Assisted and Autonomous Driving on Driving Simulators

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Abstract

With the upcoming diffusion of autonomous vehicles, a substantial modification of the human role in the driving action is taking place. While most of the effort has been put on making the car capable of safely moving in a complex environment, the human in the control loop is becoming a critical problem: on the one hand, the driver attention in driving actions is necessary to guarantee safety in any conditions, on the other hand the driver comfort has to be considered to make the driving experience satisfactory. In this paper balancing between these two aspects is effectively investigated by means of dynamic driving simulators, particularly addressing the impact of vehicle dynamic setup.

The target user for these applications is a non-professional driver, which does not easily fit into the virtual environment. Proprietary Active Seat (AS) and Active Belts (AB) technologies are used in the driving simulator to reduce the gap between real and virtual environment. Advanced Multi-Sensory Motion Cueing Algorithm based on Nonlinear Model Predictive Control technique is used to coordinate somatosensory stimulation (AS/AB) with the vestibular one (Motion Cues).

Moreover, cognitive aspects have to be considered to collect information regarding driver attention and comfort, which are not retrievable by motion analysis. To this aim, an advanced biotelemetry device is used to collect driver's Heart Rate Variability and Skin Potential Response, which are recognized bio-signal for stress load, and that are processed by means of statistical tools to infer cognitive features. Finally, practical use cases will be presented analysing the effects of different vehicle setups on human perception while experiencing autonomous driving on the simulator.

Preliminary

It's known that OEM's attention in the development of autonomous vehicles is already very high now and will increase more and more in the immediate future. Sensor engineering and their fusion is just one of aspects of the entire problem. Among others and just from a general point of view, important areas of research being vehicle-environment simulation and its spatial resolution (micro-macro-mesa), V2X communication, trajectory planning and tracking, human-robot co-existence, human monitoring.

If we consider the aspects more related to vehicle engineering, autonomous driving is a much more challenging task than one could think it to be. It is likely that it's not just a matter of connecting sensors and actuators to the system in order to have it moving autonomously, but instead it will be essential to study in depth all aspects that relates humans in contact with robotized systems. In this respect, a few points are of fundamental importance.

Robotization acceptance (uncanny valley)

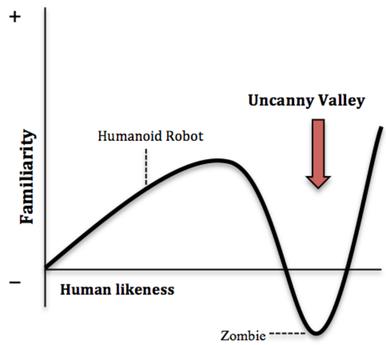


Fig 1: Uncanny valley (Picture taken from [19])

The uncanny valley principle is a known and generic problem of robotization. Basically, it states that human beings are pleased with robot actions when they are repeatable and expectable, maybe simple but consistent. Whenever a robotic action becomes weird, or the robot behaves like an (even only apparently) inconsistent human, then the level of trust to the machine decreases and the human tends to monitor the robot without trusting it blindly anymore. If we apply the principle to robotized driving, this means on one hand that the human will again need to focus visually to what happens around, therefore nullifying the efforts that are supposed to be made to make the car comfortable under unmanned control; on the other, the optimization of comfort will require a special monitoring of the human action while being driven around by the autonomous system: it is possible that an adaptive and progressive automatic setup of the vehicle dynamic characteristics is required during the familiarization phase of the robotic actions.

