MOTION CUEING: WHAT IS THE IMPACT ON THE DRIVER'S BEHAVIOR?

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Abstract

As inertial cues play a significant role in self-motion estimation, a growing number of driving simulator users integrates motion systems to provide the vehicle acceleration feedback. However, the platform workspace limitations do not enable a one-to-one feedback. The filtering of the "real" vehicle accelerations into admissible platform commands is commonly referred as to motion cueing algorithm. Unfortunately, there is a lack of full understanding the impact of this algorithm design on drivers' behavior. Indeed, most of the works done in the driving simulation area analyse the effects according to the simulator configurations (dynamical / static), see Repa *et al.* (1982); Watson at DSC 2000; Siegler *et al.* and Panerai *et al.* at DSC 2001, Jamson & Smith at DSC 2002. A few of them deal with the impacts of the tuning parameters, see Kuge *et al.* at DSC 2002; Grant at DSC 2004; Brunger-Koch *et al.* at DSC 2006.

This paper presents the results of a new experimentation carried out at Renault to measure drivers' ability to follow a car in three configurations:

- static;
- dynamical based on a classical motion cueing algorithm (Reid & Nahon, 1985);
- dynamical based on an adaptive motion cueing algorithm (Parrish *et al.*, 1975).

The classical and adaptive algorithms were tuned to optimize the acceleration rendering while keeping the motion system within its physical limits over a typical car driving session.

Renault exploits two dynamical driving simulators: ULTIMATE and CARDS. ULTIMATE is a high performance simulator equipped of a moving base hexapod on 7 m rails to study vehicle dynamics and driver aid systems (Dagdelen *et al.*, 2006). The CARDS simulator used in this experimentation is more representative of a typical dynamic driving simulator: an instrumented vehicle cockpit with force feedback systems on the steering wheel and on the pedals, with an earth-fixed display system and a six d.o.f. Stewart platform that allows accelerations up to 5 m/s² over ± 30 cm.

Although drivers had a subjective preference for dynamical sessions, the effect of the cueing algorithm design on their tracking performance is not significant. The analysis of the rendered acceleration profile with respect to the motion perception characteristics suggests that the classical and adaptive algorithms can only generate an "equivalent" acceleration perception in such platform workspace.

New directions for motion cueing algorithm development (such as taking into account explicitly the platform workspace and the cognitive aspects of self-motion perception) are discussed in this paper to render acceleration/jerks adapted to the driving task.

Introduction

It is well known that in driving simulators, inertial cues play a significant role in the fidelity of drivers' behavior. Subjects prefer verbally dynamical to static configuration (Parrish & Martin, 1976; Reid & Nahon, 1988 and Hall, 1989) and simulation sickness is less frequent in dynamical driving simulators (7 times lower in the experiment carried out by Curry *et al.* (2002); 12 times in another one carried out by Watson (2000)). Their ability to perform basic driving tasks seems to depend on these cues: Repa et al. (1982) observed in a line following task that the maximum lateral shift decreased of 30 % and the maximal magnitude of steering wheel angle of 15 % with motion, and Wierwille *et al.* (1983) reported a decrease of 0.12 s in drivers' reaction time. During a breaking task, Siegler *et al.* (2001) showed motion rendering prevents subjects from reaching too high and unrealistic decelerations, which are otherwise observed in a static simulator. The authors also mentioned a global effect of motion cueing on the trajectory pattern of the driven vehicle inside a 90° curve, confirmed by Reymond *et al.* (2001), showing that lateral acceleration plays a significant role in the drivers' ability to regulate their speed in a bended road.

These results led a growing number of driving simulator users to integrate motion systems that provide the driver with the vehicle acceleration feedback. Most of these motion systems correspond to parallel Stewart-Gough platforms: the vehicle cockpit is fixed to a plate that can be moved by electromechanical or hydraulic actuators while the actuators. Hexapods are usually used since they can move heavy cockpits in six dof. In advanced dynamical simulators, the hexapods are put on rails, to be moved in the simulation room along the surge and/or sway axis (NADS, ULTIMATE, Leeds, PSA), increasing the motion rendering workspace.

RENAULT exploits two dynamical driving simulators: CARDS (Figure 1) and ULTIMATE (Figure 2).

