Proceedings Paper:
Markkula, G orcid.org/0000-0003-0244-1582, Romano, R orcid.org/0000-0002-2132-4077, Waldram, R et al. (3 more authors) (2018) Modelling visual-vestibular integration and behavioural adaptation in the driving simulator. In: Proceedings of the Driving Simulation Conference 2018. Driving Simulation Conference 2018, 05-07 Sep 2018, Antibes, France. Driving Simulation Association .

Modelling visual-vestibular integration and behavioural adaptation in the driving simulator

Gustav Markkula[1], Richard Romano[1], Rachel Waldram[2], Oscar Giles[1], Callum Mole[2], and Richard Wilkie[2]

(1) Institute for Transport Studies, University of Leeds, LS2 9JT, Leeds, UK.
(2) School of Psychology, University of Leeds, LS2 9JT, Leeds, UK.
e-mail : {g.markkula, r.romano, um13rjw, o.t.giles, c.d.mole, r.m.wilkie}@leeds.ac.uk

Abstract - *To test hypothesised mechanisms behind driver response to down-scaled motion cues in simulators, a driver steering model was developed, by extending an existing modelling framework with models of multisensory integration and behavioural adaptation. In a slalom task, the model robustly reproduced several empirical findings : Removing motion cues initially resulted in decreased task performance and increased steering effort, but after behavioural adaptations, performance improved and steering effort went down. Unexpectedly, the model also reproduced another empirical finding : Optimal path-tracking for an intermediate motion scaling, smaller than unity. Overall, together with the existing empirical findings, the simulation results suggest that : (1) Drivers make direct use of vestibular inputs as part of determining appropriate steering input, and (2) motion down-scaling causes drivers to behave as if they are underestimating the vehicle's rate of rotation. However, (3) in the slalom task, a certain degree of such underestimation brings a path-tracking performance benefit. Furthermore, (4) behavioural adaptation, as empirically observed, may occur in the form of (a) down-weighting of vestibular cues, and/or (b) increased sensitivity to control errors, in determining when to adjust steering and by how much, but (c) seemingly not in the form of a full compensatory reinterpretation of the down-scaled vestibular input.*

Keywords: *multisensory integration, motion scaling, driver model, steering, slalom*

Introduction

Driving simulators can be valuable tools for research on driver behaviour, industrial prototyping of vehicles, and training of drivers [Fis11], but only as long as the realism of the simulated driving is satisfactory for the application at hand. For this reason, research into driving simulator realism and validity is an active field of work, not least when it comes to the *motion cueing* in motion-based simulators ; i.e., how to best control the motion base within its limited motion envelope to nevertheless create a subjectively realistic experience of vehicle movement for the driver, and to elicit objective driver behaviour that is successful, and ideally similar to that in a real vehicle [Sie01, Fis16, Sal17].

Typical motion cueing algorithms attempt to leverage the properties and limitations of the vestibular (motion) sensory organs in the inner ear, the otoliths and semicircular canals, and these systems are relatively well understood and modelled [Nas16]. However, much less is known about how drivers then integrate this vestibular information with information from other sensory modalities (e.g., vision) to support vehicle control, how these processes are affected by the specific nature of the non-perfect motion cues being provided, and how drivers adapt over time to such imperfections. As a consequence, it is currently not known how to optimise motion cueing algorithms to yield low-effort, high-performance driver behaviour in the simulator, and/or behaviour that is similar to that in a real vehicle.

Below, the aims and structure of this paper will be described, after first providing brief overviews of (i) existing empirical knowledge about drivers' response to down-scaled of motion cues, a special case of motion cueing, and (ii) existing models of multisensory integration.

Studies on simulator motion scaling

Most motion cueing algorithms will include some element of linear down-scaling of the actual motion of the vehicle, to stay within the motion envelope of the simulator, all the way down to zero motion scaling in fixed base simulators. One often observed effect of motion scaling is that drivers adapt speed inversely to the provided motion, seemingly to keep perceived acceleration within acceptable limits, resulting in more aggressive driving when motion is scaled-down or absent altogether [Sie01, Jam10, CG11, Ber13].

Some tasks, which stay within a constrained lateral area, can be carried out with linear motion scaling as the only motion cueing manipulation in the lateral direction. Slalom tasks have been studied in this way by several authors, providing converging evidence for some behavioural phenomena : Steering effort, for example measured as steering reversal rates or high frequency steering content, generally increases when motion cues are removed [Fee10, CG11, Sav14], and task performance, objectively measured or subjectively assessed, generally deteriorates [CG11, Ber13], although not always [Sav14]. After repeated exposure to the slalom task, control efforts decrease [Fee10] and task performance improves [CG11]. There are also consistent reports from several studies of a local optimum at sub-unity motion scaling, in the 0.4-0.8 range, of task performance and subjective preferences [Ber13, Sav14], and in one case also of steering effort [Sav14].

Models of multisensory integration

Multisensory integration has been studied for a long time, especially in simplified perception and sensorimotor tasks in the laboratory ; see for example the reviews in [Fet13] and [Nas16], from neurobiological and vehicle control perspectives, respectively. It is well established that humans often behave as near-ideal Bayesian observers, combining cues from different modalities as weighted sums, with weights computed from the *reliability* (inverse variance) of the respective sensory cues. [Nas18] has proposed a driver steering model incorporating this concept into a Kalman filter step of an optimal control theoretic model. This framework seems promising, but validation against driving data has not yet been published, and the framework also does not include any account of mechanisms for behavioural adaptation, nor is there any account of how the driver's brain identifies the reliabilities of the respective sensory signals.

Another type of framework, which seems to provide a plausible handle on such reliability estimation, emphasises *predictive processing*, the idea that a fundamental function of the brain is to predict its own sensory inputs [Fri10]. In our reading of this theory, if one has a predictive (generative model) of one's own sensory input that is relatively stable, reliabilities can be estimated from the deviations between received and predicted sensory data.

