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Adequacy of models and sensory stimuli: how does it impact the controllability of systems?

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Abstract – *Simulator sickness, an adverse physiological reaction to a simulated driving situation, is often attributed exclusively to sensory conflict or sometimes to postural instability. We postulate that simulator sickness occurrence is a negative effect of poor- or non-controllability of the virtual vehicle that induces badly controlled ego-motion in the virtual scene and uneasiness. We believe that this non-controllability stems from a mismatch between the complexity of the virtual vehicle model and that of the simulator's hardware architecture. The architecture limits the quality of the sensory stimuli that can be provided to the user, which is problematic because of the driver's expectations based on their prior real-life driving experience. We designed and conducted a simple within-participants experiment using a small proof-of-concept system to explore our hypothesis. The experiment consisted of the stabilization of a virtual pendulum's oscillations using a haptic-feedback actuator. Twenty-four participants faced situations where (1) the visual feedback and the dynamic behavior of the simulated pendulum were coherent, and (2) they were mismatched. Our results show a significant effect of training on motor control and task performance; mismatch between visual feedback and dynamic model on motor control, task performance, and participant's discomfort. We interpreted these results as supporting our hypothesis.*

Keywords: simulator discomfort, motor control, driving simulation.

Introduction

The visual, haptic, vestibular, and auditory systems are human sensors essential to drivers. Multisensory integration makes human beings aware of the movement of their body in relation to itself and their environment. The feedback provided by the aforementioned sensors hence informs drivers on the current state (position, speed, acceleration) of the driven vehicle (Reymond, 2000). This is however not enough to guide the said vehicle to the desired situation. To perform this control-command task, human beings need to predict the consequences of their actions to converge towards precise control, with minimal oscillations. This requires anticipation and thus a model of the system to control. In human motor control, this model is learned and reinforced by experience. It is called the internal model.

Simulator Sickness (SS) is an adverse physiological reaction to a simulated driving situation and is to some extent akin to Motion Sickness (MS). Symptoms of both afflictions range from oculomotor symptoms, e.g. blurred vision or headache, to disorientation and nausea (Kennedy, et al., 1993). However, MS mostly affects passengers; whereas SS may affect drivers of driving simulators (Rolnick

& Lubow, 1991), and, as such, be detrimental to experiment duration and/or task performance (Money, 1970; Bittner, et al., 1997), with some subjects even at the risk of dropping out of the experiment. This difference in susceptibility has been linked to the difference in control degree and the possibility of anticipation (Casali & Wierwille, 1986).

SS is often explained by the widely accepted cause of MS: sensory conflict, which is either conflict between the visual, haptic, and vestibular feedback or conflict between expected and actual motion, i.e. conflict with the driver's internal model (Reason & Brand, 1975; Reason, 1978; Oman, 1990; Bos & Bles, 2002; Bos, et al., 2008). This explanation is supported by the fact that driving simulator training sessions result in less SS occurrence in initially susceptible subjects (Hoffmann, et al., 2003). Additionally, recent work has demonstrated that unpredictable motion increases MS (Kuiper, et al., 2020b) and that this effect can be mitigated by adding a cognitive cue that allows for anticipation (Kuiper, et al., 2020a). Expanding on previous computational models of MS, Wada (2021) recently proposed a computational model capable of describing the effects of dynamics learning and motion prediction on MS incidence. However, the research on the precise role of the internal model,

i.e. of anticipation, in driving simulation and thus its influence on SS is still limited.

The postural instability theory is another hypothesis that has been proposed to explain the occurrence of SS (Riccio & Stoffregen, 1991; Stoffregen & Riccio, 1991). Because driving simulators are unknown moving environments, using one requires the driver to establish designated action control strategies, in particular for posture control. This theory postulates that SS-susceptible drivers suffer from their incapability to establish an adequate strategy to maintain postural stability in driving simulators. Further work showed that postural instability precedes the onset of SS symptoms (Stoffregen & Smart, 1998; Bonnet, et al., 2006), as well as a correlation between the two (Faugloire, et al., 2007; Van Emmerik, et al., 2011). However, it is not proven that postural instability is a necessary and sufficient condition of SS occurrence. Other authors have argued that MS or SS and postural instability are effects from a common cause (Kennedy & Stanney, 1996; Bos, 2011).

