. There is also the potential for studying individual differences by analysing operators’ data individually with respect to the framework. In such cases, rather than explaining discrepancies among subjects as being due to ‘statistical variation’, differences may instead be ascribed to different levels of sampling strategy.

Contributions were also made toward the practical use of the visual occlusion technique. The self-paced paradigm was successfully applied toward understanding the different elements of sampling behaviour. For the implementation of the paradigm, the dissertation also provides a method, drawn from the asymptotic relationship found between occlusion times and glance duration, for establishing the appropriate glance duration in experimental studies.

8.3 Limitations

This section acknowledges limitations of this research. Some limitations came from the experimental platform, while others were associated with the experimental and analytical methods.

8.3.1 Limitations of Experimental Paradigm

By adopting the self-paced visual occlusion paradigm, the sampling model and experiments described in this dissertation were predicated on the assumption that operators have a surplus of time, such that intermittent interruption of the task, as represented by occlusion, is viable. Furthermore, the self-paced visual occlusion paradigm relies on participants, to the best of their ability, carefully following instructions to 'look only when necessary.' The sampling model attempts to address these limitations by including null model (Level 0) and passive monitoring (Level1) as lower level sampling behaviours. However, it stands to reason that the self-paced paradigm will not be useful for examining processes in which operators are expected to pay attention all the time, thereby leaving no room for uncertainty or predicting to take place.

8.3.2 Limitations of Experiments

This dissertation reported a number of analyses associated with three experiments, each with their own limitations. Section 3.5 described the limitations associated with the less than ideal setup in the simulated driving study, including the simplified driving environment (e.g., straight road driving without any other traffic), the over-sensitive steering wheel response, the somewhat ambiguous predictor display used in the
car following task, and the lack of motion feedback. Data collected in this study were therefore limited in their usefulness for analysing attentional capacity using the self-paced visual occlusion paradigm.

While the on-road driving study was not subject to the same drawbacks as using a (low fidelity) simulator, the study was also a simplified driving task, as it was carried out on a straight stretch of an empty highway. A more significant limitation about the on-road driving study arises from data availability. Section 6.7 explains this issue and how it may have hindered the analysis.

The two driving studies also shared the limitations inherent to the driving task itself. Driving styles and interpretation of “driving safely and normally” under occlusion likely varied from one driver to another. Further assumptions were made about vehicle control during occlusion. Section 6.8 provides a thorough discussion of these limitations.

The simple monitoring experiment was able to avoid many of the limitations associated with the driving task, as it was a carefully designed system that was intentionally free of controlling actions (see section 7.2.1). However, as mentioned earlier in Section 8.1, participants monitored the ball-in-the-basin system from an exocentric perspective, whereas participants in the automobile driving studies (both simulated and on-road) were naturally engaged with an egocentric view of the world. This distinction must be considered before generalising results from the simple monitoring experiment to an egocentric monitoring task such as automobile driving.

Finally, it is acknowledged that participants for both the simulated driving study and the simple monitoring experiment were recruited from a narrow population of male engineering graduate students at the University of Toronto. The graduate student population is unlikely to be representative of the general public. They may be more focused and driven to perform well and their engineering background may cause them to be more affected by issues associated with the low-fidelity simulator setup. It is also possible that engineers are more likely to engage in predicting behaviour given that they may grasp the underlying dynamics of the system better and more quickly than non-engineers.

8.3.3 Limitations of Analytical Approach

Both predictions and errors associated with predictions attributed to participants were estimated in this study by assuming that people can extrapolate information they previously observed before being occluded, given an adequate knowledge of how the system functions. This predicting behaviour was demonstrated to a certain extent in the on-road driving study (Chapter 6) and, more conclusively, in the simple monitoring experiment (Chapter 7). However, analyses to determine the presence of predicting relied on optimal estimates or models of predictions attributed to the human observer. Results of such
analyses were therefore limited to how the predictions are being estimated. In other words, by comparing human behaviour to the best possible estimated predictions, failure to find evidence of human sampling decisions that are compatible with such optimal predictions could mean either that human predicting does not take place or that predicting takes place but not to an extent that compares with theoretical optimal prediction behaviour. Data analysis for the simple monitoring experiment made an effort to demonstrate that such estimates can be achieved by a number of means: from simple indication of direction to modelling of predictions using the real outcome of the system. While none of these methods are expected to match the actual predictions participants were making, having results that support the hypotheses demonstrates the usefulness of these methods for representing predictions.

Another limitation in the analytical approach was the use of the Akaike’s information criterion (AIC) for assessing the goodness of fit of models. As explained in Section 1.5.3, AIC is a relative measure that aids one in selecting the appropriateness of a model whenever two or more models, fitted for the same set of dependent measures, are compared. Using AIC in combination with the significance testing of parameter estimates in the mixed model analyses provided indications for the level of sampling behaviour participants were achieving, but was limited in terms of expressing quantitatively how well a particular model explains the variance of the data.

8.4 Future Research

The present work can be extended further in several different directions. In addition to applying the model and research approach to different application domains, some unique opportunities are highlighted here.

To revisit the domain of automobile driving, new experiments can be carried out, preferably on-road, to allow researchers to exercise the analytical modelling approaches introduced in this thesis. New experiments can test other parameters and tasks associated with automobile driving, and will also overcome limitations of data availability in the present work.

One limitation of the study discussed earlier is the need for researchers to estimate predictions made by the operators. Future research may address this issue by designing an experiment that would elicit predictions more explicitly. The simple monitoring experiment was contrived to make predictions easy, such that participants were expected to predict if they were at all capable of predicting. A future experiment could be contrived to make predictions necessary for participants to achieve the task objective, such that the ability of human operators to predict information may be more carefully assessed.
The analyses of variability in occlusion data suggested that sampling strategies likely vary from subject to subject. Therefore, the framework may be used to analyse individual differences in sampling behaviour (see Section 6.7.2 for some discussion and examples). This provides an enticing opportunity for future research to go beyond the confines of the present research and consider applying the methods presented in this work as a means for evaluating members of a particular population with respect to their perceptual and cognitive abilities.

Opportunities for future work also exist for augmenting the current experimental paradigm to include a secondary task during periods of occlusion in self-paced occlusion studies. This paradigm may address the following research questions: does inclusion of a secondary task prevent operators from achieving active predicting? Do operators adjust their sampling strategy to compensate for the additional workload? Does a secondary task affect experienced and inexperienced operators differently? As the real world is more likely to involve multi-tasking situations, such research may provide more practical insights for various application domains.
References


Appendix A – Definition of Information Redundancy based on an Autoregressive Model

To compute the measure of information redundancy, we first seek the variance function and prediction error variance functions associated with the univariate autoregressive model (Cryer and Chan, 2008).

A univariate, p<sup>th</sup> order autoregressive model can be defined as follows:

\[ Y_t = \varphi_1 Y_{t-1} + \varphi_2 Y_{t-2} + \cdots + \varphi_p Y_{t-p} + \epsilon_t \]  \hspace{1cm} (1)

\( Y_t \) is the current value, as a function of one or more prior values, \( Y_{t-1}, Y_{t-2}, \ldots, Y_{t-p} \). \( \varphi_1, \varphi_2, \ldots, \varphi_p \) are the parameters of the model and \( \epsilon_t \) is the white noise. Assuming a stationary process with zero mean, \( \epsilon_t \) is independent of \( Y_{t-1}, Y_{t-2}, \ldots, Y_{t-p} \).

Multiplying Equation (1) by \( Y_{t-k} \), where \( k=1,2,... \), and taking expectations would yield the important recursive relationship for finding the autocorrelation function at \( k \):

\[ \rho_k = \varphi_1 + \varphi_2 \rho_1 + \varphi_3 \rho_2 + \cdots + \varphi_p \rho_{k-p}, \text{ for } k \geq 1 \]  \hspace{1cm} (2)

The general Yule-Walker equations can be obtained from using \( k=1,2,...,p \) into Equation(2) and using \( \rho_0 = 1 \), and \( \rho_{-k} = \rho_k \). The numerical values of \( \rho_k \) can then be obtained by solving these linear equations.

Note that \( E(Y_t \epsilon_k) = E(\epsilon_k (\varphi_1 Y_{t-1} + \varphi_2 Y_{t-2} + \cdots + \varphi_p Y_{t-p} + \epsilon_k)) = E(\epsilon_k^2) = \sigma_\epsilon^2 \)

We can multiple Equation (1) by \( Y_t \), take expectations and find:

\[ Y_0 = \varphi_1 Y_1 + \varphi_2 Y_2 + \cdots + \varphi_p Y_p + \sigma_\epsilon^2 \]  \hspace{1cm} (3)

Using \( \rho_k = \frac{y_k}{y_0} \), Equation (3) can be written as:

\[ Y_0 = \frac{\sigma_\epsilon^2}{1-\varphi_1 \rho_1 + \varphi_2 \rho_2 + \cdots + \varphi_p \rho_p} \]

On the other hand, the time series can also be represented as a weighted linear combination of present and past white noise terms:

\[ Y_k = e_k + \alpha_1 e_{k-1} + \alpha_2 e_{k-2} + \cdots \]  \hspace{1cm} (4)
The $\alpha$ coefficients are complicated functions of the parameters $\varphi_1, \varphi_2, \ldots, \varphi_p$, and are not presented here. However, note that a similar approach of multiplying Equation (4) by $Y_{t+k}$ and taking expectations would lead to finding that:

$$\sigma^2_e(k) = \sigma^2_e(1 + \alpha_1^2 + \alpha_2^2 + \cdots + \alpha_{k-1}^2)$$

$$\sigma^2_e(k) = \gamma_0 (1 - \varphi_1 \rho_1 + \varphi_2 \rho_2 + \cdots + \varphi_p \rho_k) (1 + \alpha_1^2 + \alpha_2^2 + \cdots + \alpha_{k-1}^2)$$

For a more complete explanation of deriving the variances and covariances from the AR(p) model, please see Cryer and Chan (2008) section 4.3.