Human-robot transition

It is very important (especially for the non-US market of autonomous vehicles, which seems to definitely pass through a few years of human-robot co-existence) to study all the possible combinations of human robot interactions, on the one hand to make the consequences of a natural contemporary (human, robot) action manageable, on the other to study what could be accepted by the (distracted) human in terms of robot manoeuvring. Vehicle dynamics is very important in these cases: under autonomous control, the feeling of the car should be natural; under conflicting action the human should override the robot, and the feeling should be the one that the human expects to have when fully empowered in control. For example, when the human grabs the steering wheel control from the robot, special attention should be dedicated to potential dynamic overshoot due to an excessive overriding effort. Moreover, the robot should learn how the human in that particular car drives and should adapt itself to that style, with specific reference to:

- Handling actions
- Handling cues to the driver
- Ride cues to the driver

It is possible that, for a distracted human subjected to autonomous driving several rules of ideal handling/ride setup for a given vehicle are not valid as they have been traditionally and commonly accepted. For example, it is expected that under robotic driving an excessive pitch during braking or roll during turning could cause discomfort, while under human driving control they are necessary to better perceive vehicle dynamics. Similarly, it is possible that low frequency (heave, pitch, roll) compensation under robotic driving could reduce the excitation of the vestibular system of a distracted human.

Simulation and Driving Simulators

All the aspects mentioned above would require enormous resources for being studied in depth in real life, with all the risks associated having a real robotized vehicle moving in all the several needed traffic scenarios.

It is of course possible to intensively use traditional off-line vehicle simulation for assessing most of the principles for best tuning the vehicle taking into account the new requirements, for maximizing (passive) driver and passenger comfort. The metrics for deciding whether that tuning is the "best" is not completely clear, especially due to lack of experience for such robotized vehicles. One fundamental difference with respect normal human driving is that the visual control is enormously reduced (the driver/passenger watches the external scenario with a much reduced level of attention, if any). One other big difference is that the driver might not havehands on the steering wheel, and if yes , the steering (when still existing) could rotate under robotic control. As a consequence, vehicle dynamics is not any more dominantly perceived with visual cues from the scene and haptic ones from the steering, but rather from body contact to the seat and limb contact to the interior of the car, which traditionally are more cues that expert drivers use. The vestibular and somato-sensorial systems are mainly responsible to perceive the vehicle motion and are the major source of cues for the guests of a robotized car.

VI-grade and University of Padova (DEI) propose a revolutionary approach to the problem of driver/passenger comfort maximization under autonomous vehicle control:

o Application of some of the principles used for developing VI-MotionCueing (including the body contact effects as described below)as described above), to minimize the difference between motion perception in a car and on a driving simulator;

o Assessment of the driver/passenger comfort by monitoring some key psycho-pysiological parameters during driving session on a driving simulator, comparing self to robot driving in the same scenarios.

Integrated Vestibular/Somatosensory Motion Cueing

The effectiveness of driving simulators is strongly related to the quality of driver's motion perceptions, hence motion control algorithm must generate both realistic and feasible inputs to the platform. Such strategies are called Motion Cueing Algorithms (MCAs). A promising approach is that of designing MCAs based on Model Predictive Control (MPC) technique, that helps in efficiently handling platform workspace and is very effective in reproducing sense of motion, [2], [3], [4], [6], [8]. Differently from the typical usage of driving simulators, the target user for autonomous driving applications is the non-professional driver, which does not fit into the virtual environment easily [1]. Active Seat (AS) with integrated Active Belts (AB) have been introduced to reduce the gap between real and virtual environment in simulators, by providing information about sustained accelerations to the driver. These accelerations cannot be simply reproduced by the motion platform, due to its intrinsic mechanical limits. The AS/AB working principle can be seen as a somatosensory stimulation, used as a haptic feedback [13]: the pressure is interpreted by the brain as an added information on the vehicle status. The greater is the realism in the pressure reproduction and the easier should be the capability of the driver in using this information, thanks to a reduction of the perceptual conflict [14]. The same idea has been widely exploited for flight simulators [16], where AS (G-seat) is generally applied into a static environment. The typical control strategy of such tools is almost straightforward: pressure is directly associated with accelerations on the specific directions. In dynamic simulation this approach results to be misleading. As an example, let us consider a giant simulator [18], [9]: the available work-space allows to reproduce part of the sustained accelerations by means of the motion itself, and the applied pressure/tension on the AS/AB should be coordinated with that. More in general, the AS/AB has to adapt in real time to the undergoing motion behaviour.