Research question

In driving simulation, the driver does not drive a real vehicle but teleoperates a vehicle model, and thus we consider that teleoperation control-command rules apply. Non-controllability may lead to erratic, oscillating movements of the virtual vehicle. This induces uncontrolled rotational movements of the image which has been demonstrated to be negatively linked to SS (Golding, et al., 1995; Golding, et al., 2003). Moreover, the control difficulties may induce anxiety and discomfort that have also been demonstrated to be negatively linked to SS (Bertin, et al., 2004).

We postulate that the non-controllability of a driving simulator stems from the mismatch between the complexity of its underlying vehicle model and that of its architecture from a hardware standpoint. It is possible to simulate the dynamics of the real vehicle with high precision using a high-complexity model. However, such a model cannot be controlled with a limited number of actuators and cues (e.g. with a joystick). Sensory fidelity, defined as the objective degree of exactness with which sensory stimuli inherent to the real driving situation are reproduced by the driving simulator, depends on the simulator's architectural complexity (e.g. degrees-of-freedom). We hypothesize that adequacy of model fidelity and sensory fidelity leads to better control of the virtual vehicle, which minimizes erratic movements and thus discomfort and/or SS occurrence.

Our postulate does not refute the previously posited theories but encompasses them. Erratic, oscillating movements of the virtual vehicle and the resulting image translations and rotations are indeed unexpected for the driver, which is a “neural

mismatch”. We also believe that postural instability can be identified as a symptom of anxiety and discomfort, which would explain the fact that it is correlated to SS symptoms.

In this study, we aim to demonstrate the relevance of the coherence between visual perception and the dynamic model for a simple control task of stabilizing a simulated object's oscillations. For this purpose, our within-participants experiment compares the results in terms of motor control of such a task on the one hand (1) when the visual feedback provided by the simulator and the dynamic behavior of the simulated object rendered using a haptic feedback actuator are coherent and, on the other hand (2) when they are mismatched. Per our hypothesis, adequacy of models and sensory stimuli is crucial to the controllability of a simulated object. In the case of a driving simulator, mismatched models and sensory stimuli would provoke difficulties in controlling the simulated vehicle, inducing erratic oscillating movements of it. This is perceived by the driver as erratic self-motion which in turn induces SS. Focusing on a simple motor control task without self-motion allows us to highlight the importance of adequacy of models and sensory stimuli for the control of a simulated object, a result which can then be transposed to driving simulation.

Methods

Participants

Twenty-four participants (five women, nineteen men) between the ages of 23 and 64 (mean $\mu = 40$ years, \pm standard deviation S.D. = 13.9 years) took part in our experiment. All participants gave their informed consent before the beginning of the experiment. Four participants (one woman, three men) who failed to follow our instructions were excluded from the study.

Apparatus

The study was conducted using a haptic feedback actuator for the rendering of haptic cues and a Head-Mounted Display (HMD) for visual feedback, as represented in Figure 1.

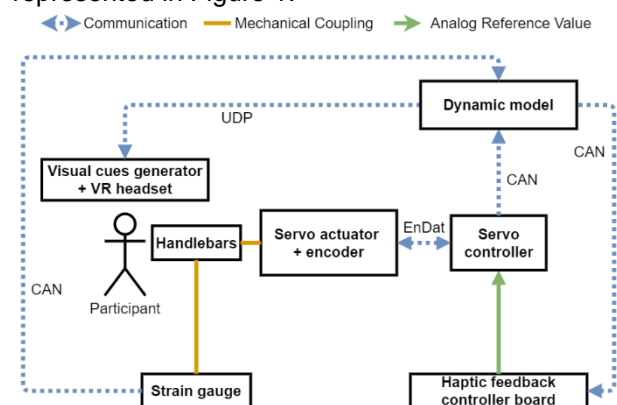


Figure 1. Schematic representation of the system used for our experiment

The haptic feedback actuator consisted of motorcycle handlebars mechanically coupled to a CanisDrive-20A-160-AM-H-SIE servo actuator, pictured in Figure 2. Visual cues were provided using the HTC Vive Pro system (field of view FOV = 110°, image resolution = 2880 × 1600 pixels), with a refresh rate of 90 frames per second (FPS). Before the experiment, participants were asked to put the HMD on and to adjust it to their heads. They were also asked to adjust the HMD to their vision, i.e. to set the interpupillary distance (IPD). These settings were done as instructed in the HMD user guide.