Aims of this paper

Here, a slightly less complex base steering model than [Nas18] will be proposed, and then complemented with some hypothesised mechanisms for cue reliability estimation and behavioural adaptation, with the aim being to investigate whether this model is enough to account for the aforementioned findings on (i) how humans first react to down-scaled motion cues, and (ii) how this behaviour changes with repeated task exposure. It was not an original aim of this work to study the phenomenon of a sub-unity local optimum in motion scaling, but as will become clear below, the model turns out to be applicable also to this phenomenon.

Below, the steering model is first introduced. Then, results from model simulations are presented, before a discussion and conclusions are provided.

Driver steering model

Fig. 1 provides a schematic overview of the model being tested here, further described in the sections below.

Slalom desired path

The model adopts the commonly used concept pf a *desired path* [Plo07] to define the sinusoidal slalom task, which was here based on [Fee10], with 62.5 m spacing between cones, and a 3 m lateral amplitude, carried out at 70 km/h constant longitudinal speed.

Intermittent control framework

The model includes a framework for intermittent sensorimotor control, defined in detail in [Mar18a] (orange dashed box in Fig. 1). In brief, this framework assumes that a continuously calculated estimate of currently needed control adjustment $\Delta\delta$ is compared to a prediction of the same, to yield a prediction error. This prediction error is then fed, with a gain k, into an *evidence accumulation*, or *drift diffusion*, step where it is integrated over time to a threshold of ± 1, mimicking neurobiological decision-making mechanisms [Gol07], to decide on when a control adjustment is needed. When a decision threshold is reached, the evidence accumulation integrator is reset to zero, a steering adjustment is initiated, and a prediction is made of how $\Delta\delta$ will be affected. The steering adjustment is applied in the form of a kinematic *motor primitive* [Gis15], a fixed-duration (ΔT = 0.4 s) stepwise movement with a bell-shaped rate profile, and total amplitude from the current $\Delta\delta$ prediction error, with signal-dependent motor noise [Fra11]. The prediction is also applied in the form of a primitive, stereotyped response, mimicking neurobiological corollary discharge [Cra08, Req14] (an alternative to formulations based on *efference copy*, avoiding the need for an explicit forward model [Pic14]).

Needed steering adjustment

In the engineering literature, there are several driver steering models [Gor06, Tan12, Mar14] on the general form :

$$\Delta\delta = -K\hat{\omega}_{\text{err}} = -K(\hat{\omega} - \hat{\omega}^*), \tag{1}$$

where $\hat{\omega}^*$ and $\hat{\omega}$ are desired and actual vehicle yaw rate, as perceived by the driver, and K is a response gain. Interestingly, models in the psychological literature, emphasising more plausible visual inputs such as sight point rotations, can be shown to be equivalent to Eq. (1) [Mar13].

Here, $\hat{\omega}^*$ is defined as the yaw rate that would take the vehicle back to the desired path in a preview time T_{P}. This formulation has been shown to successfully replicate human slalom steering, with $T_{\text{P}} \in [1.4, 2.2]$ s [Mar18b] ; here T_{P} = 1.8 s was used.

Visual-vestibular integration

As indicated in Fig. 1, the dynamics of the sensory organs are not explicitly modelled here. This is in part to limit model complexity, but primarily because even though detailed models exist of how for example vestibular inputs get transformed into neural firing rates in the inner ear, there is very limited knowledge of what happens with this information in the rest of the brain. Here, in line with much psychophysical work [Fet13], the multisensory integration is modelled as operating directly on estimates of the external stimulus, in this case vehicle yaw rate, where otoliths and semicircular canals are subsumed into a single estimate of yaw rate (note that in a vehicle, lateral acceleration, as sensed by the otoliths, typically provides good information on yaw rate also) :

$$\begin{aligned}\hat{\omega} &= W_{\text{vis}}\hat{\omega}_{\text{vis}} + W_{\text{ves}}\hat{\omega}_{\text{ves}} \\ &= W_{\text{vis}}(\omega_{\text{vis}} + \nu_{\text{vis}}) + W_{\text{ves}}(\omega_{\text{ves}} + \nu_{\text{ves}}),\end{aligned} \tag{2}$$