In this paper, we propose an NMPC based Multi-Sensory Cueing Algorithm (MSCA), containing a model of a seated human body subjected to accelerations and coupled with the vestibular system. A nonlinear model is developed, taking into account the inertial body reaction, the frictions between body and seat and the damping effect. The model is then adapted to be used into an NMPC framework. An ad-hoc implementation is provided to reach real time performance. A scheme of the procedure is in Fig. 2:

1) the vehicle translational accelerations and rotational velocities {a,v} are computed by using a dynamical simulation engine;

2) signals {a,v} are then pre-processed (according to given application/performance objectives);

3) the vestibular/pressure model is used to compute the reference for the controller;

4) the platform displacements and the AS/AB pressures/tensions are computed by means of an NMPC controller, and then given as reference inputs to the motion controller.

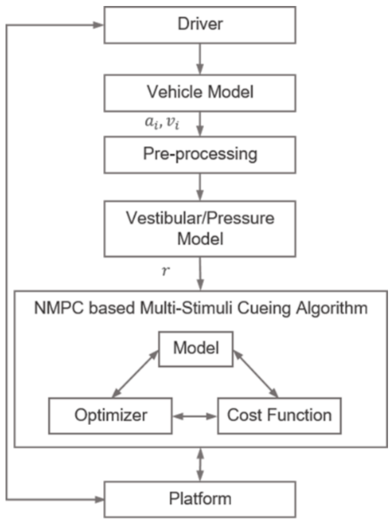


Fig. 2: Scheme of Multi-Stimuli Cueing Algorithm

The advantages of such approach are manifold:

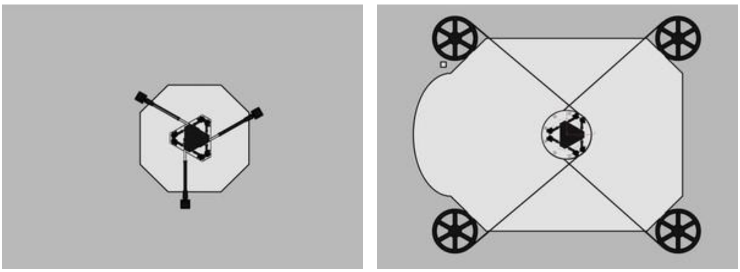
1) the platform motion, the AS and the AB are perfectly coordinated thanks to a coupled model;

2) the usage of an optimization based controller allows to have an haptic stimulus that is as closer as possible to the real one, improving the overall realism;

3) the sickness could be reduced even for non-professional drivers, extending the class of potential users; 4) the AS/SB systems do not require to be re-tuned every time the motion strategy is modified.

Reference Motion Platforms

The algorithm has been designed to be applied to the Driver in Motion (DiM) family of simulation platforms: DiM 150 and DiM.C9/700 (see [5] for a detailed description of the DiM150). DiM150 is based on a mechanical architecture with redundant DOF: the simulator consists of a hexapodal structure mounted on a tripod frame, which moves on a flat, stiff surface sliding on airpads. The planar tripod is used to produce most of the longitudinal, lateral, and yaw sliding movements, whereas the hexapod is used for pitch, roll, vertical, and smaller longitudinal, lateral, and yaw movements. DiM.C9 is designed with the same hexapod and air-pads system, replacing the tripod with a central pulley called ”discframe” driven by cables. DiM150 tripod cover a range of ±0.75[m] while the DiM.C9 specific model used for this example features a range of ±3.5[m]and is presented in fig. 3.



(a) (b)

Fig. 3: top view sketch of DiM150 and DiM.C9/700.