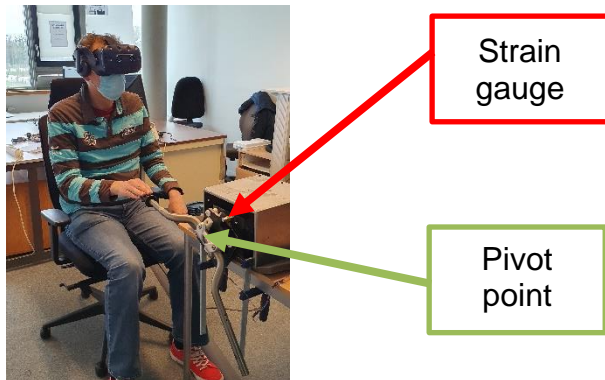


Figure 2. Participant during the experiment

Experimental design and procedure

The participants were tasked with stabilizing a simulated pendulum's oscillations. The dynamic model of the simulated pendulum was that of a damped driven pendulum. Two dynamic models were used: either a heavy (H) or a light (L) pendulum, with different masses and a damping coefficient directly dependent on the mass. The pendulum was represented by two visual objects: also either heavy or light. These objects moved in the sagittal plane with a single degree of freedom: pitch only. The corresponding visuals are pictured in Figure 3. The movement of the handlebars was controlled using the pendulum's angular position and speed (outputs of the dynamic model) as position and speed references in its control loop.

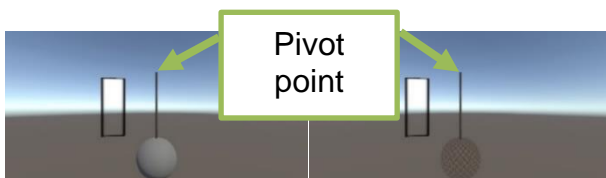


Figure 3. Visuals of the heavy (on the right) and light (on the left) pendulum at equilibrium position (0°)

Initially, the pendulum was stable and the participants were asked to destabilize it. The goal for the participants was then to stabilize the amplitude of the pendulum's oscillations by pushing it away when it was in front of them, using the handgrip of the haptic feedback actuator (see Figure 2 where the participant is pushing the pendulum away from them). The torque they applied was measured using

a strain gauge and used as the driving force of the modeled damped driven pendulum.

The pendulum's oscillations were considered stabilized when the maximum angular position, i.e. the furthest position that the pendulum reached before returning towards the participant, was maintained within the interval $80^\circ \pm 5^\circ$.

The visual scene also included a bar graph where the vertical axis represented the current angular position of the pendulum, ranging from -120° to 120° . The color of this bar graph provided the participants with feedback on their task performance, using a color gradient from white (when the maximum position reached was smaller than 75°) to green to red (when the maximum position reached was greater than 85°) (see Figure 4 for examples).

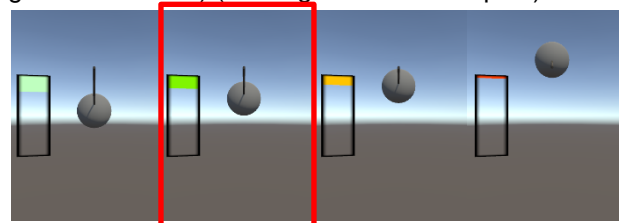


Figure 4. Examples of the visual scene during the experiment (the desired maximum position was achieved by the participant in the red frame)

Our experiment consisted of four variants:

1. one "coherent" variant where the visual and the dynamic model were both of a heavy object. This variant will be noted heavy/heavy (HH) variant in the following;
2. a second "coherent" variant where the visual and the dynamic model were both of a light object. This variant will be noted light/light (LL) variant in the following;
3. one "mismatched" variant where the dynamic model was of a light object but with the visual of a heavy object. This variant will be noted heavy/light (HL) variant in the following;
4. a second "mismatched" variant where the dynamic model was of a heavy object but with the visual of a light object. This variant will be noted light/heavy (LH) variant in the following.