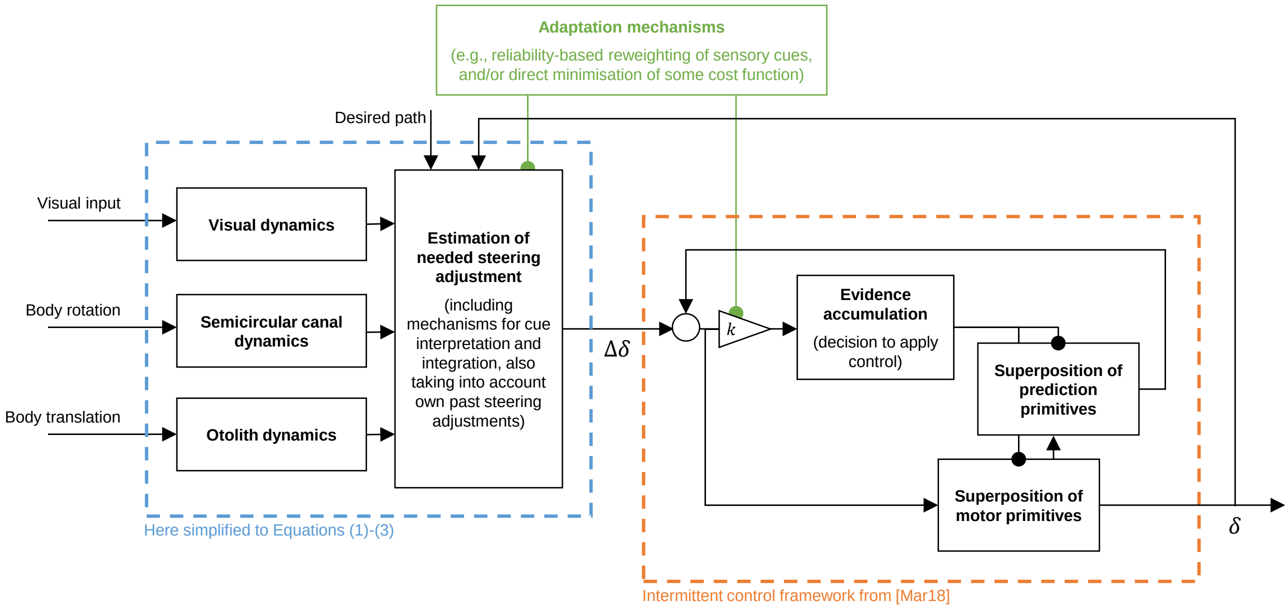

Figure 1: Schematic illustration of the driver steering model tested in this paper.

where $\omega_{\text{vis}} = \omega$ and $\omega_{\text{ves}} = \omega_{\text{body}} = \alpha\omega$, with ω_{body} the actual rotation of the driver's body, α the motion scaling being applied, ω the yaw rate of the simulated vehicle, and ν_{vis} and ν_{ves} being Gaussian white noise with standard deviations σ_{vis} and σ_{ves}. The weights are obtained in line with the aforementioned optimal cue integration theory :

$$W_{\text{vis}} = \frac{r_{\text{vis}}}{r_{\text{vis}} + r_{\text{ves}}}, \quad W_{\text{ves}} = \frac{r_{\text{ves}}}{r_{\text{vis}} + r_{\text{ves}}}, \tag{3}$$

with r_{vis} and r_{ves} being the respective sensory reliabilities.

Thus, overall, what is suggested here (in the blue dashed box in Fig. 1) is that drivers might behave *as if* (i) they transformed the neural output from their sensory organs into estimates of yaw rates, presumably considering also predictions based on knowledge of past steering input, allowing counteraction of sensory delays which are therefore not modelled here, (ii) integrated these yaw rate estimates as per Eqs. (2) and (3), and then (iii) compared the result to a visually estimated desired yaw rate, to calculate the needed steering adjustment as per Eq. (1). Note the, "as if"– it is not assumed that drivers' brains necessarily directly encode things like desired paths or yaw rates, desired or actual, anywhere.

Here, $\sigma_{\text{vis}} = 0.5$ °/s was used, loosely based on [Nes15], who found that humans could discriminate between visual rotation stimuli of about 5 °/s, at which yaw rates typically peak in the present slalom task, if they were different by 1 °/s. The 0.5 °/s noise level gives 75 % correct direction classification, by a drift diffusion model such as in the intermittent control framework used here, of a 1 °/s stimuli if presented during 10 s, a similar duration of presentation as in [Nes15]. The literature on how visual and vestibular sensory systems compare in terms delays or noise levels provide conflicting information for different types of experimental condition [Nas16], so for simplicity we here set $\sigma_{\text{ves}} = \sigma_{\text{ves}}$, to begin with. Further below we examine model sensitivity to noise levels.

It is assumed that when entering the simulator, based on prior driving experiences, reliabilities are preset based on the sensory noise levels, $r_\bullet = \sigma_\bullet^{-2}$, which with $\sigma_{\text{vis}} = \sigma_{\text{ves}}$ gives $W_{\text{vis}} = W_{\text{ves}} = 0.5$.

Behavioural adaptation

A number of mechanisms for behavioural adaptation are assumed to be operating, alone or in combination :

(A) Adapting steering response K.

(B) Adapting effort by changing the gain k in the evidence accumulation.

(C) Sensory cue reweighting, with reliabilites estimated from deviations from expected yaw rate as mentioned above. It is assumed here that the driver has learned a relatively accurate model of how yaw rate will change with a given change of steering. This means that the model can correctly estimate σ_{vis} from deviations $\hat{\omega}_{\text{vis}} - \omega$, and also similarly estimate σ_{ves} as long as motion scaling is unity, $\alpha = 1$. However, when $\alpha \neq 1$, the estimation of σ_{ves} will be affected by the bias

$$\omega_{\text{body}} - \omega = -\omega(1 - \alpha). \tag{4}$$

(D) Reinterpreting downscaled vestibular cues, by relearning the mapping from vestibular organ output to ω_{ves}, i.e., $\omega_{\text{ves}} = \omega_{\text{body}}/\alpha$, which at the same time also scales up the vestibular noise by $1/\alpha$. Reweighting of cues as in (C) was also included here.

The first two above require some form of target for the formal optimisation, here in the form of a cost function to be minimised, by means of exhaustive search over a grid of the optimised parameters :

$$J_{\text{tot}} = k_{\text{path}} J_{\text{path}} + k_{\text{steer}} J_{\text{steer}}$$
$$= k_{\text{path}} \frac{1}{N} \sum_{k=1}^{N} (y_k - y_k^*)^2 + k_{\text{steer}} \frac{1}{T} \sum_{i=1}^{n} g_i^2 \quad (5)$$

for a simulation of duration T, with N discrete samples, in which n discrete steering adjustments with amplitudes g_i are applied, and with lateral positions of vehicle and desired path y_k and y_k^*, respectively. The weighting parameters were set to $k_{\text{path}} = 1$ and $k_{\text{steer}} = 10$ to get similar magnitudes across both terms in typical simulations with the model. Using this cost function, also the following alternative adaptation mechanism was tested :

(E) Adapting sensory weights not based on reliabilities, but instead to minimise J_{tot}.

And finally :

(F) All adaptations (A)-(C) at the same time.