Following Milgram et al. (1982), the redundancy value at $k^{th}$ sample into the future, $R(k)$, can be obtained by the difference between maximum average amount of uncertainty resolved, $H_{\text{max}}$, and the conditional entropy at the $k^{th}$ forecast, $H_{\text{actual}}$. As uncertainty is modelled after the forecast errors associated with the autoregressive predictions, the following equations made use of the overall variance and the forecast error variance at $k$ found in the AR(p) model:

$$R(k) = H_{\text{max}} - H_{\text{actual}}$$

$$= \frac{1}{2} \log_2 \left\{ \frac{\sigma^2_x}{\sigma^2_e(k)} \right\} \quad \text{where} \quad \sigma^2_x = \gamma_0$$

$$= \frac{1}{2} \log_2 \left\{ \frac{1 + \alpha_1^2 + \alpha_2^2 + \cdots + \alpha_{k-1}^2}{(1 - \varphi_1 \rho_1 + \varphi_2 \rho_2 + \cdots + \varphi_p \rho_k)} \right\}$$
Appendix B – List of Occlusion Research Compiled by Green and Tsimhoni (2001)

Farber, E., Gallagher, V., & Lehman, F. D. (1972). Attentional demand as a measure of the influence of visibility conditions on driving task difficulty with discussion
Appendix C – Experimental Materials

Appendix C.1 - Driving Simulator Setup and Scenes

Screenshot of simulator setup
Screenshot of a typical car-following scenario, showing lead vehicle and predictor display ahead

Screenshot of a typical lane-keeping task, showing empty road ahead
Appendix C.2 – Experimental Materials for Driving Simulator Study

Information Sheet for Participants in Research Project

"Using visual occlusion as a means of modelling human dynamic visual information processing"

Investigators: Huei-Yen Winnie Chen and Paul Milgram

Thank you for agreeing to participate in this study, the purpose of which is to investigate the use of visual occlusion in modelling human visual information processing behaviour. Our research is based on the fact that, when we carry out such complex information processing tasks as automobile driving, in addition to paying attention to the road ahead, it is typically necessary also to attend to a number of different visual inputs, such as the rear-view mirror, the radio, a navigation system, and other passengers. In other words, drivers do not allocate all their attention all the time to the road ahead. In this experiment, we are aiming to improve our understanding of how people decide when to acquire new visual information when forced to carry out a task – in this case, simulated automobile driving – while not looking at the road all the time.

As explained below, you will be given a set of “visual occlusion spectacles”, which will block your view of the simulated road while driving. Whenever you feel that it is necessary to get a new glimpse of the road, you will press a button, which will immediately cause the spectacles to open for a brief period of time. In this way, we will be able to investigate how people are able to perform their task using the minimum amount of information.

Please note that this is not an experiment in risk taking; your primary task, as in the real world, is to ‘drive’ safely at all times.

In this experiment, we aim to establish an important parameter for subsequent experiments, which is the duration for the spectacles to remain open upon each button press. As you may imagine, the shorter such duration, the more frequently one might need to request a view of the road. However, we anticipate that there exists an optimal glance duration. If the glance duration were made shorter than this optimal duration, the driver would not obtain enough information to maximize the duration of the subsequent occlusion period; but if the glance duration were any longer there would be no additional gain on the subsequent period for which one could remain occluded. Your participation in this study will contribute to validating this hypothesis and subsequently finding an optimal duration for future studies. The data collected from your participation will also contribute to the modelling of human visual information processing behaviour as explained earlier.

The experimental setup consists of a low-fidelity driving simulator with a large screen projection, a PC steering wheel and pedals used as the input devices, and a pair of PLATO visual occlusion goggles, a device developed by Professor Milgram, one of the investigators in this study. The study comprises 44 trials, each lasting 2 minutes. The trials will be conducted over 2 sessions, carried out on 2 successive days. Each session has its own task scenario. Prior to the experiment, you will be asked to fill in a questionnaire. At the beginning of each session, you will undergo a training period to familiarise yourself with the experimental setup and the task. After the training period, you will complete 1 baseline trial and 24 experimental trials during each session. Each session of the experiment is expected to last 2 hours or less, for a total of 4 hours.

In the baseline trial, you will perform the task without any occlusion to establish a baseline performance. The rest of the trials will involve occlusion. In the ‘normal’ state, your vision will be occluded with the occlusion goggles, but at any time during the experiment, you may request a quick view of the screen via a button press. The duration of each view will be 0.5, 0.75, 1, 1.5, 2 or 4 seconds, depending on the trial.
Your goal is to perform the task as well as you would without any occlusion (i.e. like the baseline trial), but you are asked to request to view the road only when you feel that it is necessary.

There are two task scenarios in this experiment: car following and lane keeping. In the car following scenario, we will ask you to follow a lead vehicle shown on the projector screen. The lead vehicle will drive along a straight road at about 40 or 60 km/hr, depending on the trials. You have control of the pedals but not of the steering wheel. Your vehicle is automatically centred in the lane and you need not worry about the heading. You will be asked to maintain a safe temporal headway relative to the LV, but remain within 3 seconds of headway from the LV. ‘Temporal (time) headway’ refers to the time that it would take you to reach the car ahead of you, if you keep travelling at the same speed. (In real world driving, this corresponds to leaving more distance between you and the car ahead when you are travelling at high speeds, and vice versa.)

To help you perceive the 3 second headway, a predictor display will appear in the form of an arrow on the ground level to show where your vehicle will be 3 seconds in the future. This predictor of 3 second headway is based on your instantaneous speed, such that its distance from you would vary depending on your speed and acceleration. Your temporal headway is within 3 seconds if you control your speed such that the vehicle ahead of you stays behind the arrow. Please keep in mind that at all times your goal is to follow the lead vehicle as safely as possible, without falling behind for more than the 3 second time headway.

In the lane keeping scenario, we will ask you to use the steering wheel to maintain your vehicle within the lane boundaries. There will be no lead vehicle, and your vehicle will travel on cruise control (without your pedals input) once it accelerates from 0 km/h to the necessary speed (20 or 40 km/h).

In both task scenarios, there are some moderate wind disturbances. Depending on the scenario, you will need to brake, accelerate or adjust the steering wheel to compensate for the wind.

For your participation in the experiment, you will be paid a total of $40. You will be free to withdraw from the experiment at any time, with no negative consequences. In that event, you will be paid for your participation to that point, at a rate of $10 per hour. In addition, your data to that point will still be processed, unless you explicitly request that they be destroyed.

Your identity will remain anonymous with respect to the data collected; no reference to the identity of the participants in this study will be possible through publication of its results.

Thank you for your participation, and we hope that you enjoy the experiment!
PARTICIPANT CONSENT FORM

“Using visual occlusion as a means of modelling human dynamic visual information processing”

I hereby consent to participate in the research project entitled “Using visual occlusion as a means of modelling human dynamic visual information processing,” as explained to me in the accompanying “Information Sheet for Participants in Research Project.”

I understand that participation in the study involves:
- Filling out one questionnaire before any experimental trials
- Performing a series of simulated car following and lane keeping tasks, which have been explained to me

I understand that the experiment will comprise 2 sessions of about 2 hours each, over 2 successive days.

I understand that any questions that I have asked have been answered to my satisfaction, but that I may ask now, or in the future, any further questions I may have about the study or the research procedures.

I understand that I will be assigned a coded identity, that all data files will be identifiable by only that code, and that the code file will not be identifiable to anyone other than the researchers. In other words, my name will not appear on the questionnaires and or on any of the performance data files. The anonymized data files will be stored on a password protected computer accessible only by the researchers. Consequently, no reference to the identity of the participants in this study will be possible through publication of its results, thereby ensuring that all participants will remain anonymous.

I understand that, participation in this study is strictly voluntary. After completing both sessions, I will be reimbursed $40 for my time and participation. I do, however, have the right to refuse answering any questions asked on the questionnaires. I also have the right to withdraw from the study at any time without any penalty, and to request that my data be destroyed. (Without an explicit request, the data will be retained and possibly used in the study). In that case my remuneration will be calculated based on the actual time I shall have spent in the study, at a rate of $10 per hour.

I understand that, whereas I may not otherwise benefit directly from the study, the information gained may provide a better understanding of human visual information processing performance. I also understand that Professor Milgram, one of the investigators of this study, is the developer of the PLATO visual occlusion spectacles that will be used in the experiment and is a major shareholder in Translucent Technologies Inc., the manufacturer of the spectacles. Consequently, it is conceivable that publication of the results of this study could potentially result in increased sales for Translucent Technologies, and thus in financial gain to Professor Milgram.

I understand that results of this study will be published as part of a Ph.D. dissertation, and may be presented at conferences or in scientific journals. I understand also that I shall be able to request a final copy of the reports and publications resulting from this study by contacting the researchers.

