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Cognitive Driver Distraction Improves Straight Lane Keeping: A Cybernetic Control Theoretic Explanation

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Abstract: Experimental data revealed that drivers performing a visual secondary task exhibited deteriorated lane keeping performance, but that the same drivers performing a cognitive secondary exhibited an improvement in lane keeping compared to baseline driving. In this paper we present a computational cybernetic driver model that characterizes the effect of difference in eye fixation durations between on and off road glances across the three task conditions on straight lane keeping performance. The model uses perceptual cues as control input, maintains internal representations of these cues across fixations through Bayesian updating, and each time a change in cue magnitude is perceived based on mechanisms akin to signal detection theory a change in control is applied. The model is shown to be able to capture the experimental results encouragingly well. The model also sheds light on the relative magnitude of lane keeping performance degradation caused by glancing away from the road and the fact that internal representations are degraded each time a saccade takes place. The adopted approach to modeling driver perception during and across fixations is expected to lead to new insights into the effects that various in-vehicle activities have on driving performance and risk.

Keywords: Driver Distraction, Driver Model, Cybernetics, Perceptual Motor Control, Driver Assessment.

1. INTRODUCTION

Driver multitasking has been shown to not always result in degraded performance on some performance metrics. For example, when drivers drive on a relatively low demand road, their standard deviation of lateral position (SDLP) has been shown to decrease when they engage in a low demand cognitive secondary task (Kountouriotis and Merat, 2015; He, McCarley and Kramer, 2015). A purely cognitive distraction is defined as a secondary task that does not require any eye or hand movements to obtain/manipulate task information; the secondary task only requires cognitive resources (memory and attention). On the other hand, when drivers engage in a low demand visual distraction secondary tasks, their SDLP increases (Ibid.). While this phenomenon has long been known, the mechanism underlying this opposite performance effect of cognitive and visual distraction remains debated. Here we propose a simple visual motor control theory that may help shed additional light on this phenomenon.

A visual secondary task by definition requires eye movements away from the driving task. During normal or baseline driving without performing any secondary tasks drivers naturally move their eyes around the scene as well as to the side and rear view mirrors. During a cognitive secondary task, it is well known that drivers' eye gaze distribution narrows to primarily forward and is often referred to as tunnel vision ((Kountouriotis and Merat, 2015).

Here we entertain the hypothesis that this tunnel vision is one source of the improved lateral driving performance. The underlying mechanism is that eye fixations on stable elements in the environment improve sensitivity with which changes in vehicle state can be perceived and therefore improve the ability to control the vehicle more accurately. To the best of our knowledge a computational model that links gaze stability to control stability has not been previously established except in postural control (Morimoto et al., 2011). Cognitive architecture and queuing network based driver models have been developed and shown degraded lateral control while engaged in secondary tasks (Bi et al. 2012); they have not shown an improvement in lateral position when engaged in a purely cognitive task.

Before presenting details of the eye fixation mediated control improvement it is important to note that while low-level vehicle control improves this does not mean that situation awareness improves and that drivers are also more responsive to unexpected events – to the contrary, cognitive distraction increases risk to unexpected events (Strayer et al., 2006).

2. CYBERNETIC HYPOTHESIS

Straight lane keeping is a control task to keep the state of the vehicle between constraining lane boundaries. The relevant vehicle states are lateral position and heading. The relevant constraints are spatial and temporal proximity to the lane boundaries. Many different control algorithms ranging from classical to optimal control and satisficing control have been proposed and many more can be devised. The goal here is not to discuss or develop a driver control model but to show how an increase in forward eye fixations can improve control.

The straight lane keeping control driver model is defined as a simple PD control of lateral position and heading. Drivers can not perceive lateral position and heading directly but indirectly perceive them through different perceptual cues. In straight lane keeping these cues are splay angle and splay rate as well as focus of expansion relative to the road's vanishing point. The assumption is that lateral position and heading are perceived separately and independently to simplify the explanatory value of the model and simulation results.

