Abstract: This paper explores the application of numerical optimal control (NOC) to the synthesis of motion cueing algorithms for race-car simulators. These techniques are used to design washout filters that address the limitations of the commonly-employed linear quadratic Gaussian (LQG) regulator and classical frequency shaping strategies. The primary disadvantage of the LQG and classical tuning methods is that they do not recognize explicitly the hardware limitations of the platform and thus have to rely on an iterative process to address workspace limitations. In two new algorithms a kinematic model of the platform is used to constrain explicitly the platform’s motion within the available workspace. The first algorithm is directed to the optimization of the parameters of a linear washout filter, while in the second approach the platform motion is governed by an open-loop optimal control. The results of the two new algorithms are tested on race-car minimum lap-time simulations, and then compared with a linear-optimal-control-based solution. The race-car scenario presents different challenges from the passenger car and aircraft contexts; these differences are discussed.

Keywords: Automotive Control; Motion Cueing Algorithms; Optimal Control; Parameter Optimisation.

1. INTRODUCTION

Car simulators are used in a variety of applications ranging from behavioural research to driver training and vehicle development. Regardless of the specific purpose they all aim to create a realistic environment in which the driver will behave as he/she would in a real car. In order to operate the vehicle, the driver needs a set of controls, and sensory stimuli from the vehicle and its setting (such as the vehicle’s speed, its acceleration and its position on the road). This is communicated to the simulator driver through visual, auditory and motion-based cues.

The graphics are of primary importance, not only providing images of the location and driving conditions, but also for conveying the vehicular speed. Auditory cues and haptic feedback through the steering wheel and pedals also supply the driver with information about the vehicle - the engine speed and tyre slip. Acceleration and orientation is detected in humans by the vestibular system in the inner ear Dichgans and Brandt [1978]. A simulator that provides motion cues is able to stimulate this organ thereby providing a better sense of the motion of the vehicle.

Figure 1 shows the integration of various subsystems into a complete simulator and illustrates how the driver generates control commands in response to sensory cues. These inputs are fed into a vehicle model that generates a vehicle state that contains physical information about the car including its acceleration, velocity and position. This data is then used to update the visual, auditory and motion cues.

The fidelity of the simulator driving experience is always limited by the quality of the cues. Advanced 3D image projection with fast refresh rates and low latency together with high-quality computer generated images (CGI) produce excellent visual cues. In the case of the motion cues the platform workspace and bandwidth restrict the quality of the cues rather than technology; to reproduce the vehicle motion exactly, the simulator would need to move in a workspace as large as the track itself. Since this is practically infeasible, different strategies have been developed to generate motion cues. While not perfect, they improve the driver’s feeling of realism and thus his/her ability to drive normally. These strategies are referred to as motion cueing algorithms (MCA) and they use the vehicle’s translational accelerations and its rotational velocities to move the platform appropriately without exceeding its physical limits. Most MCA development has been in the context of passenger cars and flight simulators Reid and Nahon [1985], Telban and Cardullo [2005]. In contrast, the research presented here focuses on the race car setting. This scenario differs from the passenger cars because the
dynamics are fast and the drivers experience much larger accelerations, particularly during cornering and braking. As a result, the race car scenario represents a more demanding MCA design challenge, not only when trying to reproduce the increased accelerations, but also with regards to the suppression of micsues that occur when the platform approaches its physical limits.

The most widely used motion cueing strategies are based on classical frequency-shaping Colombet et al. [2008], Larsen [2011] and linear-optimal-control centred algorithms Sivan et al. [1982], Reid and Nahon [1985], Telban and Cardullo [2005]. These algorithms involve the design of high-pass filters that are manually tuned so that the low-frequency demands, that would otherwise produce large displacements, are removed in order to ensure that the platform operates within its workspace limits.

The research presented in this paper makes use of general nonlinear numerical optimal control to produce motion cues. These optimal-control-based techniques are used to generate either platform accelerations directly, or to design linear filters that explicitly recognise platform workspace constraints. In both cases the problem and problem formulation are nonlinear and track specific, but the approach taken addresses the primary limitation of existing methods that only respect platform workspace limits iteratively and indirectly. This removes the repetitive tuning processes characteristic of the classical and LQG strategies.

Both the linear-optimal-control and numerical optimal control based algorithms are implemented for the yaw, lateral and longitudinal freedoms. As was previously discussed, the input to the MCA is a combination of the vehicle’s translational acceleration and its angular velocity. This is usually produced by a vehicle model in response to the driver control inputs. In this study vehicle telemetry data is generated by a minimum-lap-time optimal control procedure and can be found in Helinski [1990].