The persons in charge of this experiment are both located in the Department of Mechanical and Industrial Engineering, and may be reached as follows:
Huei-Yen Winnie Chen, 416-978-3776, or hwchen@mie.utoronto.ca
Prof. Paul Milgram, 416-978-3662, or milgram@mie.utoronto.ca

I may also contact the Ethics Review Office at ethics.review@utoronto.ca or 416-946-3273, if I should have any questions about my rights as a participant.
Questionnaire

For participation in the experiment “Using visual occlusion as a means of modelling human dynamic visual information processing.”

Participant number: _____  Date: _______________________

1. Age (please circle one): <20  20-24  25-29  30-34  35-39  ≥40

2. Do you ordinarily wear corrective lenses of any kind? Yes   No

If yes, are you wearing your prescribed lenses right now? Yes   No

3. Do you have a G driver license or equivalent? Yes   No

4. How many years of driving experience do you have? _____ years

5. Have you ever played any video game that involves driving? Yes   No

If yes, please indicate how often you ordinarily play such games:
□ very rarely; □ a few times a month; □ at least a few times a week

6. Have you ever driven in a driving simulator? Yes   No

If yes, please indicate how familiar you are with it (please select one):
□ I have just tried it once or twice; I don’t know too much about driving simulation
□ I have lots of experience with driving simulation and I know a fair amount about them
□ I have been involved in researching/developing a driving simulator

7. In actual driving, how would you rate your driving behaviour? Please mark line:

Conservative
I----------------I----------------I----------------I----------------I----------------I

Aggressive

8. May we contact you for similar studies in the future? Yes   No

Thank you for your cooperation!
Appendix C.3 – Experimental Materials for Simple Perceptual Experiment

Information Sheet for Participants in Research Project

"Model of information sampling behaviour using visual occlusion"

Thank you for agreeing to participate in this experiment, the purpose of which is to investigate the use of visual occlusion in modelling human visual information processing behaviour. More specifically, our research is based on the fact that, when we carry out such complex information processing tasks as automobile driving, it is typically necessary to pay attention to a number of different visual inputs, such as the rear-view mirror, the radio, a navigation system, and other passengers. In other words, drivers do not allocate all their attention all the time to the road ahead. In this experiment, we are attempting to better understand how people decide when to acquire new visual information when forced to carry out such a monitoring task, while not looking at it all the time.

In this experiment, a straightforward perceptual task is used instead of an automobile driving task. You will be asked to observe on a computer screen a simple, two dimensional representation of a ball (as a circle) inside a swinging basin, represented as a semi-circle. The ball sits at the bottom of the basin as it oscillates back and forth. However, when the basin swings too far to one side, the ball can drop off the side of the basin. If and when this happens, the ball is immediately replaced by another ball at the same location where it dropped off.

Your task is to monitor this system and report whenever the ball drops by pressing the ENTER key on the keyboard in front of you. You have only half a second to detect any ball drop event, as the ball will disappear half a second after it starts to drop. To provide you with some additional information, the ball will turn red as it is dropping.

Each timely response to a ball drop event will be counted as a hit. Responding too long after the ball has disappeared will not be considered as a hit. (Note also that responding too soon (that is, before a ball begins to drop) will also not be considered a hit. This is especially relevant, since you must realise that not every ball that approaches the edge will in fact fall off the edge.) Your detection performance of each trial is measured as the number of hits divided by the number of ball drop events. This number, compared to the baseline performance (without occlusion), will help us keep track of your performance in different trials.

You may find the prospect of simply monitoring for ball drop events to be fairly easy. To make things “interesting”, however, three seconds into each trial, the computer screen will black out to block your
view of the on-going system. From that point onwards, you will have to request a look in order to continue your task. To do so, you can press the SPACE bar at any time to activate a glance. Each glance allows you the full view of the system for a fixed duration of time, as specified by the experimenter.

Because we are interested in exploring the minimum amount of information necessary for you to perform your task, you are requested TO LOOK ONLY WHEN NECESSARY. Please note that we are not asking you to take any “risks”. In other words, your goal is not to try and look as little as possible, but rather to look as often as you feel necessary (but not more than you deem necessary) in order to maintain performance (i.e. to detect and respond to the ball dropping events).

We will familiarize you with the task using a series of practice trials. The experimenter will provide more verbal explanation as you go through the practice trials. Data collection will begin when you feel very comfortable with the task.

You are one of ten participants in this study. The study comprises 9 trials (a baseline trial without occlusion, and two blocks of 4 glance duration times). Each block of trials will last 2 minutes. Together with the practice trials, the whole experiment is expected to last just under one hour.

As a token of our gratitude for your participation in this experiment, you will receive $15 at the end of the study. Should you decide to withdraw from the experiment early, remuneration will be calculated at $15 per hour from the beginning of the session.

Thank you for your participation, and we hope that you enjoy the experiment!
PARTICIPANT CONSENT FORM

“Model of information sampling behaviour using visual occlusion”

I hereby consent to participate in the research project entitled “Model of information sampling behaviour using visual occlusion,” as explained to me in the accompanying Information Sheet.

I understand that the experiment will take place for about an hour, and that participation in the study involves performing a series of visual monitoring tasks, which have been explained to me.

I understand that I may ask now, or in the future, any questions I may have about the study or the research procedures.

I understand that I will be assigned a coded identity, that all data files will be identified by only that code, and that the code file will not be identifiable to anyone other than the researchers. The anonymized data files will be stored on a password protected computer accessible only by the researchers. Consequently, no reference to the identity of the participants in this study will be possible through publication of its results, thereby ensuring that all participants will remain anonymous.

I understand that participation in this study is strictly voluntary. After completing the study, I will be paid $15 for my time and participation. I do, however, have the right to withdraw from the study at any time without any penalty, and to request that my data be destroyed. (Without an explicit request to delete my data, they will be retained and possibly used in the analysis of the study results.) In the event my early withdrawal, my remuneration will be calculated based on the actual time I shall have spent in the study, at a rate of $15 per hour.

I understand that, whereas I may not otherwise benefit directly from the study, the information gained through my participation may provide a better understanding of human information processing performance.

I understand that results of this study will be published as part of a Ph.D. dissertation, and may be presented at conferences or in scientific journals. I understand also that I shall be able to request a final copy of the reports and publications resulting from this study by contacting the researchers.

I have been given a copy of this consent form. I understand what this study involves and agree to participate.

The researchers are located in the Department of Mechanical and Industrial Engineering, and may be reached as follows:

Huei-Yen Winnie Chen, 416-978-3776, or hwchen@mie.utoronto.ca
Prof. Paul Milgram, 416-978-3662, or milgram@mie.utoronto.ca

You may also contact the Ethics Review Office at ethics.review@utoronto.ca or 416-946-3273, if you should have any questions about your rights as a participant.
Appendix D – Supplementary Results

D.1 Supplementary Statistics from Chapter 3

Analysis of Task Performance

F-tests for task performance measures

<table>
<thead>
<tr>
<th>Task</th>
<th>Measure</th>
<th>Fixed Effects</th>
<th>F-value</th>
<th>P</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lane Keeping</td>
<td>Mean Lane Position</td>
<td>Speed</td>
<td>$F(1,241)=0.079$</td>
<td>n.s.</td>
</tr>
<tr>
<td></td>
<td></td>
<td>GD</td>
<td>$F(5,241)=1.407$</td>
<td>n.s.</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Speed x GD</td>
<td>$F(5,241)=0.417$</td>
<td>n.s.</td>
</tr>
<tr>
<td></td>
<td>Standard Deviations of Lane Position</td>
<td>Speed</td>
<td>$F(1,240)=0.000$</td>
<td>n.s.</td>
</tr>
<tr>
<td></td>
<td></td>
<td>GD</td>
<td>$F(5,240)=5.50$</td>
<td>0.000*</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Speed x GD</td>
<td>$F(5,240)=0.958$</td>
<td>n.s.</td>
</tr>
<tr>
<td>Car Following</td>
<td>Mean Time Headway</td>
<td>Speed</td>
<td>$F(1,240)=2.77$</td>
<td>n.s.</td>
</tr>
<tr>
<td></td>
<td></td>
<td>GD</td>
<td>$F(5,240)=0.972$</td>
<td>n.s.</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Speed x GD</td>
<td>$F(5,240)=1.047$</td>
<td>n.s.</td>
</tr>
<tr>
<td></td>
<td>Standard Deviations of Time Headway</td>
<td>Speed</td>
<td>$F(1,240)=0.561$</td>
<td>n.s.</td>
</tr>
<tr>
<td></td>
<td></td>
<td>GD</td>
<td>$F(5,240)=2.20$</td>
<td>n.s.</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Speed x GD</td>
<td>$F(5,240)=0.782$</td>
<td>n.s.</td>
</tr>
</tbody>
</table>

Note: n.s. indicates not significant, for p > 0.05.