Active Seat and Active Belts Systems

A regular or special car passive seat is converted into active by mean of eight to ten air bladders which are inflated with compressed air via proportional valves control (see Fig. 4) properly installed in the structure of the seat.

The AB are 3, 5 or 6 points belts tensioned by means of fluidic muscles controlled by pneumatic valves. The bladders are designed to have a distributed contact area and placed to act on the body similarly to what happens in reality. Proportional valves are used to have a progressive and continuous variation of pressure, which can be controlled in the range [0-1.5] bar for the seat and [0-8] bar for the muscles.

(a)

(b)

Fig. 4: Active seat and active belts system

Model for Control

The Inertial body reaction, the friction between body and seat, the seat material, the nonlinear stiffness and damping effect of the body have been considered in the model formulation. A combined vestibular/somatosensory model for control is then proposed, to be used both to compute the perceived pressure/acceleration and within an NMPC based control implementation (see scheme in Fig. 2). The proposed model neglects the pressure on legs (bladders 1 and 6) and on glutes (bladders 7 and 8), although an extension of the model to consider those elements can be derived adopting the same principles.

Lateral Pressure model

The lateral dynamic of the body is characterized by means of a mass-spring-damper model, represented by the following differential equation:

$$m\ddot{d}_y + c(d_y)\dot{d}_y + k(d_y)d_y = ma_y$$

where d_y, $\dot{d}_y$ and $\ddot{d}_y$ represent respectively the position, velocity and acceleration of the center of mass of the trunk along the lateral direction; m is the driver mass which is subjected to lateral acceleration; $c(d_y)$ is a nonlinear viscous damping coefficient; $k(d_y)$ is a nonlinear stiffness; ma_y is the external force that acts on the human body, caused by the lateral acceleration. The underlying idea is that the inertial properties of the body are considered in the mass, whereas the nonlinear stiffness/damping are used to emulate the seat elastic/viscous reaction, and $k(d_y)d_y + c(d_y)\dot{d}_y$ can be seen as the overall contact force on the trunk.

To determine the

value of m, let us define M as the mass of the driver trunk, including arms and hands, which is assumed to be about the 67% of total body weight (see [11] for details on body-mass distribution). The trunk is considered as a vertical rod of length L and center of gravity l, which rotates around the bottom edge of an angle α. According to this, the

$$I\ddot{\alpha} = F_y l$$

conservation of angular momentum law can be simplified as

The final model results to be

$$\begin{cases} \ddot{d}_y &= -\frac{c(d_y)}{m}\dot{d}_y - \frac{k(d_y)}{m}d_y - \frac{F_f(x_f)}{m} + a_y + g\phi \\ \dot{x}_f &= \dot{d}_y - \frac{|\dot{d}_y|}{h(\dot{d}_y, a_x)}x_f \\ y_{p,y} &= \frac{(k(d_y)-k_0)}{A}d_y + \frac{(c(d_y)-c_0)}{A}\dot{d}_y + \bar{u}_{p,y} \end{cases}$$

where $k(d_y)$ and $c(d_y)$ have the form

$$k(d_y) = k_p d_y^p + k_0,$$
$$c(d_y) = c_p d_y^p + c_0$$

and x_f defined the friction dynamic as described in [7].

Longitudinal Pressure Model

The model that considers longitudinal acceleration describes the human body as free to move in forward direction and pressed backwards on the seat in case of positive longitudinal acceleration. In the former situation the AB system has to provide the correct tension to the driver, in the latter the task has to be accomplished by the bladders on the back. Since no significant friction phenomena between driver and seat occur, the pressure exerted by the driver's body has been determined through a linear model.