Simulations and results

Method

Simulations were run with a linear vehicle model, fitted to multibody simulations of a Jaguar XF driving slaloms, mostly in the linear tyre regime.

For the gains k and K to be adapted, initial values, emulating already attained driving skill, were set by minimising average J_{tot} across ten repetitions of the slalom (since the driver model is stochastic) with full motion ($\alpha = 1$), searching an exhaustive grid of values for both gains. Optimal model performance was obtained for $k = 300$ (arbitrary units) and $K = 2.04$ s. It may be noted that this latter figure is very close to the theoretically optimal 1/0.510 s = 1.96 s, with 0.510 s^{-1} being the steady state yaw rate response gain of the vehicle model.

For motion gains $\alpha \in \{0, 0.2, ..., 1\}$, simulations were then run both without any behavioural adaptations, with each of the behavioural adaptations (A)-(F) described above. Again, each condition was repeated ten times. For all adaptations including reliability-based cue reweighting (C, D, and F), this was achieved by setting the reliabilities based on the sensory deviations observed in the previous repetition of the slalom. To allow this process to converge from the initial, default sensory weights, two repetitions were simulated before the ten to be analysed.

Impact of motion scaling and behavioural adaptation mechanisms

Yaw rate estimation

Fig. 2 provides an illustration of the visual-vestibular estimation of yaw rate, from simulations with the model under different conditions. The top panel shows a simulation with full motion cues, the other three are all simulations with downscaled motion cues ($\alpha = 0.4$). Note that without any adaptation whatsoever (second panel from top), the integrated estimate of yaw rate becomes strongly biased towards zero, as per Eq. (4). This bias all but disappears when reweighting the cues based on prediction-estimated reliabilities (third panel). If reinterpreting the vestibular

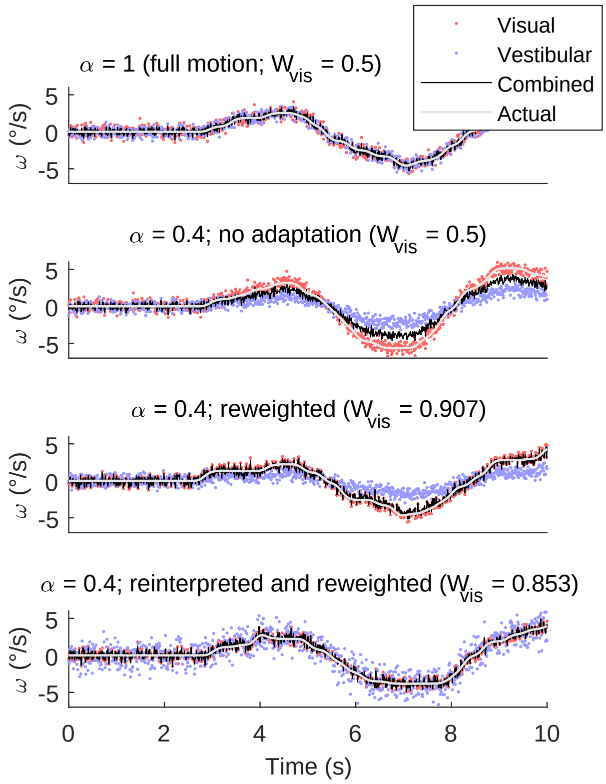

Figure 2: Yaw rate estimation by the driver model in four different simulations.

cues (bottom panel), a completely non-biased estimate can again be obtained, making what would seem like a theoretically optimal use of the vestibular cue, despite the noise also becoming inflated with the reinterpretation.

Model time series behaviour

Fig. 3 shows example time series behaviour of the model in the same four conditions as in Fig. 2. Without any adaptation, the model's steering becomes unstable when motion is scaled down, resulting in increasing path and steering costs. This instability is counteracted when downweighting vestibular cues, both with or without prior reinterpretation of the vestibular input, but steering efforts still remain higher than in the full motion case. Note, however, that the lowest path cost is obtained for the simulation with reweighted (but not reinterpreted) cues.

Task performance and steering effort

A more complete overview of path-tracking and steering costs, as a function of motion scaling and adaptation mechanisms, is provided in Fig. 4. It can be noted that, in line with most empirical reports, steering efforts increase with decreasing α. This is especially true in the no-adaptation condition, but all of the behavioural adaptation mechanisms succeed at improving the situation, aligning with the empirical reports of decreasing steering efforts after prolonged exposure to the slalom task.

Related patterns can be observed for the path tracking costs, but with the important difference that

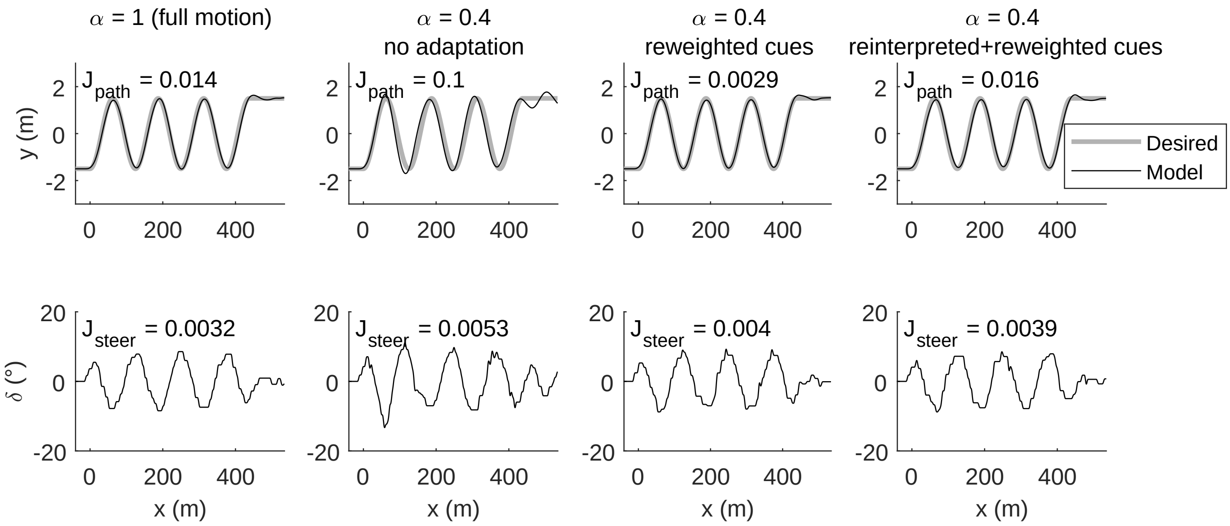

Figure 3: Example time series behaviour of the model in three different simulations.