After being explained the task they had to accomplish, participants were first trained to use both of the coherent variants. Then, each participant was exposed to both of the mismatched variants, with a second exposure to the HH variant inserted between the two. The purpose of this second exposure was to verify that the training had a positive effect on the participant's control and task performance for an already-encountered variant. To do so, the variability of both those aspects before and after training was compared.

The training phase lasted for up to 15 oscillations for each variant but ended after 10 to 14 oscillations if the participant stabilized the amplitude of the oscillations for at least 5 oscillations. During the second phase, each variant lasted for the duration of 10 oscillations. The mean total duration of the experiment was $\mu = 334\text{s}$ (\pm S.D. = 29.9s).

There were four possible orders of exposure ((1) HH – LL – HL – HH – LH ; (2) HH – LL – LH – HH – HL ; (3) LL – HH – HL – HH – LH ; (4) LL – HH – LH – HH – HL), which were balanced between the participants.

The position and speed of the object, i.e. the angular position and rotation speed of the servo actuator as reported by the servo controller, were recorded for the duration of the experiment to indicate task performance. We also recorded the torque applied by the participant to the simulated pendulum to control its oscillations, measured using a strain gauge, as well as the current torque reported by the servo controller. This raw data was recorded at a 1ms period.

Participants were asked to vocally rate their experience on a misery scale (MISC) (Bos, et al., 2005) at four instants: (1) before the experiment, (2) after training with the first coherent variant, (3) after training with the second coherent variant, and (4) after the experiment. This scale was explained to them before the experiment.

Independent variables

As described, our study used a within-subjects design. The within-subjects factor we considered is the experimental condition. Taking into account our objective of underlining the effect of the training phase, we separated the experiment variants into 7 levels of experimental condition: (1) HH during discovery, i.e. during the first 5 oscillations (HH_i); (2) HH after training, i.e. during the last 5 oscillations (HH_r); (3) LL during discovery (LL_i); (4) LL after training (LL_r); (5) HL during discovery; (6) HH during repetition, i.e. during the first 5 oscillations of the second exposure (HH_r); (7) LH during discovery.

Dependent variables

From the raw data recorded during the experiment, we computed several motor control-related variables for analysis (see Table 1 for a summary). First, we determined the duration of each oscillation T . We also separately considered:

- the time difference between the instant when the pendulum began its return towards the participant (last maximum position) and the instant when it reached its minimum position T_1 . During this time, the participant caught the pendulum and accompanied its movement to estimate its weight, before stopping it.
- the time between the minimum position, i.e. the instant when the participant stopped the

pendulum, and the next maximum position, noted T_2 . After stopping the pendulum, the participant, as was asked of them, pushed it pendulum away from them intending to maintain the amplitude of the last oscillation. During this time, the torque applied by the participant is active.

Additionally, we extracted the amplitude of each oscillation A_θ , as well as the amplitude of the torque A_τ applied by the participant to the pendulum during each oscillation. We chose these measures because they are all directly indicative of both the participant's task performance in terms of stabilization of the pendulum's oscillations and the participant's control of the simulated object.

Table 1. Description of the dependent variables. \bar{x} represents the mean value of x and \bar{x} its coefficient of variation.

Variable	Description
T	Duration of the oscillation
T_1	Time difference between the pendulum last returning towards the participant and the participant stopping it
T_2	Time difference between the participant stopping the pendulum and the pendulum next returning towards them
A_θ	Amplitude of the oscillation
A_τ	Amplitude of the torque applied by the participant

Results

Motor control-related dependent measures were input into repeated-measures analyses of variances (ANOVAs) with Greenhouse-Geisser corrections. The significance level was set at 0.05. When the ANOVA revealed significant effects, these were further analyzed using post hoc tests with a Holm correction. MISC scores were analyzed using a paired samples t-test.

Repeated-measures ANOVAs validated that there was no significant effect of the order of exposure to the experiment variants, on any of the dependent variables we considered. There was however always a significant effect of the Experimental condition \times Order of exposure interaction. We identified this effect as existing between the very first experiment variant and the others because the participants' initial strategies to control the simulated pendulum were diverse. Thus, we focused only on within-participants effects.