Post-hoc analysis for comparing STD-LP between each GD and the baseline condition

<table>
<thead>
<tr>
<th>GD</th>
<th>Δ</th>
<th>t (df)</th>
<th>p</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.5s</td>
<td>0.152</td>
<td>4.71</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>1s</td>
<td>0.120</td>
<td>3.70</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>1.5s</td>
<td>0.129</td>
<td>3.99</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>2s</td>
<td>0.073</td>
<td>2.27</td>
<td>0.024</td>
</tr>
<tr>
<td>4s</td>
<td>0.112</td>
<td>3.47</td>
<td>&lt;.001</td>
</tr>
</tbody>
</table>

Analysis of MOT for the driving simulator study

Parameter estimates for the linear mixed model on occlusion data

<table>
<thead>
<tr>
<th></th>
<th>Lane-keeping</th>
<th>Car-following</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Value</td>
<td>Std. Err</td>
<td>t-statistics</td>
</tr>
<tr>
<td>Intercept</td>
<td>2.29</td>
<td>0.23</td>
<td>t(223)=9.92</td>
</tr>
<tr>
<td>Speed(higher)</td>
<td>-0.20</td>
<td>0.06</td>
<td>t(223)=-3.46</td>
</tr>
<tr>
<td>1/GD</td>
<td>-0.20</td>
<td>0.04</td>
<td>t(223)=-4.91</td>
</tr>
</tbody>
</table>

*Significance level: p < 0.05
**Analysis of MOT from the on-road driving study**

Asymptotic model summary for the on-road driving study using a) experienced drivers and b) inexperienced drivers

<table>
<thead>
<tr>
<th></th>
<th>Experienced Drivers</th>
<th></th>
<th>Inexperienced Drivers</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Est.</td>
<td>SE</td>
<td>t-statistics</td>
<td>p-value</td>
</tr>
<tr>
<td>Intercept</td>
<td>6.33</td>
<td>0.31</td>
<td>t(167) = 20.6</td>
<td>&lt;.0001</td>
</tr>
<tr>
<td>Speed (60)</td>
<td>-2.38</td>
<td>0.17</td>
<td>t(167) = -14.0</td>
<td>&lt;.0001</td>
</tr>
<tr>
<td>Speed (100)</td>
<td>-3.11</td>
<td>0.17</td>
<td>t(167) = -18.2</td>
<td>&lt;.0001</td>
</tr>
<tr>
<td>1/GD</td>
<td>-0.46</td>
<td>0.06</td>
<td>t(167) = -7.75</td>
<td>&lt;.0001</td>
</tr>
<tr>
<td>Speed(60): 1/GD</td>
<td>0.30</td>
<td>0.08</td>
<td>t(167) = 3.63</td>
<td>0.0004</td>
</tr>
<tr>
<td>Speed(100): 1/GD</td>
<td>0.31</td>
<td>0.08</td>
<td>t(167) = 3.73</td>
<td>0.0003</td>
</tr>
</tbody>
</table>
Appendix D.2 Supplementary Statistics from Chapter 4

F-test results on information redundancy values from lane keeping trials. (a) Full model with all interaction effects and (b) Final model, removing interactions

<table>
<thead>
<tr>
<th>Fixed Effects</th>
<th>Full Model</th>
<th></th>
<th>Model without interactions</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>F(1, 206) =28.5</td>
<td>&lt;.0001</td>
<td>F(1,219)=55.4</td>
<td>&lt;.0001</td>
</tr>
<tr>
<td>Speed</td>
<td>F(1, 206) =0.116</td>
<td>n.s.</td>
<td>F(1,219)=9.42</td>
<td>0.002</td>
</tr>
<tr>
<td>Glance</td>
<td>F(4, 206) =0.498</td>
<td>n.s.</td>
<td>F(4,219)=4.66</td>
<td>0.001</td>
</tr>
<tr>
<td>STD-LP</td>
<td>F(1, 206) =3.64</td>
<td>0.058</td>
<td>F(1,219)=11.6</td>
<td>0.001</td>
</tr>
<tr>
<td>Speed x Glance</td>
<td>F(4, 206) =0.109</td>
<td>n.s.</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Speed x STD-LP</td>
<td>F(1, 206) =0.253</td>
<td>n.s.</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Glance x STD-LP</td>
<td>F(4, 206) =1.95</td>
<td>n.s.</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Speed x Glance x STD-LP</td>
<td>F(4, 206) =0.086</td>
<td>n.s.</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

F-test results on information redundancy values from car following trials: (a) Full model with all interaction effects and (b) Final model, removing interactions

<table>
<thead>
<tr>
<th>Fixed Effects</th>
<th>Full Model</th>
<th></th>
<th>Model without interactions</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>F(1, 205) =12.7</td>
<td>&lt;.0001</td>
<td>F(1,218)=39.6</td>
<td>&lt;.0001</td>
</tr>
<tr>
<td>Speed</td>
<td>F(1, 205) =0.048</td>
<td>n.s.</td>
<td>F(1,218)=4.87</td>
<td>0.028</td>
</tr>
<tr>
<td>Glance</td>
<td>F(4, 205) =0.464</td>
<td>n.s.</td>
<td>F(4,218)=5.77</td>
<td>0.002</td>
</tr>
<tr>
<td>STD-LP</td>
<td>F(1, 205) =0.003</td>
<td>n.s.</td>
<td>F(1,218)=4.50</td>
<td>0.035</td>
</tr>
<tr>
<td>Speed x Glance</td>
<td>F(4, 205) =0.557</td>
<td>n.s.</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Speed x STD-LP</td>
<td>F(1, 205) =0.140</td>
<td>n.s.</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Glance x STD-LP</td>
<td>F(4, 205) =0.976</td>
<td>n.s.</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Speed x Glance x STD-LP</td>
<td>F(4, 205) =0.890</td>
<td>n.s.</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Appendix D.3  Supplementary Statistics from Chapter 6

Analysis of data collected from experienced drivers

(Experienced Drivers) F-test results for the Level 1 model of occlusion data using MOT.

<table>
<thead>
<tr>
<th>Fixed Effects</th>
<th>F-value</th>
<th>P</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>( F(1, 170) = 358 )</td>
<td>&lt;.0001</td>
</tr>
<tr>
<td>Speed</td>
<td>( F(2, 170) = 170 )</td>
<td>&lt;.0001</td>
</tr>
</tbody>
</table>

(Experienced Drivers) F-test results for the Level 2 model of occlusion data using MOT.

<table>
<thead>
<tr>
<th>Fixed Effects</th>
<th>F-value</th>
<th>P</th>
<th>F-value</th>
<th>P</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>( F(1, 143) = 40.6 )</td>
<td>&lt;.0001</td>
<td>( F(1, 165) = 182 )</td>
<td>&lt;.0001</td>
</tr>
<tr>
<td>Speed</td>
<td>( F(2, 143) = 3.03 )</td>
<td>0.051</td>
<td>( F(2, 165) = 263 )</td>
<td>&lt;.0001</td>
</tr>
<tr>
<td>GD</td>
<td>( F(4, 143) = 2.38 )</td>
<td>0.054</td>
<td>( F(4, 165) = 14.9 )</td>
<td>&lt;.0001</td>
</tr>
<tr>
<td>Std. Lane Position</td>
<td>( F(1, 143) = 4.04 )</td>
<td>0.046</td>
<td>( F(1, 165) = 0.726 )</td>
<td>0.395 (n.s)</td>
</tr>
<tr>
<td>Speed: GD</td>
<td>( F(8, 143) = 1.07 )</td>
<td>n.s.</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Speed: Std. Lane Position</td>
<td>( F(2, 143) = 0.106 )</td>
<td>n.s.</td>
<td></td>
<td></td>
</tr>
<tr>
<td>GD: Std. Lane Position</td>
<td>( F(4, 143) = 1.22 )</td>
<td>n.s.</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Speed: GD: Std. Lane Position</td>
<td>( F(8, 143) = 1.20 )</td>
<td>n.s.</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

(Experienced Drivers) F-test results for the Level 2 Reduced model of occlusion data using MOT.

<table>
<thead>
<tr>
<th>Fixed Effects</th>
<th>F-value</th>
<th>P</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>( F(1, 158) = 199 )</td>
<td>&lt;.0001</td>
</tr>
<tr>
<td>Speed</td>
<td>( F(2, 158) = 32.7 )</td>
<td>&lt;.0001</td>
</tr>
<tr>
<td>GD</td>
<td>( F(4, 158) = 18.1 )</td>
<td>&lt;.0001</td>
</tr>
<tr>
<td>Speed x GD</td>
<td>( F(8, 158) = 2.91 )</td>
<td>0.005</td>
</tr>
</tbody>
</table>

(Experienced Drivers) F-test results for Level 3 Model of occlusion data

<table>
<thead>
<tr>
<th>Fixed Effects</th>
<th>F-value</th>
<th>P</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>( F(1, 2690) = 579 )</td>
<td>&lt;.0001</td>
</tr>
<tr>
<td>Speed</td>
<td>( F(2, 2690) = 161 )</td>
<td>&lt;.0001</td>
</tr>
<tr>
<td>GD</td>
<td>( F(4, 2690) = 29.4 )</td>
<td>&lt;.0001</td>
</tr>
<tr>
<td>LD observed</td>
<td>( F(1, 2690) = 10.1 )</td>
<td>0.002</td>
</tr>
<tr>
<td>Speed x GD</td>
<td>( F(8, 2690) = 3.71 )</td>
<td>0.000</td>
</tr>
<tr>
<td>Speed: LD observed</td>
<td>( F(2, 2690) = 0.157 )</td>
<td>n.s.</td>
</tr>
<tr>
<td>GD: LD observed</td>
<td>( F(4, 2690) = 0.651 )</td>
<td>n.s.</td>
</tr>
<tr>
<td>Speed: GD: LD observed</td>
<td>( F(8, 2690) = 2.18 )</td>
<td>0.026</td>
</tr>
</tbody>
</table>
### Experienced Drivers F-test results for Level 4 model of occlusion data