Human perception is not one hundred percent accurate nor instantaneous. When the driver perceives changes in lateral position and heading she generates a control action that is represented as a new target steering angle that is reached much like a new hand position is reached in a reaching task (ref). This means that the targeted steering angle change is constrained by neuromuscular dynamics that cause the change in steering wheel position to essentially follow a velocity profile that resembles a raised cosine (smooth increase in steering wheel velocity followed by a smooth decrease as the target angle is reached).

3. COMPARATIVE DATA

The computational simulations presented herein are grounded in and compared against data collected in the University of Leeds Driving Simulator (UoLDS) in the European FORWARN (Kountouriotis and Merat, 2015). The UoLDS is a full Jaguar S-Type cabin inside a dome with surround visuals on top of a hexapod/xy-table motion base.

15 participants each drove a two lane, rural road consisting of both straight and curved road segments. Each segment was approximately 7.5 Km long. For this paper only straight road segments were taken into consideration; each segment was 30s long. Participants drove on average 27mps and their lateral position and eye gaze direction was recorded (v4.5 Seeing Machines faceLAB at 60Hz). The standard deviation of lateral position (SDLP) was computed as well as the duration of glances at the road and the duration of glances at the dashboard or secondary task display. These eye movement data are used to parameterize the model and the SDLP data is used to assess whether the model is capable of replicating the experimental data.

FORWARN studied the effect of two distraction tasks; a visual search task and a counting backwards task. The former "Arrows task" originally developed for the HASTE project (Jamson and Merat, 2005) presents participants a 4x4 grid of left and right orientation arrows on a touch screen high in the central console. Participants needed to press a YES or NO button on the touchscreen to indicate the existence of an upwards pointing arrow in the grid. The experiment was designed so that half of the grids would contain the target arrow. An auditory notification was given when the trial started and when it ended 30 seconds later.

The counting backwards task is a non-visual/cognitively demanding task ("Count Back") where each participant heard a 3-digit numbers through the speakers of the vehicle and had to count backwards in increments of seven starting from that 3-digit number. The task was terminated when a 'beep' sound was heard. The duration of the task, i.e. time from the presentation of a random 3-digit number until the 'beep' was also 30 seconds. Apart from these two distraction tasks, 30s segments of baseline data were also collected ("Baseline), where the driver would simply drive.

For each straight road drive, participants performed the two secondary task conditions for two 30s periods and baseline driving for four 30s periods all interleaved.

The experimental data showed that the "Arrows Task" produced an increase in SDLP but that the "Count Back" task produced a decrease in SDLP (coloured disks in Fig. 8) for the average glance behaviour in Table 1. In this paper we explore in simulation whether a simple driver model can explain the differences in SDLP given the different glance behaviours observed in each task; we do not model the glance behaviour itself only its effect on perception of relevant cues.

4. MODEL

The driver model is divided into a perceptual and a control component. The model is made as simple as possible to highlight the benefits of prolonged eye fixations at perceptual cues that inform about vehicle states as well as to demonstrate the effect of different eye glance patterns on lane keeping performance.

4.1 Perceptual Model

A change in cue magnitude is easier to detect during continued fixation at the cue than across saccades away from the cue (Sec. 2). Here we describe how we modelled this effect using Bayesian combining and signal detection theory.

Perception Dynamics

To keep the model relatively simple at this stage we ignored the neural dynamics of differencing new sensory input against an array of delayed past sensory inputs. Instead we assumed that only a single internal representation is maintained that is a Bayesian combination of past perceptions. Furthermore, we assumed that a new perception is made every 50ms (Salvucci, Boer and Liu 2001; Salvucci and Taatgen, 2010). This new cue perception (represented by a Gaussian distribution) is compared against the internal representation (Gaussian distribution) and depending on whether a change is detected a different event occurs. If a change is not detected, then the cue perception is combined with the internal representation of the cue magnitude in a Bayesian fashion. This yields a narrower internal representation distribution that makes detection of change more accurate and is the mechanism underlying the improved detection of change sensitivity due to prolonged fixation on a cue. If, on the other hand, a change is detected, then the internal representation is replaced by the new percept. This means in general that the standard deviation of the internal representation temporarily increases.