Duration of the oscillation

We computed the mean duration of the oscillation \bar{T} for the 5 oscillations of each of the 7 levels of experimental conditions. A repeated-measures ANOVA revealed that it differed significantly between experimental conditions; $F(2.58, 41.35) = 22.96$, $p < 0.001$, $\eta_p^2 = 0.589$. In

particular, post hoc tests showed significant differences in \bar{T} between: (a) HH before training and after / during repetition ($p = 0.022$ / $p < 0.001$ respectively); (b) HH after training and LL after training ($p < 0.001$); (c) HL and HH after training and during repetition (both $p < 0.001$); (d) LH and LL after training ($p < 0.001$); (e) HL and LH ($p < 0.001$). There was however no significant difference ($p > 0.05$) between (α) HL and LL after training; or (β) LH and HH after training or during repetition.

Additionally, we computed the coefficient of variation (CV) of the duration \bar{T} for the 5 oscillations of each of the 7 levels of experimental conditions. A repeated-measures ANOVA revealed that it differed significantly between experimental conditions; $F(3.17, 50.78) = 6.07$, $p = 0.001$, $\eta_p^2 = 0.275$. In particular, post hoc tests showed significant differences in \bar{T} between:

- HH before training ($\mu = 3.74\% \pm \text{S.D.} = 4.13\%$) and after ($\mu = 2.02\% \pm \text{S.D.} = 2.00\%$; $p = 0.030$) / during repetition ($\mu = 1.44\% \pm \text{S.D.} = 0.612\%$; $p = 0.006$);
- LL before ($\mu = 4.91\% \pm \text{S.D.} = 3.98\%$) and after training ($\mu = 2.24\% \pm \text{S.D.} = 1.12\%$; $p = 0.022$);
- HL ($\mu = 3.97\% \pm \text{S.D.} = 2.90\%$) and HH during repetition ($p < 0.001$);
- HL and LH ($\mu = 1.60\% \pm \text{S.D.} = 0.797\%$; $p = 0.003$),

but no significant difference ($p > 0.05$) between LH and HH during repetition. These results are represented in Figure 5.

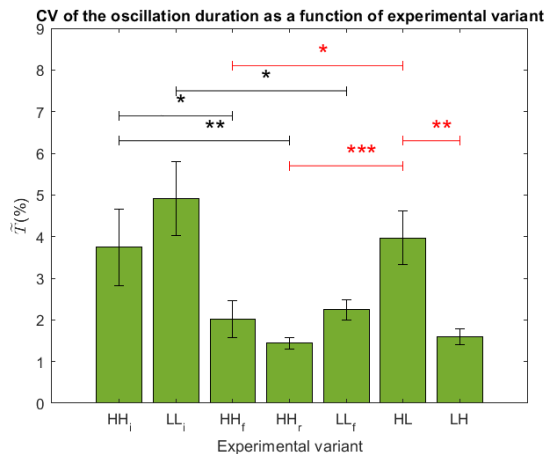


Figure 5. \bar{T} (%) as a function of experimental variant (*: $p < 0.05$; **: $p < 0.01$; ***: $p < 0.001$; black: effect of training; red: effect of incongruence)

A repeated-measures ANOVA revealed that \bar{T}_1 differed significantly between experimental conditions; $F(2.55, 40.82) = 7.69$, $p < 0.001$, $\eta_p^2 = 0.325$. In particular, post hoc tests showed significant differences in \bar{T}_1 between the same experimental conditions as for \bar{T} . The results are similar for \bar{T}_2 : there was a significant difference

between experimental conditions; $F(2.71, 43.33) = 64.56$, $p < 0.001$, $\eta_p^2 = 0.801$; for the same experimental conditions as for \bar{T} .

Moreover, a repeated-measures ANOVA showed that \bar{T}_1 did not differ significantly between experimental conditions; $F(2.86, 45.71) = 5.0$, $p = 0.05$. On the other hand, a repeated-measures ANOVA revealed that \bar{T}_2 differed significantly between experimental conditions; $F(2.87, 45.85) = 9.06$, $p < 0.001$, $\eta_p^2 = 0.361$. In particular, post hoc tests showed significant differences in \bar{T}_2 between the same experimental conditions as for \bar{T} .