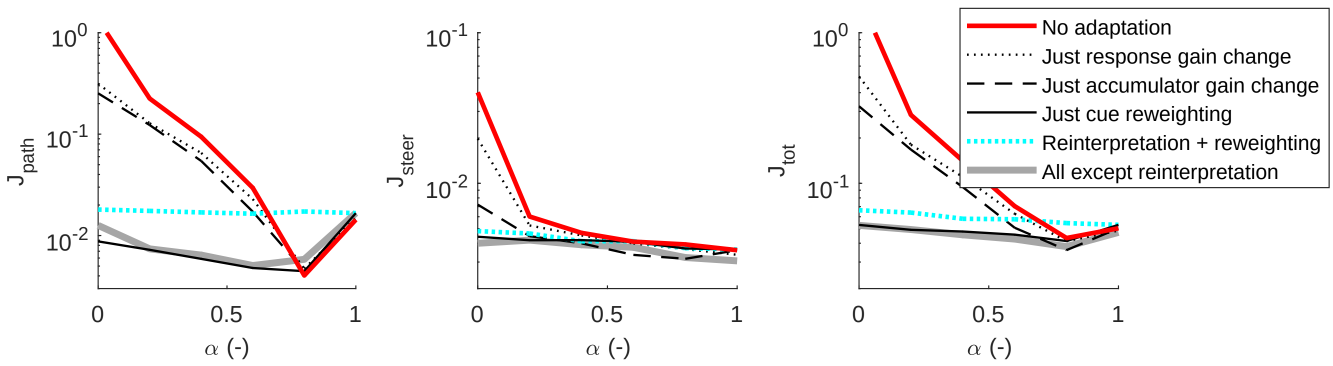

Figure 4: Costs as a function of motion scaling, for the various hypothesised adaptation mechanisms

for all simulations except the one with cue reinterpretation (adaptation D), there is a local minimum at $\alpha \in [0.6, 0.8]$, i.e., the model reproduces also the sub-unity local optimum for motion scaling that has been reported in the empirical literature. After applying the reinterpretation adaptation, there is virtually no effect of motion scaling on the model's task performance.

Analysing the values of adapted parameters provides further insight into how the adaptation mechanisms operate. Fig. 5 shows that the weight of the visual cue obtained by measuring reliability as deviations from expected sensory input, a type of reliability that should be readily available to the brain, was relatively close to the optimal visual weight obtained when formally optimising for minimal cost J_{tot}. Fig. 6 shows that the performance improvements from adapting evidence accumulation and steering response gains were both had by increasing these gains, resulting in more frequent and/or higher-amplitude steering adjustments.

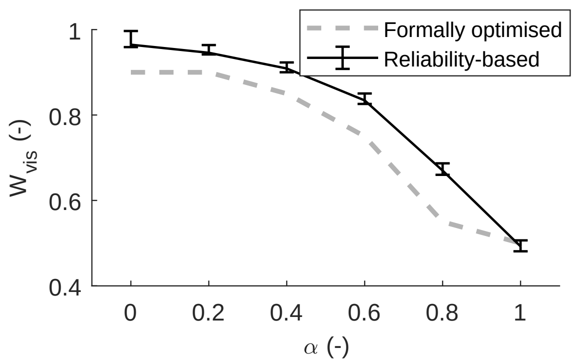

Figure 5: Adapted visual cue weights as a function of motion scaling, estimated from prediction-based sensory reliabilities (shown as average and total spread across ten task repetitions), and by means of formal optimisation.

Impact of task and model variations

Slalom difficulty

Fig. 7 shows that the qualitative nature of the model is insensitive to the spacing of the cones in the slalom task. In fact, the model can be seen to reproduce another empirical observation [Sav14]; the motion scaling optimum occurs at lower α for more difficult slaloms (shorter cone spacing, requiring higher lateral accelerations).

Sensory noise

As mentioned earlier, it is difficult to know what magnitudes to choose for the sensory noises. However, as long as $\sigma_{\text{vis}} = \sigma_{\text{ves}}$, changing these up or down

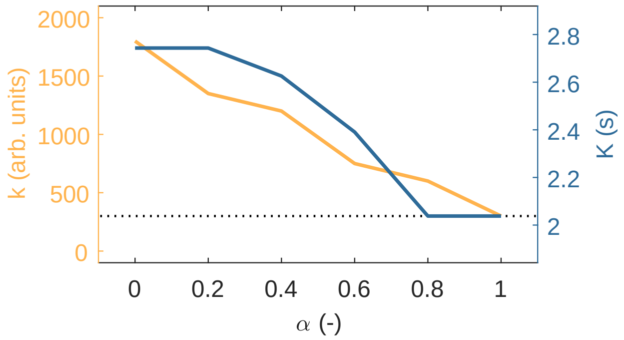

Figure 6: Adapted evidence accumulation gain (k) and steering response amplitude gain (K), as a function of motion scaling.