Pressure Vestibular-Coupled Model

To obtain a unique model describing both the motion and pressure perceptions, longitudinal and lateral models have to be coupled with a vestibular model. We adopt the same vestibular model used in [6] to develop a fast MPC based MCA, which is briefly reported in the following.

$$\begin{cases} \dot{\mathbf{x}}_V = A_V \mathbf{x}_V + B_V \mathbf{u}_V \\ \mathbf{y}_V = C_V \mathbf{x}_V + D_V \mathbf{u}_V \end{cases}$$

with state, input and output vectors

$$\mathbf{x}_V = \begin{bmatrix} \mathbf{x}_s^T & \mathbf{x}_{\bar{o}}^T & \mathbf{x}_I^T \end{bmatrix}^T \in \mathbb{R}^{21}$$
$$\mathbf{u}_V = \begin{bmatrix} a_x & a_y & a_z & \dot{\phi} & \dot{\theta} & \dot{\psi} \end{bmatrix}^T \in \mathbb{R}^{6}$$
$$\mathbf{y}_V = \begin{bmatrix} \mathbf{y}_s^T & \mathbf{y}_{\bar{o}}^T & \boldsymbol{\beta}^T & \mathbf{x}_I^T & \dot{\boldsymbol{\beta}}^T \end{bmatrix}^T \in \mathbb{R}^{18}$$

The state equation of the overall NMPC model results to be

$$\begin{cases} \ddot{d}_y &= -\frac{c(d_y)}{m}\dot{d}_y - \frac{k(d_y)}{m}d_y - \frac{F_f(x_f)}{m} + a_y + g\phi \\ \dot{x}_f &= \dot{d}_y - \frac{|\dot{d}_y|}{h(\dot{d}_y, a_x)}d_y \\ \ddot{d}_x &= -\frac{c}{m}\dot{d}_x - \frac{k}{m}d_x + a_x + g\theta \\ \dot{\mathbf{x}}_V &= A_V\mathbf{x}_V + B_V\mathbf{u}_V \end{cases}$$

and the input and output vectors are, respectively,

$$\mathbf{u} = \begin{bmatrix} \bar{u}_{p,y} & \bar{u}_{p,x} & \mathbf{u}_V^T \end{bmatrix}^T \in \mathbb{R}^8$$
$$\mathbf{y} = \begin{bmatrix} y_{p,y} & y_{p,x} & \mathbf{y}_V^T \end{bmatrix}^T \in \mathbb{R}^{20}$$

Non linear MPC Implementation

The following optimal control problem (OCP) is solved on-line at each sampling time

$$\begin{aligned} \min_{\mathbf{x}(\cdot),\mathbf{u}(\cdot)} \quad & \int_{t_0}^{t_f} \phi(t, \mathbf{x}(t), \mathbf{u}(t))\mathrm{dt} \\ s.t. \quad & \dot{\mathbf{x}}(t) = f(\mathbf{x}(t), \mathbf{u}(t)), \\ & \underline{x} \leq \mathbf{x}(t) \leq \bar{x}, \\ & \underline{u} \leq \mathbf{u}(t) \leq \bar{u}, \end{aligned}$$

where φ is the control objective, which includes the tracking error on accelerations and displacements. Function f represents the system dynamics. The Real-Time Iteration (RTI) strategy [10] is used to satisfy the hard real-time constraint (200Hz sampling frequency or 5ms sample time). As a result, the OCP is discretized into N intervals by multiple shooting and solved by Sequential Quadratic Programming (SQP) algorithm with only one iteration. According to the common approach of formulating the problem with respect to the input and the state differences, $\mathbf{\Delta U}$ and $\mathbf{\Delta X}$, respectively, the resulting Quadratic Programming problem (QP) is