<table>
<thead>
<tr>
<th>Fixed Effects</th>
<th>F-value</th>
<th>P</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>F(1, 2660) = 510</td>
<td>&lt;.0001</td>
</tr>
<tr>
<td>Speed</td>
<td>F(2, 2660) = 60.0</td>
<td>&lt;.0001</td>
</tr>
<tr>
<td>GD</td>
<td>F(4, 2660) = 13.5</td>
<td>&lt;.0001</td>
</tr>
<tr>
<td>LD observed</td>
<td>F(1, 2660) = 4.00</td>
<td>0.045</td>
</tr>
<tr>
<td>LD predicted</td>
<td>F(1, 2660) = 1.84</td>
<td>n.s.</td>
</tr>
<tr>
<td>Speed x GD</td>
<td>F(8, 2660) = 2.06</td>
<td>0.036</td>
</tr>
<tr>
<td>Speed: LD observed</td>
<td>F(2, 2660) = 1.56</td>
<td>n.s.</td>
</tr>
<tr>
<td>GD: LD observed</td>
<td>F(4, 2660) = 2.38</td>
<td>0.050</td>
</tr>
<tr>
<td>Speed: LD predicted</td>
<td>F(2, 2660) = 4.55</td>
<td>0.011</td>
</tr>
<tr>
<td>GD: LD predicted</td>
<td>F(4, 2660) = 9.80</td>
<td>&lt;.0001</td>
</tr>
<tr>
<td>LD predicted: LD observed</td>
<td>F(1, 2660) = 5.45</td>
<td>0.020</td>
</tr>
<tr>
<td>Speed: GD: LD observed</td>
<td>F(8, 2660) = 1.82</td>
<td>n.s.</td>
</tr>
<tr>
<td>Speed: GD: LD predicted</td>
<td>F(8, 2660) = 1.80</td>
<td>n.s.</td>
</tr>
<tr>
<td>Speed: LD predicted: LD predicted</td>
<td>F(2, 2660) = 2.10</td>
<td>n.s.</td>
</tr>
<tr>
<td>GD: LD observed: LD predicted</td>
<td>F(4, 2660) = 2.98</td>
<td>0.018</td>
</tr>
<tr>
<td>Speed: GD: LD observed: LD predicted</td>
<td>F(8, 2660) = 2.24</td>
<td>0.022</td>
</tr>
</tbody>
</table>

### Experienced Drivers F-test results for the simplified Level 4 Model, excluding variable LD observed.

<table>
<thead>
<tr>
<th>Fixed Effects</th>
<th>F-value</th>
<th>P</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>F(1, 2698) = 609</td>
<td>&lt;.0001</td>
</tr>
<tr>
<td>Speed</td>
<td>F(2, 2698) = 286</td>
<td>&lt;.0001</td>
</tr>
<tr>
<td>GD</td>
<td>F(4, 2698) = 27.5</td>
<td>&lt;.0001</td>
</tr>
<tr>
<td>LD predicted</td>
<td>F(1, 2698) = 51.3</td>
<td>&lt;.0001</td>
</tr>
<tr>
<td>Speed x GD</td>
<td>F(8, 2698) = 4.92</td>
<td>&lt;.0001</td>
</tr>
<tr>
<td>Speed: LD predicted</td>
<td>F(2, 2698) = 5.65</td>
<td>0.004</td>
</tr>
<tr>
<td>GD: LD predicted</td>
<td>F(4, 2698) = 26.8</td>
<td>&lt;.0001</td>
</tr>
</tbody>
</table>
### Analysis of data collected using inexperienced drivers

#### (Inexperienced Drivers) F-test results for the Level 1 model of occlusion data using MOT.

<table>
<thead>
<tr>
<th>Fixed Effects</th>
<th>(F)-value</th>
<th>(P)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>(F(1, 172) = 225)</td>
<td>&lt;.0001</td>
</tr>
<tr>
<td>Speed</td>
<td>(F(2, 172) = 131)</td>
<td>&lt;.0001</td>
</tr>
</tbody>
</table>

#### (Inexperienced Drivers) F-test results for the Level 2 model of occlusion data using MOT.

<table>
<thead>
<tr>
<th></th>
<th>Full Model</th>
<th>Parsimonious Model</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Fixed Effects</strong></td>
<td>(F)-value</td>
<td>(P)</td>
</tr>
<tr>
<td>Intercept</td>
<td>(F(1, 145) = 8.40)</td>
<td>0.004</td>
</tr>
<tr>
<td>Speed</td>
<td>(F(2, 145) = 0.224)</td>
<td>n.s.</td>
</tr>
<tr>
<td>GD</td>
<td>(F(4, 145) = 1.08)</td>
<td>n.s.</td>
</tr>
<tr>
<td>Std. Lane Position</td>
<td>(F(1, 145) = 3.47)</td>
<td>n.s. (0.064)</td>
</tr>
<tr>
<td>Speed x GD</td>
<td>(F(8, 145) = 0.825)</td>
<td>n.s.</td>
</tr>
<tr>
<td>Speed: Std. Lane Position</td>
<td>(F(2, 145) = 0.303)</td>
<td>n.s.</td>
</tr>
<tr>
<td>GD: Std. Lane Position</td>
<td>(F(4, 145) = 0.653)</td>
<td>n.s.</td>
</tr>
<tr>
<td>Speed: GD: Std. Lane Position</td>
<td>(F(8, 143) = 0.865)</td>
<td>n.s.</td>
</tr>
</tbody>
</table>

#### (Inexperienced Drivers) F-test results for the Level 2 Reduced model of occlusion data using MOT.

<table>
<thead>
<tr>
<th>Fixed Effects</th>
<th>(F)-value</th>
<th>(P)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>(F(1, 160) = 134)</td>
<td>&lt;.0001</td>
</tr>
<tr>
<td>Speed</td>
<td>(F(2, 160) = 16.4)</td>
<td>&lt;.0001</td>
</tr>
<tr>
<td>GD</td>
<td>(F(4, 160) = 2.15)</td>
<td>0.077 (n.s.)</td>
</tr>
<tr>
<td>Speed x GD</td>
<td>(F(8, 160) = 0.446)</td>
<td>0.892 (n.s.)</td>
</tr>
</tbody>
</table>

#### (Inexperienced Drivers) AIC values found for models fitting MO

<table>
<thead>
<tr>
<th>Level</th>
<th>Mixed Effects Model</th>
<th>AIC</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Mean OT = g(Speed)</td>
<td>391</td>
</tr>
<tr>
<td>2– Reduced</td>
<td>Mean OT = g(Speed, GD)</td>
<td>403</td>
</tr>
<tr>
<td>2</td>
<td>Mean OT = g(Speed, GD, std(Lane Position))</td>
<td>395</td>
</tr>
</tbody>
</table>

#### (Inexperienced Drivers) F-test results for the Level 2 Reduced model fitted using individual OT

<table>
<thead>
<tr>
<th>Fixed Effects</th>
<th>(F)-value</th>
<th>(P)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>(F(1, 3497) = 230)</td>
<td>&lt;.0001</td>
</tr>
<tr>
<td>Speed</td>
<td>(F(2, 3497) = 361)</td>
<td>&lt;.0001</td>
</tr>
<tr>
<td>GD</td>
<td>(F(4, 3497) = 26.7)</td>
<td>&lt;.0001</td>
</tr>
<tr>
<td>Speed x GD</td>
<td>(F(8, 3497) = 2.46)</td>
<td>0.012</td>
</tr>
</tbody>
</table>
(Inexperienced drivers) F-test results for Level 3 Model of individual occlusion times

<table>
<thead>
<tr>
<th>Fixed Effects</th>
<th>F-value</th>
<th>P</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>$F(1, 3482) = 215$</td>
<td>&lt;.0001</td>
</tr>
<tr>
<td>Speed</td>
<td>$F(2, 3482) = 136$</td>
<td>&lt;.0001</td>
</tr>
<tr>
<td>GD</td>
<td>$F(4, 3482) = 14.5$</td>
<td>&lt;.0001</td>
</tr>
<tr>
<td>LD observed</td>
<td>$F(1, 3482) = .270$</td>
<td>n.s.</td>
</tr>
<tr>
<td>Speed x GD</td>
<td>$F(8, 3482) = 2.93$</td>
<td>0.003</td>
</tr>
<tr>
<td>Speed: LD observed</td>
<td>$F(2, 3482) = 4.45$</td>
<td>0.012</td>
</tr>
<tr>
<td>GD: LD observed</td>
<td>$F(4, 3482) = 1.58$</td>
<td>n.s.</td>
</tr>
<tr>
<td>Speed: GD: LD observed</td>
<td>$F(8, 3482) = 2.66$</td>
<td>0.007</td>
</tr>
</tbody>
</table>
Appendix D.4 Supplementary Statistics from Chapter 7

Level 3 Sampling Behaviour

F-test results for the Level 3 model of occlusion data.