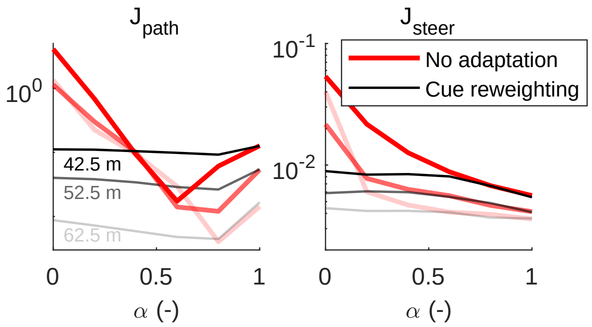

Figure 7: Effect of slalom cone spacing on path and steering costs as a function of motion scaling, without any adaptations and with reliability-reweighted cues.

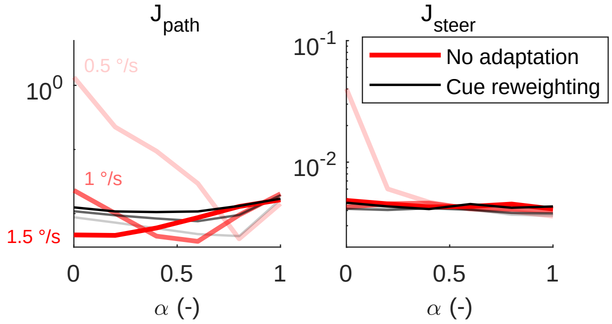

Figure 8: Effect of variations in vestibular sensory noise levels on path and steering costs as a function of motion scaling, both without any adaptations and with reliability-reweighted sensory cues.

does not change the shape of the path-tracking and steering cost curves ; these simply go up and down with the noise levels.

However, it could be argued, based on perceptual threshold experiments, that the Visual system is more sensitive than the semicircular canals in discrimination of pure yaw motion [Rie81, Soy12]. Therefore, as shown in Fig. 8, simulations were run where the vestibular noise was increased, while maintaining $\sigma_{\text{vis}} = 0.5°$/s. The figure shows that doing so maintains the high-level qualitative effects of motion scaling, but the impact of motion scaling is reduced. This is in line with what one may have expected, since with higher vestibular noise levels, Eq. (3) prescribes lower vestibular sensory weights to begin with, so one needs to reduce α more to see any effects. One consequence of this phenomenon is that the local optimum for path-tracking cost shifts to lower α with increased vestibular noise.

Discussion and conclusions

Sensory integration and adaptation

The model used here was relatively simple, especially at the level of multisensory integration. Nevertheless, the main targeted empirical phenomena, in terms of task performance and steering efforts, were all qualitatively captured by the model. Put in more specific terms, low task performance and high steering efforts upon first exposure to downscaled motion cues can be understood as drivers (behaving as if they are) directly underestimating vehicle yaw rate, because of the small-magnitude vestibular cues, and then using this underestimation when shaping their steering, which as a result becomes more effortful, and in many cases also more unstable.

In this statement, the part about "using this underestimation..." is interesting in its own right. Much of the existing empirical literature on driving simulator motion can be interpreted conservatively in this sense, to say that motion cues mainly cause drivers to change adopted speeds or trajectories at a high level, to avoid experiencing large accelerations [Sie01, Jam10, CG11, Ber13], or that motion cues mainly support rejection of unexpected disturbances like wind gusts [Rep82, Gre03]. The present model and simulation analyses, together with the empirical findings from the slalom experiments, suggest a stronger account than this, whereby drivers make direct use of motion information as part of shaping their steering to reach their intended targets, also in the absence of any disturbances or high-level adaptations of trajectory. It is clear that existing multisensory driver models [Nas18] (as well as pilot models, e.g., [Mul13]) also suggest this deep form of involvement of vestibular cues in control, but we are not aware of any prior analysis of empirical data providing support for it in driving.

With respect to the behavioural adaptation, the results presented here indicate that especially three mechanisms, or several of them in combination, are candidates for causing the empirically observed effects of repeated task exposure : increased gains in evidence accumulation or in steering response, or sensory cue reweighting based on reliabilities inferred from deviations between received and expected sensory input. Especially this latter mechanism seems readily implementable in neural systems, and it also provided the most dramatic performance improvements. Interestingly, the cue weights obtained in this way came close to the formally optimal values (Fig. 5) ; that this would be the case beforehand was not clear, since the formally optimal values depend on the specific task and chosen cost function.

Also the increases in accumulator and steering gains can actually be interpreted in neurobiological terms ; increases in global cortical arousal by means of broad diffusion of noradrenaline (also known as norepinephrine) has been found to have the specific effect of increasing gains in neuronal response to inputs [AJ05]. Thus, the driver's brain may respond to unsatisfactory task performance with release of noradrenaline, increasing the evidence accumulation and response gains.

The present analyses do not provide any conclusive insight into which of the three adaptation mechanisms mentioned above may have been more important in the empirical studies. However, the results can possibly be taken to suggest that complete reinterpretation of the vestibular input may not have occurred in these studies, since if so there should not, according to the model simulations, have remained any local optimum in task performance for $\alpha < 1$. This leads on to the next section.

Sub-unity optimum in motion scaling

It was not expected beforehand that the model would exhibit the local performance optimum for sub-unity motion scaling. Previously, it has been proposed that this phenomenon might be due to imperfections and false cues in motion systems becoming more prominent at higher α, or to motion downscaling being needed to ensure coherence with underestimated visual speeds [Ber13], or to accurate steering control becoming more difficult when the body is subjected to higher and more uncomfortable accelerations [Sav14]. However, none of these mechanisms were included in the model, yet it still reproduced the phenomenon.