Figure 1. CARDS driving simulator

The CARDS simulator is a full-scale instrumented generic cockpit fixed on a Rexroth Hydraudyne electromechanical platform. The 6DOF-1000kg hexapod allows about ± 30cm (surge, sway, and heave) and ± 30° (yaw, pitch, and roll) maximum displacements. Force feedback on the steering wheel, brake, clutch and accelerator pedals are provided by active and passive systems. Six PCs (Pentium Windows XP, 3 Ghz) generate in real time at 60 Hz the front and rear view of the road environment, Barco CRT 808S projectors displaying these views.

The ULTIMATE simulator was built by RENAULT's Technical Center for Simulation in the framework of a European research project (Eureka Σ! 1493, in corporation with Bosh Rexroth Hydraudyne, SEOS and CNRS LPPA), for the design of advanced automotive R&D applications and to study driver-vehicle behavior. The simulator is situated in Renault Technocentre facilities, inside a 250 m²

Figure 2. ULTIMATE driving simulator

simulation room including a technical room and a supervision mezzanine. This innovative simulator design is based on an ultra-light cockpit and projection screen, and on a XY motion system of movement combined with a 6-dof platform. The platform allows accelerations up to ± 7 m/s² along the surge and sway axis over 7 m and up to ± 300 °/s over 30 ° along the yaw, pitch, and roll axis (Dagdelen *et al.*, 2006).

Due to the limitations of motion system actuators (excursion, velocity and acceleration), a one-to-one acceleration feedback cannot be generally provided. The filtering of the vehicle accelerations into admissible platform commands is commonly referred as to *motion cueing algorithm*. This algorithm has to meet contradictory objectives: optimizing the acceleration rendering and keeping the motion system within its physical limits. Many algorithms are proposed to driving simulator users to define this trade-off:

1. The "classical" algorithm expresses the trade-off in the frequency domain: the platform command results from a high-pass filtering of the vehicle acceleration. By removing the low-frequency component, the high-frequency accelerations are rendered while the platform displacements are reduced (Schmidt & Conrad, 1970; Reid & Nahon, 1985).
2. The "adaptive" algorithm is based in the time and the frequency domains: its structure is derived from the classical algorithm ones', but here, the gains and the cut-off frequencies of the filters are not constant: at each computational step, they are chosen to minimize a cost that gathers the platform excursion and the gap between the vehicle acceleration and the platform acceleration (Parrish *et al.*, 1975).
3. The "optimal" algorithm, which results in a combination of linear high-pass and low-pass filters, computes the platform commands that minimize a global cost. This cost corresponding to the platform excursion and the gap between the vehicle acceleration and the platform acceleration over an infinite simulation session (Sivan *et al.*, 1982).
4. The "predictive" algorithm resolves the trade-off in the time domain by computing at each step the platform command that minimizes the gap between the vehicle acceleration and the simulator acceleration subject to explicit physical and perceptive constraints (Dagdelen *et al.*, 2004).

Unfortunately, there is a lack in fully understanding the impact of the cueing algorithm design on drivers' behavior, leaving the simulator designer in a difficult situation when the motion system workspace cannot allow one-to-one rendering. At the best of the authors' knowledge, most of the works done in the driving simulation area analyses the effects according to dynamical / static configuration, see Repa *et al.* (1982); Watson at DSC 2000; Siegler *et al.* and Panerai *et al.* at DSC 2001, Jamson & Smith at DSC 2002. A few of them deals with the impacts of a specific cueing algorithm tuning parameters, see Kuge *et al.* at DSC 2002; Grant at DSC 2004; Brunger-Koch *et al.* at DSC 2006.

This paper presents the results of a new experimentation carried out at RENAULT to measure drivers' ability to follow a car in three simulator configurations:

- static;
- dynamical with a classical motion cueing algorithm;
- dynamical with an adaptive motion cueing algorithm.

The CARDS simulator was used in this experiment since it is the more representative of a typical medium-scale dynamic driving simulator.

Motion Cueing Algorithm

Initially developed by Schmidt & Conrad for flight simulators, the classical motion cueing algorithm is the most widely used algorithm in commercial simulators. The vehicle linear and angular accelerations are high-pass filtered using second order filters to maintain the motion system in its workspace (Figure 3). A third order filter is applied to return (washout) the motion base to its neutral position (Reid & Nahon, 1985). An "anti-backlash" filter is added to reduce certain artifacts that are induced by the high-pass filters (Reymond *et al.*, 2000).