Amplitude of the oscillation

We computed the mean position amplitude \bar{A}_θ for the 5 oscillations of each of the 7 levels of experimental conditions. A repeated-measures ANOVA revealed that it differed significantly between experimental conditions; $F(2.40, 38.41) = 11.96$, $p < 0.001$, $\eta_p^2 = 0.428$. In particular, post hoc tests showed significant differences in \bar{A}_θ between: (a) HH before training and after / during repetition ($p = 0.030$ / $p = 0.004$ resp.); (b) HH after training and LL after training ($p = 0.005$); (c) HL and HH after training and during repetition (both $p < 0.001$); (d) HL and LL after training ($p < 0.001$); (e) LH and LL after training ($p < 0.001$); (f) HL and LH ($p < 0.001$). There was no significant difference ($p > 0.05$) between (α) LL before and after training; or (β) LH and HH after training or during repetition.

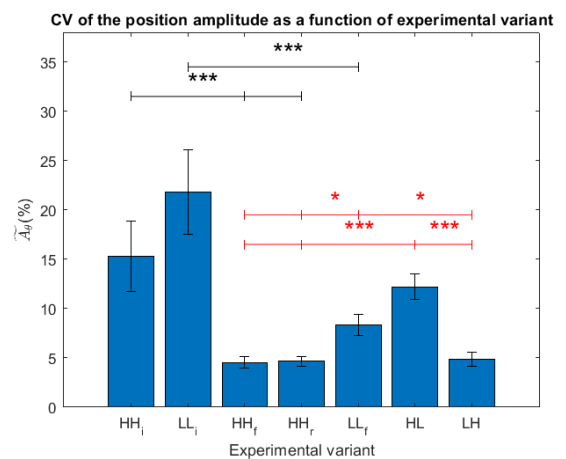


Figure 6. \bar{A}_θ (%) as a function of experimental variant (*: $p < 0.05$; ***: $p < 0.001$; black: effect of training; red: effect of incongruence)

Additionally, we computed the CV of the position amplitude \bar{A}_θ for the 5 oscillations of each of the 7 levels of experimental conditions. A repeated-measures ANOVA revealed that it differed significantly between experimental conditions; $F(2.16, 34.64) = 11.76$, $p < 0.001$, $\eta_p^2 = 0.424$. In particular, post hoc tests showed significant differences (all $p < 0.001$) in \bar{A}_θ between:

- HH before ($\mu = 15.3\% \pm \text{S.D.} = 16.1\%$) and after ($\mu = 4.53\% \pm \text{S.D.} = 2.71\%$) / during repetition ($\mu = 4.64\% \pm \text{S.D.} = 2.38\%$);
- LL before ($\mu = 21.8\% \pm \text{S.D.} = 19\%$) and after training ($\mu = 8.34\% \pm \text{S.D.} = 4.65\%$);
- HL ($\mu = 12.2\% \pm \text{S.D.} = 5.67\%$) and HH during repetition;
- HL and LH ($\mu = 4.88\% \pm \text{S.D.} = 3.11\%$),

but no significant difference ($p > 0.05$) between LH and HH during repetition. These results are represented in Figure 6.

Amplitude of the driving torque

We computed the mean torque amplitude \bar{A}_τ for the 5 oscillations of each of the 7 levels of experimental conditions. A repeated-measures ANOVA revealed that it differed significantly between experimental conditions; $F(3.27, 52.24) = 16.323$, $p < 0.001$, $\eta_p^2 = 0.505$. In particular, post hoc tests showed significant differences in the \bar{A}_τ between: (a) HH after training and LL after training ($p = 0.003$); (b) HL and HH after training and during repetition (both $p < 0.001$); (c) LH and LL after training ($p < 0.001$); (d) HL and LH ($p < 0.001$). There was no significant difference ($p > 0.05$) between (α) HH before training and after training or during repetition; (β) LL before and after training; (γ) HL and LL after training; or (δ) LH and HH after training or during repetition.