$$\begin{aligned} \min_{\Delta\mathbf{X},\Delta\mathbf{U}} \quad & \frac{1}{2}\begin{bmatrix}\Delta\mathbf{X} \\ \Delta\mathbf{U}\end{bmatrix}^T H \begin{bmatrix}\Delta\mathbf{X} \\ \Delta\mathbf{U}\end{bmatrix} + g^T \begin{bmatrix}\Delta\mathbf{X} \\ \Delta\mathbf{U}\end{bmatrix} \\ s.t. \quad & \Delta\mathbf{x}_{k+1} = A_k\Delta\mathbf{x}_k + B_k\Delta\mathbf{u}_k + c_k,\ k = 0, \ldots, N-1 \\ & \underline{x} - \mathbf{x}_k \leq \Delta\mathbf{x}_k \leq \bar{x} - \mathbf{x}_k,\ k = 0, \ldots, N-1 \\ & \underline{u} - \mathbf{u}_k \leq \Delta\mathbf{u}_k \leq \bar{u} - \mathbf{u}_k,\ k = 0, \ldots, N-1 \end{aligned}$$

where

$$\Delta\mathbf{X} = [\Delta\mathbf{x}_0^T, \ldots, \Delta\mathbf{x}_N^T]^T,$$
$$\Delta\mathbf{U} = [\Delta\mathbf{u}_0^T, \ldots, \Delta\mathbf{u}_{N-1}^T]^T$$

are collections of state and control variables defined in all intervals. The Hessian H is approximated using Gauss-Newton method, which requires only the first order derivative of the objective function. Matrices A_k, B_k are linearizations, computed at each time step, of system dynamics over the prediction horizon. To further accelerate the on-line computation, the adjoint sensitivity strategy [12] is used, i.e. fixed values for $A_k = A, B_k = B$ are computed off-line. In addition, the objective function φ has to be parameterized to be linearly dependent on all states and control variables. As a result, the Hessian H is time-invariant and can be also computed off-line.

The resulting QP can be solved either in the sparse form (with $(N + 1)n_x + Nn_u$ decision variables) or in the condensed form (with Nn_u decision variables) after the so-called condensing step which eliminates state variables from the OCP [17]. Since the problem has both state and control constraints, the Alternating Direction Method of Multipliers (ADMM) strategy for OCP problems [15] can be adopted to solve the sparse QP.

The hard real-time requirement is satisfied by implementing the NMPC algorithm in Matlab Executable on a PC with Intel core i7 3.60Ghz.

Simulative Results

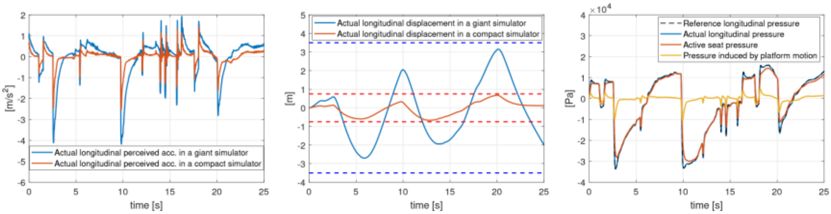
In this section, simulative results are reported in order to analyse the AS/AB system performances. The MSCA is evaluated in the first part of the *Calabogie MotorSports Track* for the longitudinal dynamics, and in a double lane change maneuver for the lateral one. In both cases a comparison between the compact DiM 150 and the greater DiM.C is proposed.

Parameter Values

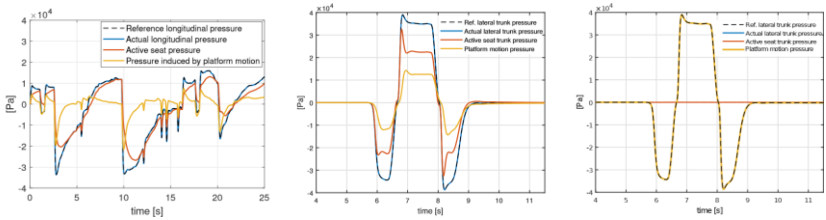
Results described in this Section are obtained with the parameter values reported in Tab. I. The nonlinear lateral pressure model $k(d_y)$ and $c(d_y)$ are described by a second degree polynomial functions. A reasonable choice for the static friction coefficient is 0.4 while the dynamic one, which is usually smaller, is set to 0.3. Stiffness and damping values and functions are set by using reasonable values and refined by an iterative tuning based on simulative results. For the application at hand, we can consider that the air cushions have size of 20 × 8 cm, hence an area of $A = 0.016$ m². Although a dedicated identification procedure would be desirable for a more precise analysis, the chosen values for parameters can be considered good enough to put in evidence advantages of the proposed algorithm.