<table>
<thead>
<tr>
<th>Fixed Effects</th>
<th>F-value</th>
<th>P</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>$F(1, 3224) = 84.8$</td>
<td>&lt;.0001</td>
</tr>
<tr>
<td>Distance (log trans.)</td>
<td>$F(1, 3224) = 707$</td>
<td>&lt;.0001</td>
</tr>
<tr>
<td>Glance Duration (GD)</td>
<td>$F(2, 3224) = 16.4$</td>
<td>&lt;.0001</td>
</tr>
<tr>
<td>Distance x Glance</td>
<td>$F(2, 3224) = 5.09$</td>
<td>0.006</td>
</tr>
</tbody>
</table>

Simultaneous Tests for General Linear Hypotheses: estimated coefficients of distance observed at different levels of GD.

<table>
<thead>
<tr>
<th>Estimate</th>
<th>Std.Error</th>
<th>Adjusted P (single-step method)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Slope at Glance 100</td>
<td>0.490</td>
<td>0.018</td>
</tr>
<tr>
<td>Slope at Glance 300</td>
<td>0.496</td>
<td>0.021</td>
</tr>
<tr>
<td>Slope at Glance 500</td>
<td>0.580</td>
<td>0.024</td>
</tr>
</tbody>
</table>

Simultaneous Tests for General Linear Hypotheses: Δ in estimated coefficients of distance observed

<table>
<thead>
<tr>
<th>Linear Hypotheses</th>
<th>Estimate</th>
<th>Std.Error</th>
<th>Adjusted P (single-step method)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Δslope: 300ms - 100ms == 0</td>
<td>0.005</td>
<td>0.028</td>
<td>0.972 (n.s.)</td>
</tr>
<tr>
<td>Δslope: 500ms - 300ms == 0</td>
<td>0.084</td>
<td>0.032</td>
<td>0.015</td>
</tr>
</tbody>
</table>

Parameter estimates for the linear mixed model at Level 3

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
<th>Std. Err</th>
<th>t-statistics</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>1.07</td>
<td>0.116</td>
<td>t(3224)=9.21</td>
<td>&lt;.0001</td>
</tr>
<tr>
<td>ln(Distance Observed)</td>
<td>0.490</td>
<td>0.018</td>
<td>t(3224)=26.6</td>
<td>&lt;.0001</td>
</tr>
<tr>
<td>GD300</td>
<td>0.165</td>
<td>0.052</td>
<td>t(3224)=3.19</td>
<td>0.001</td>
</tr>
<tr>
<td>GD500</td>
<td>0.307</td>
<td>0.054</td>
<td>t(3224)=5.68</td>
<td>&lt;.0001</td>
</tr>
<tr>
<td>ln(Distance Observed):GD300</td>
<td>0.006</td>
<td>0.028</td>
<td>t(3224)=0.196</td>
<td>0.845</td>
</tr>
<tr>
<td>ln(Distance Observed):GD500</td>
<td>0.090</td>
<td>0.030</td>
<td>t(3224)=2.99</td>
<td>0.003</td>
</tr>
</tbody>
</table>
Level 4A Predicting Behaviour – Direction

F-test results for the Level 4A model of occlusion data accounting for direction

<table>
<thead>
<tr>
<th>Fixed Effects</th>
<th>F-value</th>
<th>P</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>F(1, 3218)=120</td>
<td>&lt;.0001</td>
</tr>
<tr>
<td>log (Distance)</td>
<td>F(2, 3218)=207</td>
<td>&lt;.0001</td>
</tr>
<tr>
<td>Direction</td>
<td>F(1, 3218)=53.2</td>
<td>&lt;.0001</td>
</tr>
<tr>
<td>Glance</td>
<td>F(1, 3218)=8.74</td>
<td>0.0002</td>
</tr>
<tr>
<td>log(Distance): Direction</td>
<td>F(2, 3218)=34.3</td>
<td>&lt;.0001</td>
</tr>
<tr>
<td>log(Distance): Glance</td>
<td>F(2, 3218)=1.94</td>
<td>n.s.</td>
</tr>
<tr>
<td>Direction: Glance</td>
<td>F(1, 3218)=0.279</td>
<td>n.s.</td>
</tr>
<tr>
<td>log(Distance): Direction: Glance</td>
<td>F(2, 3218)=4.08</td>
<td>0.017</td>
</tr>
</tbody>
</table>

Parameter estimates for the linear mixed model at Level 4A

<table>
<thead>
<tr>
<th></th>
<th>Value</th>
<th>Std. Err</th>
<th>t-statistics</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>1.294</td>
<td>0.118</td>
<td>t(3218)=11.0</td>
<td>.000</td>
</tr>
<tr>
<td>ln(Distance Observed)</td>
<td>0.359</td>
<td>0.068</td>
<td>t(3218)=2.54</td>
<td>0.011</td>
</tr>
<tr>
<td>GD300</td>
<td>0.172</td>
<td>0.070</td>
<td>t(3218)=4.09</td>
<td>0.000</td>
</tr>
<tr>
<td>GD500</td>
<td>0.288</td>
<td>0.025</td>
<td>t(3218)=14.4</td>
<td>0.000</td>
</tr>
<tr>
<td>Direction(TowardEdge)</td>
<td>-0.427</td>
<td>0.059</td>
<td>t(3218)=-7.30</td>
<td>.000</td>
</tr>
<tr>
<td>ln(Distance Observed):GD300</td>
<td>-0.056</td>
<td>0.038</td>
<td>t(3218)=-1.468</td>
<td>0.142 (n.s.)</td>
</tr>
<tr>
<td>ln(Distance Observed):GD500</td>
<td>0.024</td>
<td>0.040</td>
<td>t(3218)=0.604</td>
<td>0.546 (n.s.)</td>
</tr>
<tr>
<td>Direction(TowardEdge):GD300</td>
<td>0.034</td>
<td>0.087</td>
<td>t(3218)=0.386</td>
<td>0.700 (n.s.)</td>
</tr>
<tr>
<td>Direction(TowardEdge):GD500</td>
<td>0.068</td>
<td>0.091</td>
<td>t(3218)=0.744</td>
<td>0.457 (n.s.)</td>
</tr>
<tr>
<td>ln(Distance Observed):Direction(TowardEdge)</td>
<td>0.185</td>
<td>0.032</td>
<td>t(3218)=5.85</td>
<td>0.000</td>
</tr>
<tr>
<td>ln(Distance Observed):Direction(TowardEdge):GD300</td>
<td>0.111</td>
<td>0.048</td>
<td>t(3218)=2.30</td>
<td>0.021</td>
</tr>
<tr>
<td>ln(Distance Observed):Direction(TowardEdge):GD500</td>
<td>0.128</td>
<td>0.051</td>
<td>t(3218)=2.48</td>
<td>0.013</td>
</tr>
</tbody>
</table>

Simultaneous Tests for General Linear Hypotheses: Δ estimated coefficients of distance observed, between ‘toward edge’ and ‘away from edge’ at different levels of GD.

<table>
<thead>
<tr>
<th></th>
<th>Δ Estimate</th>
<th>Std.Error</th>
<th>Adjusted P (single-step method)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Glance 100</td>
<td>0.185</td>
<td>0.032</td>
<td>&lt;.0001</td>
</tr>
<tr>
<td>Slope at Glance 300</td>
<td>0.218</td>
<td>0.075</td>
<td>0.011</td>
</tr>
<tr>
<td>Slope at Glance 500</td>
<td>0.253</td>
<td>0.079</td>
<td>0.004</td>
</tr>
</tbody>
</table>
Simultaneous Tests for General Linear Hypotheses: Δ estimated coefficients of distance observed, between levels of GD at ‘toward edge’ and ‘away from edge’, respectively.

<table>
<thead>
<tr>
<th>Linear Hypotheses</th>
<th>Δ Estimate</th>
<th>Std.Error</th>
<th>Adjusted P (single-step method)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Away from Edge</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Δslope: 300ms -100ms == 0</td>
<td>-0.056</td>
<td>0.038</td>
<td>0.428 (n.s.)</td>
</tr>
<tr>
<td>Δslope: 500ms -300ms == 0</td>
<td>0.080</td>
<td>0.043</td>
<td>0.206 (n.s.)</td>
</tr>
<tr>
<td>Toward Edge</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Δslope: 300ms -100ms == 0</td>
<td>0.055</td>
<td>0.030</td>
<td>0.215 (n.s.)</td>
</tr>
<tr>
<td>Δslope: 500ms -300ms == 0</td>
<td>0.097</td>
<td>0.033</td>
<td>0.017</td>
</tr>
</tbody>
</table>

Level 4A-R (Refitted model of Level 4A using only data from ‘toward edge’ subset)

F-test results for the Level 4A-R model

<table>
<thead>
<tr>
<th>Fixed Effects</th>
<th>F-value</th>
<th>P</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>F(1, 1953)=65.8</td>
<td>&lt;.0001</td>
</tr>
<tr>
<td>Glance</td>
<td>F(2, 1953)=28.5</td>
<td>&lt;.0001</td>
</tr>
<tr>
<td>log (Distance Observed)</td>
<td>F(1, 1953)=1090</td>
<td>&lt;.0001</td>
</tr>
<tr>
<td>log(Distance Observed): Glance</td>
<td>F(2, 1953)=16.4</td>
<td>&lt;.0001</td>
</tr>
</tbody>
</table>

Parameter estimates for the linear mixed model at Level 4A-R

<table>
<thead>
<tr>
<th>Fixed Effects</th>
<th>Value</th>
<th>Std. Err</th>
<th>t-statistics</th>
<th>P-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>0.835</td>
<td>0.103</td>
<td>t(1953)=8.11</td>
<td>.000</td>
</tr>
<tr>
<td>ln(Distance Observed)</td>
<td>0.535</td>
<td>0.016</td>
<td>t(1953)=32.9</td>
<td>.000</td>
</tr>
<tr>
<td>GD300</td>
<td>0.210</td>
<td>0.046</td>
<td>t(1953)=4.56</td>
<td>.000</td>
</tr>
<tr>
<td>GD500</td>
<td>0.361</td>
<td>0.049</td>
<td>t(1953)=7.42</td>
<td>.000</td>
</tr>
<tr>
<td>ln(Distance Observed):GD300</td>
<td>0.055</td>
<td>0.025</td>
<td>t(1953)=2.23</td>
<td>.026</td>
</tr>
<tr>
<td>ln(Distance Observed):GD500</td>
<td>0.153</td>
<td>0.027</td>
<td>t(1953)=5.73</td>
<td>.000</td>
</tr>
</tbody>
</table>

Level 4B Predicting Behaviour – Estimated Time to Drop-off (TTD)

F-test results for analysis on data corresponding to ‘approaching the edge’ subset.