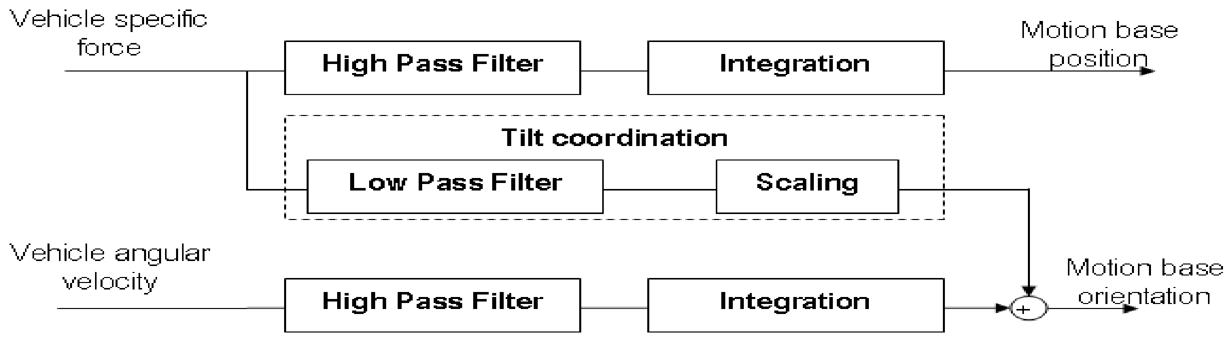

Figure 3 - Classical Motion Cueing Algorithm Filter Structure

The vehicle longitudinal and lateral accelerations are specifically low-pass filtered, scaled and passed through rate limiters to produce additional pitch and roll tilt angles. These "tilt-coordination" create an illusion of sustained acceleration through slow platform tilting. As the driver is rotated by an angle θ while the visual environment is kept stable relative to him/her, a fraction of the gravity vector can be perceived as a linear self-motion acceleration of magnitude $g.sin(\theta)$, where g is the gravity constant (van der Steen, 1998; Groen et al. 2004).

The parameters of the classical cueing algorithm must be tuned to guarantee that the outputs are always consistent with the platform limits. This is generally done by considering a "worst case" driving situation in terms of acceleration amplitude and duration. Therefore, in normal driving conditions, only part of the platform capacities is used.

To overcome this problem, Parrish *et al.* proposed an adaptive scheme, developed later by Ariel & Sivan (1984) and Reid & Nahon (1988). At each computation step, the gains (G) and the cut-off frequencies (f_c) of the classical algorithm are computed to minimize a cost function J defined as:

$$J(G, f_c) = \left[A_{veh} - A_{pf}\right]^2 + w_1 \cdot V_{pf}^2 + w_2 \cdot P_{pf}^2$$

The first term of J expresses the discrepancy between the desired acceleration A_{veh} and the platform acceleration A_{pf}, where A_{veh} is the input and A_{pf} is the output of the dynamical system defined by the transfer function $\frac{G \cdot s}{s + 2\pi f_c}$. The two other terms, composed of the platform excursion P_{pf} and velocity V_{pf} are introduced to limit the platform excursions and to washout the motion system to its neutral position during sustained accelerations. The weighting coefficients (w_1, w_2) realize a trade-off between the fidelity objective and the consistence of the trajectory of the motion system with its constraints. The resulting nonlinear cueing algorithm increases the acceleration fidelity when the simulator is near to its neutral position, compared to the linear classical algorithm.

Experiment

The experiment carried out at Renault on the CARDS simulator aimed at evaluating the impacts of three motion cueing configurations (static, dynamical based on classical cueing algorithm, dynamical based on adaptive cueing algorithm) on drivers' ability to follow a car on a straight road.

Seven subjects were asked to maintain a constant relative distance (15 m) with the lead vehicle (RENAULT Mégane) over 5 min in these three configurations. The speed profile of the lead vehicle was composed of steps in the range [0 – 80 km/h] (Figure 4).