What seems to be happening instead is that the model gets a path-tracking benefit from slightly underestimating the yaw rate in this task. From Fig. 3 (third panel from left) it can be seen that the reason for the lower path costs is that motion downscaling, and the consequent underestimation of the yaw rate, leads to the phase of the vehicle's trajectory being earlier, aligning it better with the desired path. Indeed, this exactly the same type of phenomenon that was behind the path-tracking optimum in the empirical work by Berthoz et al [Ber13]. (Savona et al [Sav14] did not provide a a trajectory phase analysis of this nature.)

Overall, the fact that the model captures so many aspects of this phenomenon–not only the existence of an optimum, but also its cause being trajectory phasing, as well as the optimal motion scaling decreasing for more difficult slaloms–seems to suggest that underestimation of yaw rate (or, as said before, behaving as if one underestimates yaw rate) may indeed be the mechanism behind this phenomenon also in humans. See also the analysis of steering angles in [Fee10] ; the observed faster adjustment of steering just as passing the cone without motion is indeed what one would expect from a driver who thinks s/he isn't rotating quickly enough in preparation for the next cone.

Since the model's yaw rate underestimation as such does not rely on control intermittency, we also tested a simpler, continuous version of the model, replacing the intermittent control (the orange dashed box in Fig. 1) with just a delay and a gain $1/\Delta T$ (see [Mar18a] for a motivation), and indeed we again obtained the local motion optimum. In fact, much of the results described in this paper for the intermittent model were reproduced also by the continuous model ; the main differences, quite expectedly, relating to steering effort : In addition to the lack of an evidence accumulation gain adaptation, which cannot be included in the continuous model, the effect of motion scaling on steering effort disappeared with all behavioural adaptations.

However, it should be noted that the local optimum in motion scaling has been observed also in subjective ratings of various types, and not necessarily at the exact same α as the path-tracking optimum [Ber13, Sav14]. While the present model simulations can *possibly* help explain why there might be a local optimum in subjective ratings of for example "ease of completing the task" or similar, it seems less certain that the yaw rate underestimation mechanism would contribute to improved subjective ratings of for example realism. One possibility is of course that there are several mechanisms are in play here ; the yaw rate underestimation mechanisms might coexist with any and all of the mechanisms reviewed above in this section.

Driver steering modelling

The main alternative to the model tested here is the one proposed by Nash and Cole [Nas18], which assumes optimal control in a more complete sense, with access to explicit internal models of the vehicle as well as of the sensory and neuromuscular dynamics. On a cursory analysis, it seems likely that also this model would exhibit lower performance and higher steering effort when motion is scaled down or turned off. Among the adaptation mechanisms studied here, the combined reinterpretation and reweighting mechanism (D) would seem to fit especially well within the framework. Here, this mechanism did not align well with the empirical data, but direct testing in model simulation is needed to see whether it fares better in the [Nas18] framework. Also the pure cue reweighting adaptation (C) could be used, if the framework is extended with a similar prediction-based estimation of reliabilities as proposed here. However, the gain adaptations (A) and (B) do not seem readily compatible with the [Nas18] model.

It would also be interesting to test whether the [Nas18] model reproduces the sub-unity motion scaling optimum phenomenon. At least in its non-adapted form, it should also underestimate yaw rate, but it might be that the very reason our model tracks the desired path better when underestimating yaw rate is because even with full motion cues its control is to some degree inherently suboptimal, in contrast with the [Nas18] model.

Future work

Besides some possible future research work that have been hinted at above, one obvious direction would be to address other tasks besides the slalom. Ideally, one would first generate predictions for these other tasks using the model, and see whether these are borne out in testing with human drivers. In such empirical work, one could also study the adaptation process itself in more detail, for example to try to distinguish better between the various hypothesised mechanisms for adaptation.

The model proposed here could also be applied in development and tuning of motion cueing algorithms, in its present form especially for direct scaling cueing.

For example, one can use the model to predict what motion scaling might yield behaviour that is as similar as possible to that in a real vehicle, or how large the differences might be between behaviour before and after adaptation to a certain motion scaling, to get an idea of what motion cueing settings might take longer time to get used to.

If the model is to be used with more complex, arbitrary motion cueing algorithms, for example affecting rotations and translations in different ways, the current simplified approach of capturing all vestibular sensing in just a yaw rate estimate will not be enough, and it needs to be better considered how different types of motion cues get used to determine needed control. One possibility is the Nash and Cole [Nas18] approach with sensory dynamics models and inverse model state estimators. A possible complication here is that empirical observations suggest that rotation and translation cues may not be used by human drivers in precisely the ways suggested by this type of engineering analysis [Lak16].

References

G. Aston-Jones and J. D. Cohen, **An integrative theory of locus coeruleus-norepinephrine function : adaptive gain and optimal performance**, *Annual Review of Neuroscience*, vol. 28 : 403–450, 2005.

A. Berthoz, W. Bles, H. H. Bülthoff, B. C. Grácio, P. Feenstra, N. Filliard, R. Hühne, A. Kemeny, M. Mayrhofer, M. Mulder *et al.*, **Motion scaling for high-performance driving simulators**, *IEEE Transactions on Human-Machine Systems*, vol. 43(3) : 265–276, 2013.

B. Correia Grácio, M. Wentink, A. Valente Pais, M. Van Paassen and M. Mulder, **Driver behavior comparison between static and dynamic simulation for advanced driving maneuvers**, *Presence : Teleoperators and Virtual Environments*, vol. 20(2) : 143–161, 2011.

T. B. Crapse and M. A. Sommer, **Corollary discharge circuits in the primate brain**, *Current Opinion in Neurobiology*, vol. 18 : 552–557, 2008.

P. Feenstra, R. van der Horst, B. Grácio and M. Wentink, **Effect of simulator motion cuing on steering control performance : Driving simulator study**, *Transportation Research Record : Journal of the Transportation Research Board*, vol. 2185 : 48–54, 2010.