<table>
<thead>
<tr>
<th>Fixed Effects</th>
<th>F-value</th>
<th>P</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>F(1,1947) = 23.0</td>
<td>&lt;.0001</td>
</tr>
<tr>
<td>log (TTD)</td>
<td>F(1, 1947)= 76.1</td>
<td>&lt;.0001</td>
</tr>
<tr>
<td>log (Distance)</td>
<td>F(1, 1947)= 594</td>
<td>&lt;.0001</td>
</tr>
<tr>
<td>Glance</td>
<td>F(2, 1947) = 1.73</td>
<td>n.s.</td>
</tr>
<tr>
<td>log(TTD): log(Distance)</td>
<td>F(1, 1947)= 51.0</td>
<td>&lt;.0001</td>
</tr>
<tr>
<td>log(TTD): Glance</td>
<td>F(2, 1947)= 16.6</td>
<td>&lt;.0001</td>
</tr>
<tr>
<td>log(Distance): Glance</td>
<td>F(2, 1947) = 3.30</td>
<td>0.037</td>
</tr>
<tr>
<td>log(TTD): log(Distance): Glance</td>
<td>F(2, 1947) = 5.88</td>
<td>0.003</td>
</tr>
</tbody>
</table>
F-test results for analysis on data corresponding to ‘approaching the edge’ subset, using distance as a three level factor, for near, mid-range, and far distances.

<table>
<thead>
<tr>
<th>Fixed Effects</th>
<th>F-value</th>
<th>P</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>$F(1, 1941) = 56.5$</td>
<td>&lt;.0001</td>
</tr>
<tr>
<td>log (TTD)</td>
<td>$F(1, 1941) = 122$</td>
<td>&lt;.0001</td>
</tr>
<tr>
<td>Distance</td>
<td>$F(2, 1941) = 124$</td>
<td>&lt;.0001</td>
</tr>
<tr>
<td>Glance</td>
<td>$F(2, 1941) = 2.21$</td>
<td>0.109 (n.s.)</td>
</tr>
<tr>
<td>log(TTD): Distance</td>
<td>$F(2, 1941) = 8.64$</td>
<td>0.000</td>
</tr>
<tr>
<td>log(TTD): Glance</td>
<td>$F(2, 1941) = 17.4$</td>
<td>&lt;.0001</td>
</tr>
<tr>
<td>Distance: Glance</td>
<td>$F(4, 1941) = 1.59$</td>
<td>0.173 (n.s.)</td>
</tr>
<tr>
<td>log(TTD): Distance: Glance</td>
<td>$F(4, 1941) = 2.63$</td>
<td>0.033</td>
</tr>
</tbody>
</table>

Simultaneous Tests for General Linear Hypotheses: $\Delta$ estimated coefficients of TTD at all 9 combinations of distance (3 levels) and glance duration (3 levels).

<table>
<thead>
<tr>
<th>GD</th>
<th>Distance (as factor)</th>
<th>Estimate</th>
<th>Std.Error</th>
<th>Adjusted P (single-step method)</th>
</tr>
</thead>
<tbody>
<tr>
<td>100ms</td>
<td>Near the edge</td>
<td>0.240</td>
<td>0.022</td>
<td>0.000</td>
</tr>
<tr>
<td></td>
<td>Mid-range</td>
<td>0.077</td>
<td>0.044</td>
<td>0.495 (n.s.)</td>
</tr>
<tr>
<td></td>
<td>Far from range</td>
<td>0.094</td>
<td>0.040</td>
<td>0.160 (n.s.)</td>
</tr>
<tr>
<td>300ms</td>
<td>Near the edge</td>
<td>0.312</td>
<td>0.026</td>
<td>0.000</td>
</tr>
<tr>
<td></td>
<td>Mid-range</td>
<td>0.303</td>
<td>0.043</td>
<td>0.000</td>
</tr>
<tr>
<td></td>
<td>Far from range</td>
<td>0.186</td>
<td>0.055</td>
<td>0.006</td>
</tr>
<tr>
<td>500ms</td>
<td>Near the edge</td>
<td>0.443</td>
<td>0.027</td>
<td>0.000</td>
</tr>
<tr>
<td></td>
<td>Mid-range</td>
<td>0.406</td>
<td>0.054</td>
<td>0.000</td>
</tr>
<tr>
<td></td>
<td>Far from range</td>
<td>0.298</td>
<td>0.054</td>
<td>0.000</td>
</tr>
</tbody>
</table>

Simultaneous Tests for General Linear Hypotheses: $\Delta$ estimated coefficients of TTD, between levels of GD at ‘toward edge’ and ‘away from edge’, respectively.

<table>
<thead>
<tr>
<th>Linear Hypotheses</th>
<th>$\Delta$ Estimate</th>
<th>Std.Error</th>
<th>Adjusted P (single-step method)</th>
</tr>
</thead>
<tbody>
<tr>
<td>100 ms</td>
<td>$\Delta$slope: MidRange - NearEdge == 0</td>
<td>-0.163</td>
<td>0.049 0.004</td>
</tr>
<tr>
<td></td>
<td>$\Delta$slope: Far - MidRange == 0</td>
<td>0.018</td>
<td>0.060 0.999 (n.s.)</td>
</tr>
<tr>
<td>300 ms</td>
<td>$\Delta$slope: MidRange - NearEdge == 0</td>
<td>-0.221</td>
<td>0.097 0.091 (n.s.)</td>
</tr>
<tr>
<td></td>
<td>$\Delta$slope: Far - MidRange == 0</td>
<td>0.014</td>
<td>0.140 1.000 (n.s.)</td>
</tr>
<tr>
<td>500 ms</td>
<td>$\Delta$slope: MidRange - NearEdge == 0</td>
<td>-0.253</td>
<td>0.100 0.050</td>
</tr>
<tr>
<td></td>
<td>$\Delta$slope: Far - MidRange == 0</td>
<td>-0.028</td>
<td>0.114 0.999 (n.s.)</td>
</tr>
</tbody>
</table>

F-test results for analysis on subsets of data corresponding the three levels of GD.

<table>
<thead>
<tr>
<th></th>
<th>100ms F-statistics.</th>
<th>300ms F-statistics.</th>
<th>500ms F-statistics.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>$F(1, 747) = 44.3$</td>
<td>$F(1, 638) = 53.0$</td>
<td>$F(1, 535) = 47.5$</td>
</tr>
<tr>
<td>Dist. factor</td>
<td>$F(2, 747) = 179$</td>
<td>$F(2, 638) = 62.9$</td>
<td>$F(2, 535) = 67.1$</td>
</tr>
<tr>
<td>log(TTD)</td>
<td>$F(1, 747) = 168$</td>
<td>$F(1, 638) = 140$</td>
<td>$F(1, 535) = 222$</td>
</tr>
<tr>
<td>log(TTD): Dist</td>
<td>$F(2, 747) = 12.8$</td>
<td>$F(2, 638) = 2.53$</td>
<td>$F(2, 535) = 99.8$</td>
</tr>
</tbody>
</table>
### F-test results for analysis on subsets of data corresponding the three levels of distance as a factor.