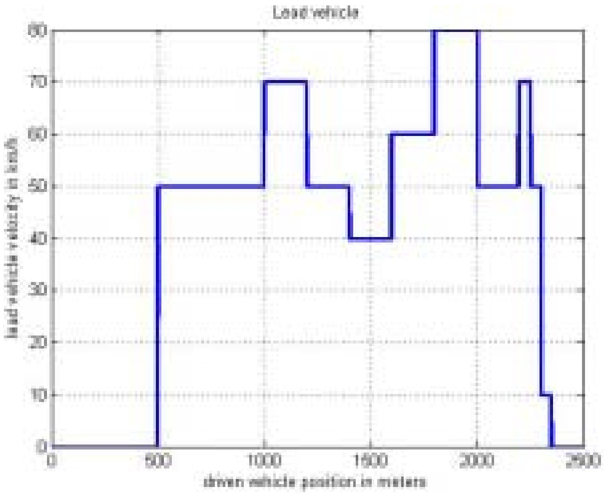

Figure 4 –Lead vehicle velocity as a function of driven vehicle position.

At the end of the second and third sessions, subjects were asked if they noticed a difference of vehicle dynamics feedback between the current and the previous sessions, and if they could indicate the most realistic driving session.

The positions, velocities and accelerations of the driven vehicle and the outputs of the cueing algorithms were recorded to make objective comparisons.

Motion cueing configurations and tuning

The classical cueing configuration rendered the vehicle acceleration using a classical motion cueing algorithm along the platform 6 dof. The configuration referred as to adaptive cueing configuration computed the platform longitudinal command using an adaptive motion cueing algorithm and the platform commands along the other dof using a classical cueing algorithm.

The trade-off between maintaining the motion system within its physical limits and optimizing the motion rendering in the simulator is defined by:

i) the cut-off frequencies and the gains of the low-pass and high pass filter, in the classical algorithm;

ii) the weighting coefficients of the cost function J associated for each DOF, in the adaptive algorithm.

As these two algorithms do not take into account explicitly neither the platform workspace nor the motion perception characteristics, their tuning is done with respect to a specific driving session.

Here, this maneuver corresponded to accelerating from 0 to 100 km/h, next maintaining the speed for 10 seconds, and finally breaking to stop the vehicle. The parameters were updated on-line by “trial and errors” to provide the most realistic vehicle feedback according to drivers’ verbal judgment. Figure 5 shows the longitudinal acceleration commands as computed by the classical and by the adaptive cueing algorithms with the final parameter sets, while the driver accelerates from 0 to 100 km/h.

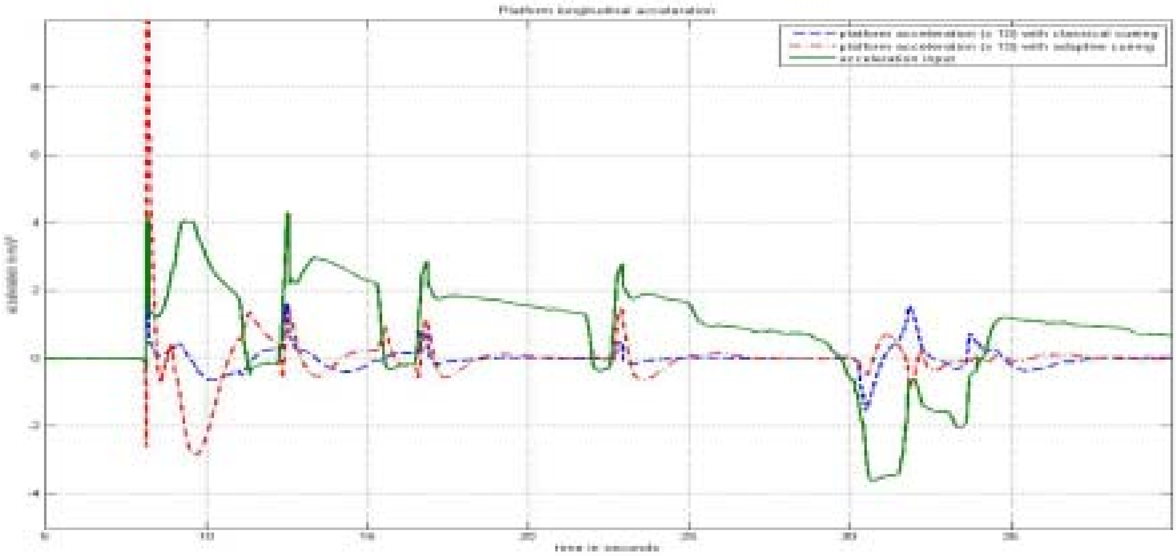

Figure 5 – Platform accelerations command computed by the classical and the adaptive cueing algorithm when driver accelerates from 0 to 100 km/h.