As soon as a saccade is made to a different fixation point, the internal representation is erased and only a rough internal representation remains of the cue magnitude (assumed at 10 times the standard deviation of the distribution associated with a single perception). This assumption is based on the fact that humans are blind during a saccade (Burr, Morrone &

Ross 1994). When the fixation returns to the original spot, a comparison is made against this rough internal representation and the process of Bayesian combination and signal detection mediated comparing repeats.

The question is what type of uncertainty or standard deviation should be assumed for a cue perception. Here we refer to the well-known concept of Just Noticeable Difference (JND).

JND Based Distribution of a Cue Perception

JND in human perception is related to the fact that a physical signal needs to change by about 10% (some more, some less) in order for the human to perceive that a change has occurred in a pairwise comparison. The assumption is that the 10% is the difference between the larger and the smaller magnitude divided by the larger magnitude to avoid singularity when comparing against zero. As in all signal detection tasks, the accuracy depends on the confidence required to make the judgment that a change took place (ref SDT). We assume here that the simulated human driver adopts a 95% confidence or hit rate in judging whether a change in cue-magnitude took place or not. To yield a 95% hit rate (5% false alarm rate) for a 10% change in cue magnitude, the standard deviation around a nominal cue magnitude can easily be computed; see below for computation of the nominal cue magnitude for lateral position (-1.3333) and heading (-2.1333). The associated standard deviation for lateral position is 0.0023 and for heading is 0.0032.

Vehicle State Change Perception

A change in vehicle state is detected when the driver is 95% confident that the current cue percept differs from the current internal representation of that cue (Fig 1).

Perceptual Vehicle State Cues

Drivers do not perceive lateral position and heading directly. They perceive many cues that are mathematically related to these relevant vehicle states. Here we assume that lateral position is defined as the angle of the lane marking (assume, without loss of argument, the right side) relative to a vertical lane marking which is perceived when the eye point is above the lane marking. Adopting a simple camera model of the human eye defined by a focal length *f* and camera height *h*, the angle of the right lane making in camera coordinates is

$$c_\delta = -\frac{\delta}{h}$$

where $h = 1.5m$ and δ is the distance from the eye point to the right lane boundary. Using the same camera model and the assumption that the road is viewed through a vertical rectangular $w = 1.6m$ meter wide windscreen placed symmetrically around the eye point at a distance $d = 0.75m$, the heading is perceived as the difference between where the right lane marking cuts through the horizon and where the right pillar or the windscreen cuts through the horizon

$$c_\phi = -f\left(\frac{w}{d} - \phi\right)$$

With the assumption that the lane width is 4m, the nominal values of these cues at the target lateral position 2m to the left of the right lane boundary at a zero heading are respectively $c_\delta^0 = -1.3333$ and $c_\phi^0 = -2.1333$.

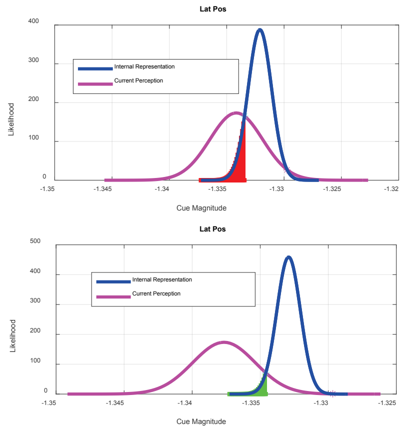

Fig. 1. Depiction of how signal detection theory is used to model when a current perception of a cue leads to the realization that a change in cue magnitude has occurred relative to the continually updated internal representation. Top panel shows that the two distributions (perception and internal representation) are not sufficiently different yet to yield a 5% false alarm rate for detection. Bottom panel shows when the distributions do differ sufficiently to register a change-detection with a 5% confidence or better.