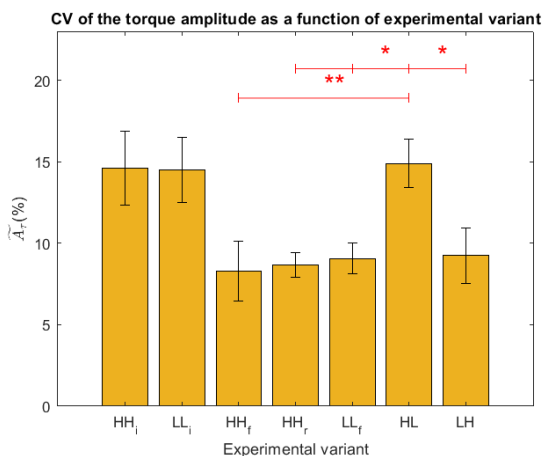


Figure 7. \bar{A}_τ (%) as a function of experimental variant
(*: $p < 0.05$; ***: $p < 0.001$; red: effect of incongruence)

Additionally, we computed the coefficient of variation of the torque amplitude \bar{A}_τ for the 5 oscillations of each of the 7 levels of experimental conditions. A repeated-measures ANOVA revealed that it differed significantly between experimental conditions; $F(3.63, 58.07) = 3.44$, $p = 0.016$, $\eta_p^2 = 0.177$. In particular, post hoc tests showed significant differences in \bar{A}_τ between:

- HL ($\mu = 14.9\% \pm \text{S.D.} = 6.66\%$) and HH during repetition ($\mu = 8.67\% \pm \text{S.D.} = 3.35\%$; $p = 0.011$);

- HL and LL after training ($\mu = 9.06\% \pm \text{S.D.} = 4.20\%$; $p = 0.019$);
- HL and LH ($\mu = 9.25\% \pm \text{S.D.} = 7.64\%$; $p = 0.023$),

but no significant difference ($p > 0.05$) between LH and HH during repetition. These results are represented in Figure 7.

MISC

Before the experiment, all the participants ($N = 20$) rated their experience a 0 on the MISC scale. This confirms that no participant was experiencing pre-existing discomfort or other SS symptoms. A paired-samples t-test was conducted to compare MISC scores before and after the testing phase. There was a significant increase in MISC score after the testing phase ($\mu = 0.6$, $\text{S.D.} = 1.231$) in comparison with before ($\mu = 0.375$, $\text{S.D.} = 0.930$); $t(19) = 2.13$, $p = 0.023$, with a medium effect size $d = 0.476$.

Discussion

Analyzing the duration and amplitude of the simulated pendulum's oscillations as a function of the experimental condition allows us to analyze the shape of these oscillations. This is relevant because it was what the participants were asked to stabilize. It does not allow direct analysis of the participant's control on the pendulum, but it is a consequence of this control. We first showed that there is a significant difference in the average values of both these quantities between (1) before training and (2) after training in the case of the coherent variant HH (in the case of LL, it also changes, but not significantly). Besides, there was a significant difference between both coherent variants after training, which means that the oscillations' driven by the participants were significantly different in shape depending on the variant. In our opinion, this is evidence of the participants building an internal model of both the heavy and the light pendulums. Moreover, analysis of the coefficients of variation (CVs) of the duration and the amplitude also supported this: both significantly decreased after training for the coherent variants. This indicates that the participants' inverse internal models were more finely tuned after training. Separating the duration into T_1 and T_2 , i.e. before and after the participant reversed the direction of the pendulum, allowed us to identify a dominant effect of the CV of the second half in the decrease of the overall CV. This difference in effect can be explained by the fact that during the first half of the oscillation, the torque applied by the participant is passive, whereas, in the second half, it is active. During the first half, the participant estimates the pendulum's weight to determine a control strategy, but they only apply this strategy in the second half.

On the other hand, to determine how the participants controlled the pendulum and what affected this

control, we analyzed the torque amplitude. We showed no significant effect of training on the mean torque amplitude for either coherent variant, although there was a significant difference in this value depending on the experimental condition, i.e. on the manipulated pendulum. This means that the participants could intuitively determine the different amplitudes needed to control both pendulums from the start of the experiment.

Moreover, during the second phase of the experiment, we highlighted that, for the oscillation duration and the torque amplitude (two of the dependent measures we analyzed):

- there was a significant difference in mean values between HL and HH (after training), but not between HL and LL (after training);
- there was a significant difference in mean values between LH and LL (after training), but not between LH and HH (after training).