The platform acceleration command computed by the classical algorithm corresponds to the transitory part of the driven vehicle acceleration. The acceleration command profile computed by the adaptive algorithm over the time period [8 – 12 s] is not correlated to the acceleration command profile over the time period [12 – 15 s] even though the driven vehicle acceleration profiles are quite similar over these two periods. This results directly from the fact that the adaptive strategy is time variant.

Results

Seven subjects participated to the experimentations. Figure 6 presents typical curves of a driving session (adaptive motion cueing configuration).

Figure 7 shows the longitudinal acceleration commands in function of platform longitudinal position commands, indicating the classical and adaptive cueing algorithms capabilities to exploit the motion system workspace to render accelerations.

The areas covered by the two trajectories are quite similar; indicating that during this driving task, the adaptive algorithm is as effective as the classical algorithm to render acceleration when the platform is near its neutral position.

As expected, all subjects detected a difference of motion feedback between the static and the dynamical configurations, and they all considered the dynamical configurations as the most realistic.

However, none of them detected a difference of acceleration feedback between the classical and the adaptive cueing configurations. The analysis of the drivers' behavior throughout objectives signals are presented for the three subjects.

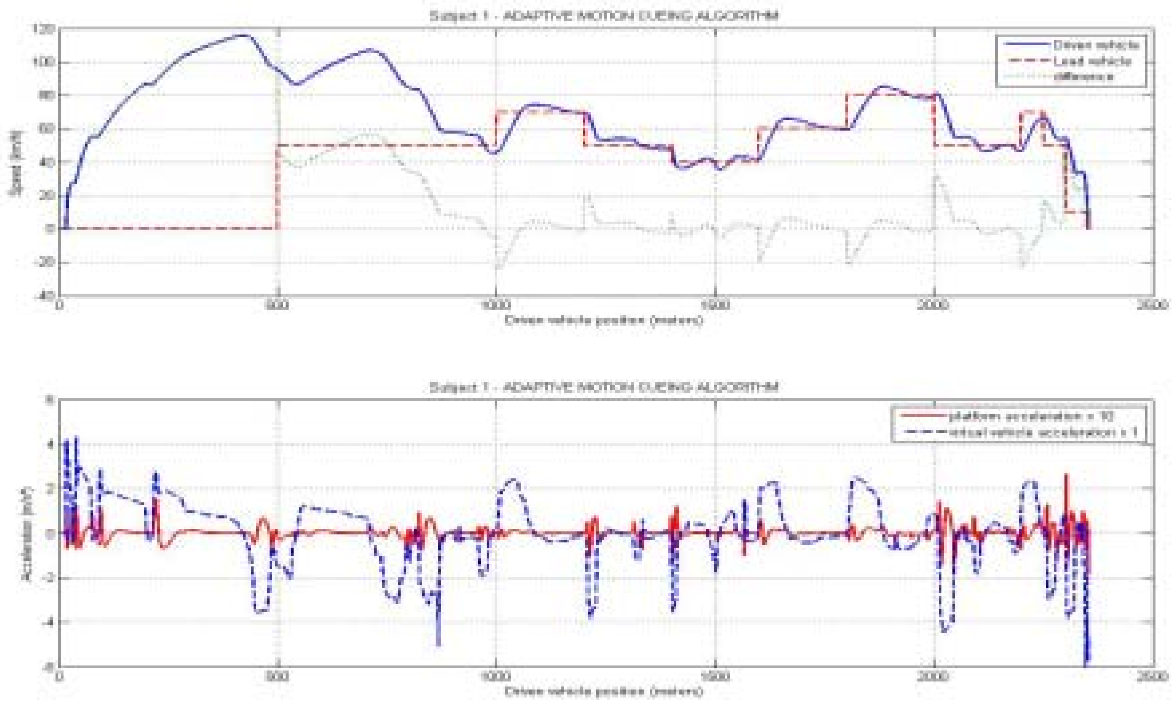

Figure 6 – Upper graph shows the driven vehicle and the lead vehicle speeds. The lower graph shows the platform longitudinal acceleration commands and corresponding driven vehicle acceleration.