4.2 Control Model

The vehicle speed v is assumed constant at the average speed of the drivers in FORWARN, namely 27mps.

Vehicle Model

The vehicle is represented as a point mass with simple 3rd order dynamics (Fig. 2). The vehicle yaw rate γ is assumed to be the output of this 3rd order vehicle dynamics filter with as input the control command (target yaw rate) based on perceived lateral position and heading cues (see below).

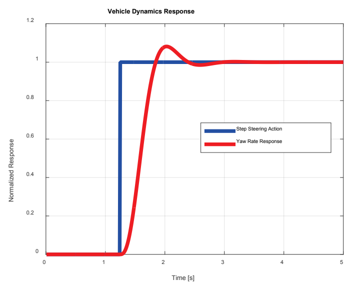

Fig. 2. Dynamic response of a simple vehicle model captured in a 3rd order Butterworth filter with a 1.0Hz cut-off frequency. Note the 0.5s lag at the 50% response magnitude.

Controller

Each time a change in vehicle state is detected, a new steering control action is issued. An important question is why drivers do not simply issue a new control action every 50ms but instead wait for a detected change in vehicle state. The reason is two-fold. First and foremost, in order to be able to learn the response characteristics of a system it is beneficial to wait for responses to issued control actions. Second, if the system is sluggish and the driver continues to issue corrective control actions the risk is that too much control is applied and instability results. Future models will distinguish between these closed loop control corrections around a steady state and open loop control actions to reach a particular state (e.g. upon curve entry or exit or upon return from a long glance away from the road when the state of the vehicle is critical or outside the satisficing set).

Control is obtained in two steps: i) a new target yaw-rate is computed from a PD controller (see below), ii) the new target yaw-rate θ^{*}_{n-1} is passed through a 3rd order filter that represents the vehicle plus neural dynamics (Fig. 2).

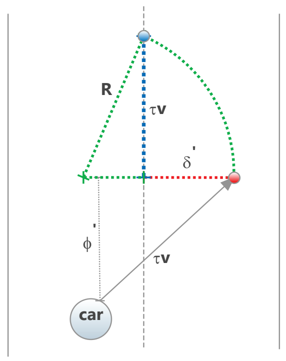

Fig. 3. Depiction of predicted and target vehicle states for the design of a geometric PD-controller.

The car lateral position δ' is predicted $\tau = 3s$ seconds ahead which is the settling time of the vehicle's dynamic response (Fig. 2). The controller is configured to bring the car's predicted lateral position δ' back to zero in 3s under the assumption of a zero heading at the predicted point. This means that the radius of the green arc target car path equals the length of the blue straight line in Fig 3. Simple geometry shows that the radius is obtained by with Pythagoras theorem

$$(R-\delta')^2 + (\tau v)^2 = R^2 \Rightarrow R = \frac{\delta'^2 + \tau^2 v^2}{2\delta'}$$

and that the target yaw-rate is therefore

$$\gamma^{*} = v\frac{1}{R} = \frac{2v\delta'}{\delta'^2 + \tau^2 v^2} \approx \frac{2\,\mathrm{v}}{\tau^2 v^2}\delta' = \frac{2\,\mathrm{v}}{\tau^2 v^2}(\delta + \tau v \phi)$$

which is a PD-controller is disguise. This yaw-rate is passed through the vehicle dynamics (Fig. 2) and integrated to heading and the heading is integrated to update vehicle x and y positions in the world. The x-position is equal to the lateral position because the centre of the lane is aligned with the y-axis. Of course a better controller can be designed but the purpose here it to show the effect of gaze fixation patterns on driving performance, not to establish an accurate representation of human straight lane keeping.