<table>
<thead>
<tr>
<th></th>
<th>Near Edge</th>
<th></th>
<th>Mid-Range</th>
<th></th>
<th>Furthest Away</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>F(1, 822) = 68.6</td>
<td>&lt;.0001</td>
<td>F(1, 566) = 1.29</td>
<td>0.257 (n.s.)</td>
<td>F(1, 531) = 17.8</td>
<td>&lt;.0001</td>
</tr>
<tr>
<td>GD</td>
<td>F(2, 822) = 1.56</td>
<td>0.211 (n.s.)</td>
<td>F(2, 566) = 3.89</td>
<td>0.021 (n.s.)</td>
<td>F(2, 531) = 1.21</td>
<td>0.300 (n.s.)</td>
</tr>
<tr>
<td>log(TTD)</td>
<td>F(1, 822) = 74.7</td>
<td>&lt;.0001</td>
<td>F(1, 566) = 4.55</td>
<td>0.033 (n.s.)</td>
<td>F(1, 531) = 6.74</td>
<td>0.001</td>
</tr>
<tr>
<td>log(TTD): GD</td>
<td>F(2, 822) = 13.9</td>
<td>&lt;.0001</td>
<td>F(2, 566) = 17.9</td>
<td>&lt;.0001</td>
<td>F(2, 531) = 3.69</td>
<td>0.026 (n.s.)</td>
</tr>
</tbody>
</table>

### Level 4C Prediction Behaviour – Predicted Distance to Edge

#### F-test results for analysis on data corresponding to ‘approaching the edge’ subset.

<table>
<thead>
<tr>
<th>Fixed Effects</th>
<th>F-value</th>
<th>P</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>F(1, 1947) = 92.8</td>
<td>&lt;.0001</td>
</tr>
<tr>
<td>Glance</td>
<td>F(2, 1947) = 26.1</td>
<td>&lt;.0001</td>
</tr>
<tr>
<td>log (Dist. observed)</td>
<td>F(1, 1947) = 233</td>
<td>&lt;.0001</td>
</tr>
<tr>
<td>log (Dist. Predicted)</td>
<td>F(1, 1947) = 6.66</td>
<td>0.010</td>
</tr>
<tr>
<td>log(Dist. observed): log(Dist. Predicted)</td>
<td>F(2, 1947) = 12.3</td>
<td>&lt;.0001</td>
</tr>
<tr>
<td>log(Dist. Predicted): Glance</td>
<td>F(2, 1947) = 28.0</td>
<td>&lt;.0001</td>
</tr>
<tr>
<td>log(Dist. Observed): Glance</td>
<td>F(1, 1947) = 50.0</td>
<td>&lt;.0001</td>
</tr>
<tr>
<td>log(Dist. Pred.): log(Dist. Obs.): Glance</td>
<td>F(2, 1947) = 4.69</td>
<td>0.009</td>
</tr>
</tbody>
</table>

#### F-test results for analysis on data corresponding to ‘approaching the edge’ subset, using distance as a three level factor, for near, mid-range, and far distances.

<table>
<thead>
<tr>
<th>Fixed Effects</th>
<th>F-value</th>
<th>P</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>F(1, 1941) = 3.58</td>
<td>0.059</td>
</tr>
<tr>
<td>Glance</td>
<td>F(2, 1941) = 37.5</td>
<td>&lt;.0001</td>
</tr>
<tr>
<td>Dist observed factor (fDist)</td>
<td>F(2, 1941) = 5.82</td>
<td>0.003</td>
</tr>
<tr>
<td>log (Dist. Predicted)</td>
<td>F(1, 1941) = 185</td>
<td>&lt;.0001</td>
</tr>
<tr>
<td>Glance: fDist</td>
<td>F(4, 1941) = 5.24</td>
<td>0.0003</td>
</tr>
<tr>
<td>Glance: log(Dist. Pred)</td>
<td>F(2, 1941) = 44.8</td>
<td>&lt;.0001</td>
</tr>
<tr>
<td>fDist: log(Dist. Pred)</td>
<td>F(2, 1941) = 6.92</td>
<td>0.001</td>
</tr>
<tr>
<td>fDist: log(Dist. Pred.): Glance</td>
<td>F(4, 1941) = 2.80</td>
<td>0.025</td>
</tr>
</tbody>
</table>
F-test results for analysis on subsets of data corresponding the three levels of GD.

<table>
<thead>
<tr>
<th></th>
<th>100ms</th>
<th>300ms</th>
<th>500ms</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>F(1,747) = 3.45</td>
<td>n.s.</td>
<td>F(1, 638) = 20.1</td>
</tr>
<tr>
<td>Dist. factor</td>
<td>F(2,747) = 10.5</td>
<td>&lt;.0001</td>
<td>F(2, 638) = 12.5</td>
</tr>
<tr>
<td>log(Dist. Pred.)</td>
<td>F(1,747) = 248</td>
<td>&lt;.0001</td>
<td>F(1, 638) = 237</td>
</tr>
<tr>
<td>log(Dist. Pred): GD</td>
<td>F(2,747) = 7.12</td>
<td>0.001</td>
<td>F(2, 638) = 6.22</td>
</tr>
</tbody>
</table>

F-test results for analysis on subsets of data corresponding the three levels of distance factor.

<table>
<thead>
<tr>
<th></th>
<th>Near Edge</th>
<th>Mid-Range</th>
<th>Furthest Away</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>F(1, 822) = 2.48</td>
<td>n.s.</td>
<td>F(1, 566) = 1.29</td>
</tr>
<tr>
<td>GD</td>
<td>F(2, 822) = 32.8</td>
<td>&lt;.0001</td>
<td>F(2, 566) = 3.89</td>
</tr>
<tr>
<td>log(Dist. Pred.)</td>
<td>F(1, 822) = 134</td>
<td>&lt;.0001</td>
<td>F(1, 566) = 4.55</td>
</tr>
<tr>
<td>log(Dist. Pred): GD</td>
<td>F(2, 822) = 39.7</td>
<td>&lt;.0001</td>
<td>F(2, 566) = 17.9</td>
</tr>
</tbody>
</table>

Simultaneous Tests for General Linear Hypotheses: Δ estimated coefficients of TTD at all 9 combinations of distance (3 levels) and glance duration (3 levels).

<table>
<thead>
<tr>
<th>GD</th>
<th>Distance (as factor)</th>
<th>Estimate</th>
<th>Std.Error</th>
<th>Adjusted P (single-step method)</th>
</tr>
</thead>
<tbody>
<tr>
<td>100ms</td>
<td>Near the edge</td>
<td>0.268</td>
<td>0.020</td>
<td>0.000</td>
</tr>
<tr>
<td></td>
<td>Mid-range</td>
<td>0.186</td>
<td>0.096</td>
<td>0.386 (n.s.)</td>
</tr>
<tr>
<td></td>
<td>Far from range</td>
<td>-0.133</td>
<td>0.108</td>
<td>0.890 (n.s.)</td>
</tr>
<tr>
<td>300ms</td>
<td>Near the edge</td>
<td>0.345</td>
<td>0.022</td>
<td>0.000</td>
</tr>
<tr>
<td></td>
<td>Mid-range</td>
<td>0.569</td>
<td>0.083</td>
<td>0.000</td>
</tr>
<tr>
<td></td>
<td>Far from range</td>
<td>0.123</td>
<td>0.097</td>
<td>0.875</td>
</tr>
<tr>
<td>500ms</td>
<td>Near the edge</td>
<td>0.600</td>
<td>0.029</td>
<td>0.000</td>
</tr>
<tr>
<td></td>
<td>Mid-range</td>
<td>0.632</td>
<td>0.094</td>
<td>0.000</td>
</tr>
<tr>
<td></td>
<td>Far from range</td>
<td>0.015</td>
<td>0.109</td>
<td>1.00</td>
</tr>
</tbody>
</table>
Simultaneous Tests for General Linear Hypotheses: Δ estimated coefficients of distance predicted, between levels of GD at ‘toward edge’ and ‘away from edge’, respectively.

<table>
<thead>
<tr>
<th>Time (ms)</th>
<th>Linear Hypotheses</th>
<th>Δ Estimate</th>
<th>Std.Error</th>
<th>Adjusted P (single-step method)</th>
</tr>
</thead>
<tbody>
<tr>
<td>100 ms</td>
<td>Δslope: MidRange - NearEdge == 0</td>
<td>-0.082</td>
<td>0.098</td>
<td>0.886 (n.s.)</td>
</tr>
<tr>
<td></td>
<td>Δslope: Far - MidRange == 0</td>
<td>-0.319</td>
<td>0.144</td>
<td>0.114 (n.s.)</td>
</tr>
<tr>
<td>300 ms</td>
<td>Δslope: MidRange - NearEdge == 0</td>
<td>0.600</td>
<td>0.257</td>
<td>0.087 (n.s.)</td>
</tr>
<tr>
<td></td>
<td>Δslope: Far - MidRange == 0</td>
<td>-0.789</td>
<td>0.306</td>
<td>0.046</td>
</tr>
<tr>
<td>500 ms</td>
<td>Δslope: MidRange - NearEdge == 0</td>
<td>-0.089</td>
<td>0.288</td>
<td>0.999 (n.s.)</td>
</tr>
<tr>
<td></td>
<td>Δslope: Far - MidRange == 0</td>
<td>-0.496</td>
<td>0.300</td>
<td>0.999 (n.s.)</td>
</tr>
</tbody>
</table>
Appendix E – List of Acronyms and Abbreviations

<table>
<thead>
<tr>
<th>Acronym</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>AIC</td>
<td>Akaike’s information criterion</td>
</tr>
<tr>
<td>AR</td>
<td>Autoregressive model</td>
</tr>
<tr>
<td>TLC</td>
<td>Time to Line Crossing</td>
</tr>
<tr>
<td>LV</td>
<td>Lead vehicle</td>
</tr>
<tr>
<td>OT</td>
<td>Occlusion time (shutter close time)</td>
</tr>
<tr>
<td>MOT</td>
<td>Mean occlusion time</td>
</tr>
<tr>
<td>GD</td>
<td>Glance duration (shutter open time)</td>
</tr>
<tr>
<td>STD-LP</td>
<td>Standard deviation of lane position over a trial</td>
</tr>
<tr>
<td>STD-Headway</td>
<td>Standard deviation of headway over a trial</td>
</tr>
<tr>
<td>LD</td>
<td>Lane deviation</td>
</tr>
<tr>
<td>TTD</td>
<td>Time-to-drop-off</td>
</tr>
</tbody>
</table>