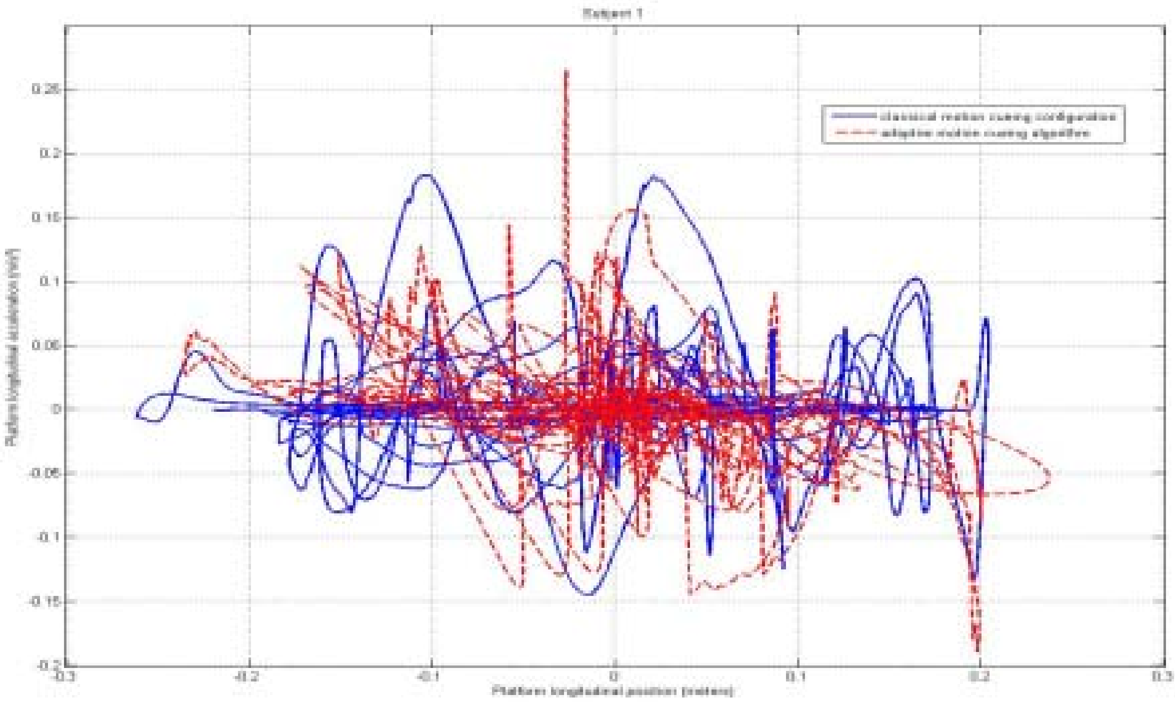

Figure 7 – Platform longitudinal acceleration in function of platform longitudinal position, in the classical and the adaptive cueing configuration.

Table 1 gives the gap between the driven vehicle speed and the lead vehicle speed over the whole session, regarding to the simulation cueing configuration. No significant variation is detected in the mean driven vehicle speed and the mean difference between the lead and the driven vehicle speed, indicating that drivers' ability to globally perform the task seems not to be influenced.

		driven vehicle speed		difference between lead and driven vehicle speed		platform longitudinal acceleration
		mean (km/h)	standard deviation (km/h)	mean (km/h)	standard deviation (km/h)	standard deviation (cm/s²)
subject 1	Static	51.63	30.94	-1.98	8.51	/
	classical cueing	47.91	31.47	-1.68	11.55	8.80
	adaptive cueing	52.49	30.01	-1.67	9.33	8.90
subject 2	Static	48.17	31.88	-1.30	11.03	/
	classical cueing	50.24	27.96	-1.48	11.68	7.61
	adaptive cueing	50.61	27.75	-0.28	9.56	6.98
subject 3	Static	47.01	31.14	-5.98	11.09	/
	classical cueing	49.08	30.24	-1.49	9.46	8.66
	adaptive cueing	51.17	31.90	-1.38	9.63	6.42

Table 1 – For three subjects and for each session: i) mean and standard deviation of driven vehicle speed ii) mean and standard deviation of speed difference between lead vehicle and driven vehicle iii) standard deviation of platform longitudinal acceleration.