Optimization of PD-Controller Coefficients

The assumption is that drivers optimize their control gains for each driving condition. Ideally the optimization should minimize a meaningful risk or safety margin metric such as the mean inverse time-to-line-crossing over the duration of the task. At the current stage of this work, we assumed the fixed controller coefficients detailed above across the three task conditions and performed the optimization on different model parameters only to produce a match in SDLP with experimental data (see Sec. 5). The response of the driver model without execution noise to an initial lateral position and initial heading offset is shown in Fig. 4.

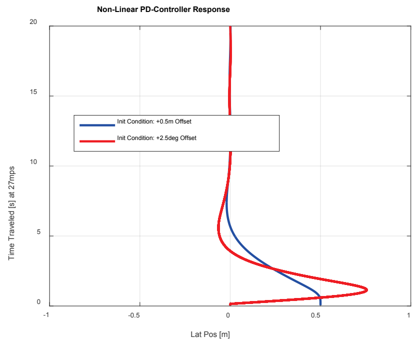

Fig. 4. Vehicle control response to a 0.5m lateral position offset (top panel) and a 10deg heading offset (bottom panel).

Control Noise

Manual vehicle control is plagued by execution noise and road noise, both of which are lumped into one noise signal that acts on the front wheel angles and thus controls yaw-rate directly. The effect of this 0.5Hz band limited Gaussian noise with the final optimal magnitude (Sec. 5) is shown for six noise incarnations in Fig. 5 where the car is only controlled by the noise while no control is applied. It is clear that within 10s the vehicle can drift almost out of the lane.

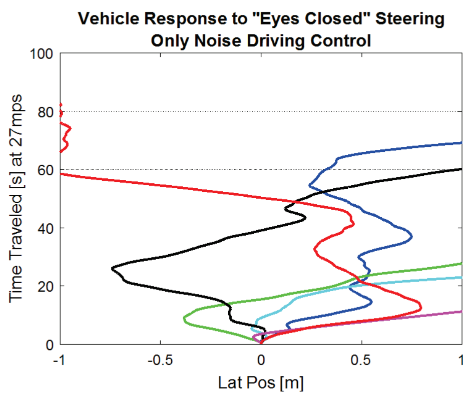

Fig. 5. Set of different trajectory of the vehicle when only execution and road noise are driving the vehicle (i.e. as if eyes are closed); different noise incarnations.

4.5 Eye Movements across Conditions

The FORWARN experimental eye fixation data were analysed and summarized in Table 1. For the driver model simulations we assume that all fixations away from the road are of the same duration as the experimentally observed mean. We also assume that drivers attempt to look away from the road after a fixed time has elapsed again equal to the observed mean; however if the risk is too high (i.e. lateral position predicted 3s ahead with straight heading prediction exceeding 1m) then the driver continues control and waits until the risk becomes acceptable before glancing away.

Table 1. Glance Statistics for experimental FORWARN data for five subjects with clean eye tracking data.

Mean Eye Glance Durations	Baseline	Count Back	Arrows Task
Look Away	0.50s	0.22s	1.34s
Look at Road	2.62s	9.20s	1.05s
Time Between Look Away Glances	3.12s	9.44s	2.39s

Each of the three task conditions' eye glance pattern are assumed to switch between two glance locations. The first is on-road to a location where the car state can be perceived (lateral position and heading); in reality these two vehicle states may require different cues and thus attention and fixation is shifted between them. At the moment we assume that both cues are fully attended to when fixation is on the road. The second glance location is off-road to a location where the visual secondary task can be performed (Arrows Task) or where the speedometer can be read (Baseline and Count Back). These three mean eye movement characteristics are used in the simulations below to quantify the effect of eye gaze profiles on lane keeping; i.e. simply cycle eye gaze location from on-road to off-road based on times in Table 1.