Parameter	Value	Unit
M	50	[kg]
m	67	[kg]
$k(d_y)$	$1000(d_y)^2+1000$	[N/m]
$c(d_y)$	$200(d_y)^2+1000$	[Ns/m]
μs	0.4	
μ_d	0.3	
γ	10	[deg]
$\sigma 0$	10^4	[N/m]
$\sigma 1$	0	[Ns/m]
vs	0.005	[m/s]
kx	20000	[N/m]
cx	1500	[Ns/m]
A	0.016	[m^2]

TABLE I: Model parameters used in simulative results.



(a) Perceived longitudinal acceleration in a compact (b) Longitudinal position displacement in a com- (c) Longitudinal pressures in a compact simulator. vs giant simulator. pact vs giant simulator.



(d) Longitudinal pressures in a giant simulator. (e) Lateral pressures in a compact simulator.

(f) Lateral pressures in a giant simulator.

Fig. 5: Performance comparison: compact vs giant simulator

Regarding the longitudinal direction, the MSCA is setup so that platform working area is exploited at best, by maximizing the accelerations, using a proper scaling on the input signal. Moreover, inspired by the common practice of reproducing the braking action by means of an ”impulse-like” acceleration at the beginning of the event, a high-pass filter is used in the pre-processing step (see scheme in Fig. 2). In Fig. 5a and 5b the perceived longitudinal acceleration and the displacement in the two simulators are reported. As expected, in the DiM.C a greater acceleration peak is achievable. In Fig. 5c and 5d the excellent tracking performance of AS/AB are shown, together with the pressure induced by the platform and the one added by the AS/AB system. It is interesting to note that a perfect coordination between motion and AS/AB system is obtained due to a coupled vestibular-pressure model. Moreover, the pressure induced by the simulator acceleration is significantly different in the two cases: in the compact DiM 150 it is smaller and shorter, because the force due to platform acceleration is almost 0. On the contrary, it is bigger and longer in the giant DiM.C, where the motion platform provides by itself the requested acceleration. As a consequence, the pressure request for the AS/AB is coordinated to have the same overall pressure. In both cases the need for a MSCA is evident, though, in the DiM.C, the required AS/AB pressure/tension plays a more relevant role.

As for the lateral dynamics a double lane change manoeuvre has been considered. In the compact DiM 150 the acceleration signal has been scaled to fulfil platform limits, while in the giant platform the acceleration can be reproduced 1:1. In Fig. 5e and 5f, AS performances are shown. In DiM.C a full scale reproduction of the manoeuvre is possible, hence pressure induced by motion is equal to the reference one, making the AS unnecessary. Conversely, in DiM 150, pressure peaks can be observed when reference acceleration crosses the zero value. Indeed, the AS/AB system provides the required pressure to the driver body in order to compensate the opposite sign accelerations, which are induced by the compact platform to be compliant with the physical limits.

Conclusions

In this paper the role of the simulator for the upcoming challenges in the widespread of autonomous vehicles is addressed. Specifically, an active seat/active belts system results to be fundamental to provide a complete information to the driver for the passive driving. To best handle this new technology, a novel approach for active seat and active belts systems is proposed, based on a real time nonlinear MPC implementation. A non-linear pressure model has been developed for the lateral dynamic and a linear one for the longitudinal dynamic. The two are then coupled with a vestibular one to describe the pressure and motion perception of a driver on a dynamic simulator. By means of an NMPC controller, references for AS/AB and platform displacements are generated. The advantages in using such an approach are highlighted comparing results on two different motion platforms.

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