Table 2 presents, the maximum of the driven vehicle acceleration and of the platform acceleration command when the lead vehicle accelerated.

	Mean of longitudinal acceleration maxima for Virtual Vehicle and Platform									
	lead vehicle speed changes									
	1st (50-->70 km/h)		2nd (70-->50 km/h)		3rd (50-->40 km/h)		4th (40-->60 km/h)		5th (60-->80 km/h)	
	Vehicle (m/s²)	Platform (cm/s²)	Vehicle (m/s²)	Platform (cm/s²)	Vehicle (m/s²)	Platform (cm/s²)	Vehicle (m/s²)	Platform (cm/s²)	Vehicle (m/s²)	Platform (cm/s²)
Static	2.65	/	3.40	/	3.88	/	2.48	/	2.21	/
classical cueing	1.77	7.79	3.56	3.94	3.00	5.23	2.64	6.55	1.96	5.13
adaptive cueing	2.21	4.16	3.64	9.66	3.00	9.27	1.81	3.24	2.02	4.51
Gap between classical and adaptive cueing	0.56	6.38	0.47	5.72	0.47	4.04	0.83	3.31	0.89	4.40

	Mean of longitudinal acceleration maxima for Virtual Vehicle and Platform							
	lead vehicle speed changes							
	6th (80-->50 km/h)		7th (50-->70 km/h)		8th (70-->50 km/h)		9th (50-->10 km/h)	
	Vehicle (m/s²)	Platform (cm/s²)	Vehicle (m/s²)	Platform (cm/s²)	Vehicle (m/s²)	Platform (cm/s²)	Vehicle (m/s²)	Platform (cm/s²)
Static (I)	4.59	/	2.43	/	3.98	/	3.95	/
classical cueing (II)	4.11	5.43	2.51	4.51	4.14	4.89	3.87	6.39
adaptive cueing (III)	4.58	13.64	2.29	4.46	3.40	10.86	4.06	14.74
Difference (III-II)	0.51	8.22	0.44	0.65	0.75	5.97	0.91	8.35

Table 2 - For each lead vehicle speed change, acceleration maxima reached by both virtual vehicle and platform (given values are means of every subjects' values)

The difference of between the maximum acceleration command computed by the classical algorithm and the maximum platform command computed by the adaptive algorithm are approximately the acceleration detection threshold in the dark, 4 cm/s²().

Discussion and perspectives

Subjects all preferred dynamical to static driving sessions. However, none of them detected a difference between the two motion cueing configurations: all subjects indicated verbally they did not detect a difference in terms of vehicle dynamics and no significant difference in the vehicle speed profiles was measured.

The difference between the platform acceleration commands computed by the classical algorithm and the platform acceleration commands computed by the adaptive algorithm being globally around the acceleration detection threshold for all driving sessions suggest that the tolerance of drivers to the cueing algorithm design results from the motion perception characteristics.

Do these results suggest that these motion cueing algorithms are "equivalent" and lead by the way the driving simulator designers to choose the motion cueing algorithm to be implemented in their simulator regarding other criterion than the driver's perception?

The motion cueing algorithm outputs depend not only on the tuning parameters and on the driving task but on the platform workspace also since it has to maintain the motion system within its limits. Therefore, tuning the classical and the adaptive algorithms for a simulator with a bigger motion workspace may indirectly lead to a larger difference in the physical and/or the perceived acceleration feedback between the classical and the adaptive configurations.

Do these results suggest that standard dynamical driving simulators provide the driver only with acceleration feedback perceived as "equivalent"?