5. SIMULATION RESULTS AND DISCUSSION

The driver model (Sec. 4) was run for the eye movement profiles associated with the three task conditions (Baseline, Count Back and Arrows Task) detailed in Table 1 and compared against experimental data from the FORWARN project subjects (Kountouriotis & Merat, 2016). The two free model parameters discussed next are manually tuned to minimize the difference between model produced and experimentally observed mean SDLP values. The results in Fig. 8 show that the model produced SDLP (diamonds) closely match those observed experimentally (disks).

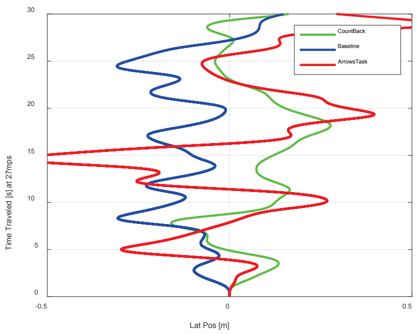

Fig. 6. Lateral position profiles for the three task conditions.

The driver model has a number of parameters most of which were fixed based on rational assumption discussed in Sec. 4. Two of the parameters were kept free to explore whether that would suffice to fit the experimental data. The *first* is the magnitude of the noise (i.e. execution plus road noise). The spectral shape of the noise was white noise limited to a 0.5Hz bandwidth (Gaussian noise passed through a 7^{th} order Butterworth filter). This parameter shapes the magnitude of the SDLP. The *second* free parameter is the threshold in predicted lateral position 3s ahead beyond which eyes are not diverted away from the road. This risk parameter shapes the non-linear increase in SDLP when eyes are taken off the road more frequently and longer as is the case in the Arrows Task. In that case the driver often does not have enough time to fully control the vehicle back to stable forward state before looking down at the task display again. The driver essentially has to adopt a threshold in risk below which he will divert his eyes away from the road. The optimal value of this risk threshold is 1.0m; thus if the straight heading predicted lateral position 3s ahead exceeds 1.0m, then eyes are not diverted yet and control is continued to bring the car to a safer state before diverting eyes.

The time series of lateral position for each of the three task conditions for a 30s period is shown in Fig. 6. Model produced SDLP results are compared against experimentally obtained mean SDLP in Fig. 8. An important point to make in reference to Fig. 6 is that the number of peaks in the lateral position within a 30s period are on the order of 10 which is the same as in the experimental data. This is important because it indicates that vehicle dynamics, noise bandwidth and control updates that are driven by the time interval between detection of changes in cues are all reasonable. In future models these assessments will be extended to actual control input at the torque level to provide more conclusive support for model validity.

A key element of the model is the fact that control is changed only when a change in lateral position or heading cue is detected (Fig. 7). It is clear from Fig. 7 that the frequency of cue change detections (density of yellow or green diamonds) is low immediately following a glance away (red) and that it then increases quickly as the gaze remains fixated on the perceptual cue until the next glance away. This is the result of the Bayesian combining discussing in Sec. 4.1.

Interestingly and unexpected, the frequency with which changes in lateral position are detected is much greater (more yellow diamonds) than for heading (green diamonds). This means that the adopted heading cue is less salient and informative than the lateral position cue. Arguably, there are many cues that drivers can use that are sensitive to lateral position and heading changes and we plan to explore a number of them analytically in future research.

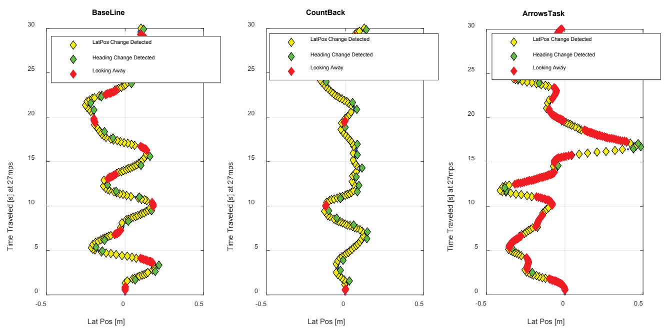

Fig. 7. Indication of when a change in lateral position (yellow) or heading (green) is perceived and when the eyes were off the road (red).