This indicates that these mean values for the mismatched variants tend to align with the mean values for the coherent variant with the same dynamic model. Secondly, the CVs of all three measures (oscillation duration, position amplitude, and torque amplitude) were found to be significantly greater for the HL variant than the CVs for the repeated HH variant and the LH variant. Coefficients of variation are particularly significant in the light of our hypothesis: important CVs indicate an important variability of the human motor control as well as of the task performance. We believe that the greater CVs in the case of the mismatched variant with the image of a heavy pendulum but the dynamic model of a light pendulum shows a negative impact of the mismatch between visual feedback and dynamic model on controllability and task performance, thus validating our hypothesis.

We propose two possible explanations as to why the reciprocal mismatch, i.e. the image of a light pendulum but the dynamic model of a heavy pendulum, did not perturb the participants.

Our first explanation is that, because the task we considered is a motor control task, haptic feedback is considered more reliable than visual feedback. Visual cues have often been shown to dominate over haptic cues (Pavani, et al., 2000), a principle that is the basis of pseudo-haptic feedback (Lécuyer, 2009; Lécuyer, 2017). However, the weighting of sensory cues has also been hypothesized to be task-dependent (Sober & Sabes, 2005). Our results would then be in line with this hypothesis. This could be tested by replacing the visual feedback with another sensory feedback, for example, auditory feedback.

Another possible explanation could be experimentation bias. As a result of both the construction of our experiment and the exclusion of some participants from the analysis, we were able to analyze more mismatched variants that followed a

HH variant (31 transitions from the HH variant to a mismatched variant) than a LL variant (9 transitions from the LL variant to a mismatched variant). Consequently, participants were overall more exposed to the dynamic model of the heavy object, which could impact our results.

Finally, questionnaire analysis showed a significant increase in MISC score after the testing phase in comparison with before (with no pre-existing symptoms before the experiment). Even if the MISC scores declared by the participants were not indicative of severe SS symptoms (maximum MISC score declared was 3 which represents slight dizziness), our results suggest that mismatch between visual feedback and dynamic model significantly increases subjective discomfort for the participants. However, it can be argued that these results could also be a consequence of the time elapsed since the beginning of the experiment, which is of course the greatest for the 4th declaration MISC score (around 5min34s).

Conclusion

Designers of driving simulators tend to favor vehicle dynamic models of the highest possible fidelity, regardless of the simulator's architecture and thus of the sensory cues' fidelity. However, we hypothesize that this design philosophy hinders the controllability of the simulator and can therefore be doubly detrimental to simulation validity, in terms of both the performance in the simulated task and SS. Our experiment focused on a very simple simulated task, whereas driving simulator tasks are inherently very complex. Multiple effects such as self-motion-related phenomena should also be considered when trying to explain SS occurrence. Nevertheless, the results of our pilot experiment, obtained by analysis of questionnaire scores and stabilization performance, support our hypothesis by demonstrating that mismatch between visual feedback and dynamic model (1) decreases controllability and task performance and (2) increases discomfort. These results draw attention to the need for adequacy among the various elements (HW/SW) of a simulator to ensure its controllability thus eliminating resulting movements that would be perceived as erratic by the driver. This guarantees its validity and the minimization of SS occurrence.

As discussed, other experiments are needed to further explore and validate our hypothesis. First, re-doing our experiment with special care into balancing the number of transitions between coherent and mismatched variants could eliminate the possibility of experiment bias affecting our results. Secondly, we could also confirm the negative effect of mismatch between visual feedback and dynamic model on participant's discomfort by integrating a

control group exposed to no mismatch but with an equal experiment duration.

We plan to explore whether the results are similar when considering different sensory feedback by introducing a mismatch between the dynamic model and auditory feedback instead of visual feedback. Auditory feedback can indeed be used as a significant cue in human motor control tasks. Additionally, we plan to conduct further analysis of the data we collected to extract and classify the different control strategies used by participants as a function of experimental variant.

Finally, as we explained, this experiment was preliminary research. Our next step will be to explore our hypothesis in the significantly more complex case of a motorcycle's dynamic trajectory control task on a simulator. To do so, we will conduct an experiment focused on the impact of the adequacy of the vehicle dynamic model with the complexity of the simulator architecture on trajectory control, presence, and SS occurrence.

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