Standard motion systems' workspace does not allow rendering vehicle accelerations over a whole driving session, but they generally allow rendering detectable inertial cues over a few seconds. Unfortunately, existing motion cueing algorithms do not sufficiently take into account the platform workspace to generate inertial cues that provide the drivers with the cues that help to perform the task. Our knowledge on self-motion perception characteristics and cognitive aspects of driving has to be improved, but there is a need to develop motion cueing algorithms that would take into account explicitly models of motion system dynamics/workspace, existing models of motion perception and of the cognitive aspects of performing a task.

References

M. Brunger-Koch, S. Briest, M. Vollrath "Virtual driving with different motion characteristics – braking manoeuvre analysis and validation" Proceedings of Driving Simulation Conference, pp 69-78, 2006.

R. Curry, B. Artz, L. Cathey, P. Grant & J. Greenberg "Kennedy ssq results: fixed- vs motion-based FORD simulators", Proceedings of DSC, 289-300, 2002

M. Dagdelen, J.C. Berlioux, F. Panerai, G. Reymond, A. Kemeny "Validation process of the ULTIMATE high performance driving simulator" Proceedings of Driving Simulation Conference, pp 37-48, 2006.

M. Dagdelen, G. Reymond, A. Kemeny, M. Bordier, N. Maïzi "MPC-based Motion Cueing Algorithm: Development and Application to the ULTIMATE Driving Simulator.", Proceedings of the DSC Europe Conference, Paris, pp 221-233, 2004.

P. Grant, Y. Papelis, C. Schwartz & A. Clark "Enhancements to the NADS Motion Drive Algorithm for Low-Speed Urban Driving", Proceedings of Driving Simulation Conference, pp 67-80, 2004.

J.R. Hall "The need for platform motion in modern piloted flight training simulators", Tech Mem, FM 35, 1989.

H. Jamson & P. Smith "How real does it feel? An "emotional" validation of the Leeds Driving Simulator", Proceedings of Driving Simulation Conference, pp 271-278, 2002.

N. Kuge, M. Kubota & K. Itoh "Study on Motion Algorithm Based on Driver Centered Approach", Proceedings of Driving Simulation Conference, pp 99-108, 2002.

F. Panerai, J. Droulez, J.-M. Kelada, A. Kemeny, E. Balligand & B. Favre "Speed and safety distance control in truck driving: comparison of simulation and real-world environment", Proceedings of Driving Simulation Conference, pp 91-107, 2001.

R. Parrish, J. Dieudonne and D. Martin "Coordinated adaptive washout for motion simulators", Journal of Aircraft, vol. 12, no. 1, pp 44-50, 1975.

R.V. Parrish & D.J. Martin "Comparison of a linear and a non linear washout for motion simulator utilizing objective and subjective data from transport landing approach", Tech Rep NASA, 1976.

L. Reid and M. Nahon "Flight simulation motion base drive algorithms: part 1 – developing and testing the equations", University of Toronto, Canada, Tech Rep. UTIAS 296, 1985.

L. Reid and M. Nahon "Simulator Motion-Drive algorithms: a designer's perspective", Journal of Guidance, 13 (2): 356-362, 1988.

B.S. Repa, P.M. Leucht & W. Wierwille "The effect of simulator motion on driver performance", Society of Automobile Engineers, 1982.

G. Reymond, A. Kemeny, J. Droulez, A. Berthoz "Role of lateral acceleration in driving: experiments on a real vehicle and a driving simulator", Human Factors 43(3): 483-495, 2001.

G. Reymond, A. Kemeny "Motion cueing in the Renault driving simulator", Vehicle System Dynamics, 34(4), 249-259, 2000.

I. Siegler, G. Reymond, A. Kemeny & A. Berthoz "Sensorimotor integration in a driving simulator: contributions of motion cueing in elementary driving tasks", Proceedings of Driving Simulation Conference, pp 21-32, 2001.

R. Sivan, J. Ish-Shalom & J.K. Huang "An optimal control approach to the design of moving flight simulators", IEEE Transactions on Systems, Man and Cybernetics, 12(6), 818-827, 1982

G. Watson "A synthesis f simulator sickness studies conducted in a high fidelity driving simulator", Proceedings of Driving Simulation Conference, pp 69-78, 2000.

W. Wierwille, J. Casali & B. Repa "Driver steering reaction time t abrupt-onset crosswinds as measured in a moving base driving simulator", Human Factors, vol. 25, no. 1, pp 103 – 116, 1983.