The other results in Fig. 8 (i.e. yellow, cyan and magenta) are generated to explore the effect of brief 50ms (one time step) away eye glance alone. We assume that a glance away has two effects on driving (Sec. 4): i) during the eye diversion away from the road the driver does not perceive visual control cues and thus cannot detect changes in vehicle state, and ii) when the driver makes a saccade, no matter how short (minimal one brain update duration of 50ms) the internal-representation of the cues used for control degrades. The relative effect of these two effects on SDLP is exposed in the yellow, cyan and magenta results in Fig. 8.

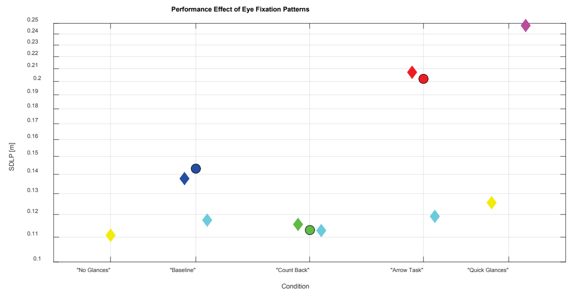

Fig. 8. Simulation results (diamonds) compared to experimental data (circles). The blue, green and red markers reflect the effect of the observed eye glance behaviour for each of the three task conditions. The yellow and cyan filled diamonds show the effect of glances that only disrupt the internal representation but have no off-road duration.

The "No Glances" yellow diamonds shows the SDLP when eyes are never diverted away from the road and thus the internal representation is never reset to a wider distribution. On the other end of the spectrum the "Quick Glances" yellow diamond shows the SDLP when a saccade is made every second but that 50ms later the eyes are back on the driving task. In this case the internal representation is reset but eyes are effectively continuously on the road. If the frequency of these "Quick Glances" is increases from every second to every 100ms (magenta diamond) we see a huge increase in SDLP exceeding that of the Arrows Task. This is due to the fact that the driver now never has the benefit of combining perceptions to improve the internal representation that boost detection of change performance.

From the simulation results it is clear that the effect of "Quick Glances" is about a 15% increase in SDLP compared to "No Glances". This "Quick Glances" SDLP falls between the impact of "Count Back" which is close to "No Glances" performance because of the very few look away glances and "Baseline" with more but relatively short away glances. The "Arrows Task" shows the worst performance because of the frequent relatively long away glances as detailed in Table 1.

The cyan diamonds associated with each task condition show what the effect on SDLP is if the frequency of eye glances is kept the same as for the task but the duration is set to one time step so as to only reset the internal representation. We see again that this greatly improves performance to a level about 5-10% worse than "No Glances".

6. CONCLUSIONS

The relatively simple cybernetic driver model shows that the protective effect of a cognitive secondary task can be reproduced by accounting for the reduced eye glance frequency and fixation durations away from the road compared to baseline driving. The other hypothesis explored was that the effect of fixating longer on the control cue without glancing away would yield an increased sensitivity in detecting cue changes that would lead to a substantial improvement in driving stability. While an effect of 15% was indeed observed, not surprisingly it is much smaller than that of frequently looking down for extended periods of time.

This paper demonstrates encouragingly that the proposed mechanism by which a saccade disrupts the internal representation of a visual cue may explain some of the apparently protective effects observed when drivers decrease their glance frequency and fixate on key visual control cues.

The paper also presents a simple model for explaining and exploring the effects of different visual scanning strategies on lane keeping performance. The model was capable of accurately replicating the experimental results that a purely cognitive task can indeed improve driving performance purely based on a change in glance behaviour.

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