C. R. Fetsch, G. C. DeAngelis and D. E. Angelaki, **Bridging the gap between theories of sensory cue integration and the physiology of multisensory neurons**, *Nature Reviews Neuroscience*, vol. 14(6) : 429, 2013.

D. L. Fisher, M. Rizzo, J. K. Caird and J. D. Lee, **Handbook of Driving Simulation for Engineering, Medicine, and Psychology**, CRC Press, Boca Raton, FL, 2011.

M. Fischer, A. Seefried and C. Seehof, **Objective Motion Cueing Test for Driving Simulators**, in Proceedings of the Driving Simulation Conference, 41–50, 2016.

D. Franklin and D. Wolpert, **Computational Mechanisms of Sensorimotor Control**, *Neuron*, vol. 72 : 425–442, 2011.

K. Friston, **The free-energy principle : a unified brain theory ?**, *Nature Reviews Neuroscience*, vol. 11(2) : 127–138, 2010.

S. F. Giszter, **Motor primitives — new data and future questions**, *Current Opinion in Neurobiology*, vol. 33 : 156–165, 2015.

J. I. Gold and M. N. Shadlen, **The Neural Basis of Decision Making**, *Annual Review of Neuroscience*, vol. 30 : 535–574, 2007.

T. Gordon and N. Magnuski, **Modeling normal driving as a collision avoidance process**, in Proceedings of the 8th International Symposium on Advanced Vehicle Control, 2006.

J. Greenberg, B. Artz and L. Cathey, **The effect of lateral motion cues during simulated driving**, *Proceedings of the Driving Simulation Conference North America*, 2003.

A. H. J. Jamson, **Motion Cueing in Driving Simulators for Research Applications**, Ph.D. thesis, University of Leeds, 2010.

P. Lakerveld, H. Damveld, D. Pool, K. van der El, M. van Paassen and M. Mulder, **The Effects of Yaw and Sway Motion Cues in Curve Driving Simulation**, *IFAC-PapersOnLine*, vol. 49(19) : 500–505, 2016.

G. Markkula, Evaluating vehicle stability support systems by measuring, analyzing, and modeling driver behavior, Licentiate thesis, Chalmers University of Technology, 2013.

G. Markkula, O. Benderius and M. Wahde, **Comparing and validating models of driver steering behaviour in collision avoidance and vehicle stabilization**, *Vehicle System Dynamics*, vol. 52(12) : 1658–1680, 2014.

G. Markkula, E. Boer, R. Romano and N. Merat, **Sustained sensorimotor control as intermittent decisions about prediction errors : computational framework and application to ground vehicle steering**, *Biological Cybernetics*, vol. in press, 2018.

G. Markkula, R. Romano, A. H. Jamson, L. Pariota, A. Bean and E. R. Boer, **Using driver control models to understand and evaluate behavioural validity of driving simulators**, *in review*, 2018.

M. Mulder, P. Zaal, D. M. Pool, H. J. Damveld and M. van Paassen, **A Cybernetic Approach to Assess Simulator Fidelity : Looking back and looking forward**, in AIAA Modeling and Simulation Technologies Conference, 2013.

C. J. Nash, D. J. Cole and R. S. Bigler, **A review of human sensory dynamics for application to models of driver steering and speed control**, *Biological Cybernetics*, vol. 110(2-3) : 91–116, 2016.

C. J. Nash and D. J. Cole, **Modelling the influence of sensory dynamics on linear and nonlinear driver steering control**, *Vehicle System Dynamics*, vol. 56(5) : 689–718, 2018.

A. Nesti, K. A. Beykirch, P. Pretto and H. H. Bülthoff, **Self-motion sensitivity to visual yaw rotations in humans**, *Experimental Brain Research*, vol. 233(3) : 861–869, 2015.

M. J. Pickering and A. Clark, **Getting ahead : forward models and their place in cognitive architecture**, *Trends in Cognitive Sciences*, vol. 18(9) : 451–456, 2014.

M. Plochl and J. Edelmann, **Driver models in automobile dynamics application**, *Vehicle System Dynamics*, vol. 45(7-8) : 699–741, 2007.

B. S. Repa, P. M. Leucht and W. W. Wierwille, **The effect of simulator motion on driver performance**, Technical Paper 820307, SAE, 1982.

T. Requarth and N. B. Sawtell, **Plastic Corollary Discharge Predicts Sensory Consequences of Movements in a Cerebellum-Like Circuit**, *Neuron*, vol. 82 : 896–907, 2014.

J. Riemersma, **Visual control during straight road driving**, *Acta Psychologica*, vol. 48(1-3) : 215–225, 1981.

I. Salisbury and D. Limebeer, **Motion cueing in high-performance vehicle simulators**, *Vehicle System Dynamics*, vol. 55(6) : 775–801, 2017.

F. Savona, A. M. Stratulat, E. Diaz, V. Honnet, G. Houze, P. Vars, S. Masfrand, V. Roussaire and C. Bourdin, **The influence of lateral, roll, and yaw motion gains on driving performance on an advanced dynamic simulator**, in Proceedings of the Sixth International Conference on Advances in System Simulation, 113–119, 2014.

I. Siegler, G. Reymond, A. Kemeny and A. Berthoz, **Sensorimotor integration in a driving simulator : contributions of motion cueing in elementary driving tasks**, in Proceedings of the Driving Simulation Conference, 21–32, 2001.

F. Soyka, P. R. Giordano, M. Barnett-Cowan and H. H. Bülthoff, **Modeling direction discrimination thresholds for yaw rotations around an earth-vertical axis for arbitrary motion profiles**, *Experimental Brain Research*, vol. 220(1) : 89–99, 2012.

H.-S. Tan and J. Huang, **Experimental development of a new target and control driver steering model based on DLC test data**, *IEEE Transactions on Intelligent Transportation Systems*, vol. 13(1) : 375–384, 2012.