Referring to Figure 2, an inertial reference frame x'y'z' is similarly defined with its origin C on the platform at the centre of the platform-leg connection joint system. The translation of the platform from the origin of the inertial reference frame is described by the vector $S$, and the matrix $R$ describes the platform in terms of 3 Euler angles. There are a number of choices for the Euler angles, and each configuration has distinct singularities. For consistency with the vehicle modelling, the Euler angles are chosen as 3-2-1 angles. This corresponds to a rotation first about $z$ (yaw angle ($\phi$)), then about $y$ (roll angle ($\theta$)) and finally about $x$ (pitch angle ($\psi$)). The singularity occurs for a roll angle of $\pm \frac{\pi}{2}$, which does not occur in this application. The rotation matrix is given (where $\cos(\theta)$ is abbreviated as $c_\theta$ and $\sin(\theta)$ as $s_\theta$):

$$R = R_z(\psi)R_y(\theta)R_x(\phi)$$

$$R = \begin{bmatrix} c_\theta c_\phi & s_\theta c_\phi & c_\theta s_\phi - s_\theta s_\phi c_\psi + c_\theta s_\psi \\ c_\theta s_\phi & s_\theta s_\phi & c_\theta c_\psi - s_\theta s_\psi c_\phi + s_\theta c_\psi \\ -s_\theta & -c_\theta & c_\theta c_\phi s_\psi - c_\theta s_\phi s_\psi \end{bmatrix}.$$  

The base joints of the hexapod legs are described by six vectors $P_j$ in the inertial frame, and the platform joints are described by vectors $P_j$ in the body-fixed frame. The platform joints can then be described by vectors $P_j$ in the inertial frame, which are related to $P_j$ by:

$$P_j = S + R \cdot P_j \quad (j = 1 \ldots 6).$$  

The platform legs can be described by vectors $L_j$, which point from the base joints to the corresponding platform joints and can be found as the difference between the platform and base vectors. The leg lengths ($L_j$) are simply the magnitude of the leg vectors and $L_j$ are unit vectors associated with the directions of the legs.
3. LINEAR OPTIMAL CONTROL

The linear optimal control approach was developed in Sivan et al. [1982], Reid and Nahon [1985], Telban and Cardullo [2005] and was then extended to include frequency-dependent weight as shown in Figure 3. This approach to filter design is based on a model of the human vestibular system with the aim of taking advantage of the body’s natural movement filtering processes; the translational accelerations and angular velocities that a person senses are not the same as those that the person actually undergoes.

The translational acceleration and rotational velocity of the actual vehicle form the input to the system. The top signal path represents the driver of the real car, where the motion he/she senses is a filtered version of the real accelerations and angular velocities. The lower signal path represents the simulator. The vehicle accelerations and angular velocities are filtered by $F(s)$ and the resulting motions are rendered by the simulator. The simulator driver’s vestibular system filters these signals to yield sensed motions. The motion perception error is the difference between the movement sensed by the simulator and car driver.

This problem can be recast in a generalised regulator form Green and Limebeer [2012] as shown in Figure 4. The vehicle states are modelled as coloured noise processes and the outputs $z_1$ and $z_2$ represent the frequency-weighted perception error and platform states (velocities and displacements). LQG theory is then used to design the filter $F(s)$ that minimises the output integral square error. Including the platform states in the cost function results in a trade-off between the perception error and the simulator motion. If the motion is heavily penalised, a larger error will result, and conversely if the error is small an increased motion is required. The frequency weights $W_1(s)$ and $W_2(s)$ are iteratively tuned until, for a sample lap, the platform remains within its workspace constraints. The selection of the weights also affects the shape of the acceleration signal and requires tuning in response to driver feedback.

4. NUMERICAL OPTIMAL CONTROL

The work in this paper makes use of a Guass-Legendre-Radua pseudospectral optimal control solution method that has been implemented in the software package GPOPS-II Patterson and Rao [2013].
5. RESULTS

5.1 LQG and Optimal Filter Parameter Design

The LQG filters were tuned using simulation data for a complete minimum-time lap of the Circuit de Barcelona-Catalunya so that the resulting hexapod movement remained within the allowed workspace. The same minimum-time lap data was used as the reference in the numerical optimal control problem, which determined the linear filter parameters. The performance of the filters are examined for the long cornering manoeuvre (shown in Figure 7), which features strong braking, acceleration and a period of sustained lateral acceleration.

There are two concepts that need to be defined before analysing the results. The first is onset cues. The idea is to accelerate the platform correctly at the beginning of a manoeuvre and then, when it runs out of workspace, stop the movement for the remainder of the manoeuvre and accept that the driver will only receive visual cues. The second is the notion of miscues, which encompasses a ‘multitude of sins’. The most common is the acceleration of the platform in the opposite direction to that of the vehicle simulation, which occurs when the platform needs to slow down as it nears the workspace limits. The magnitude of onset cues and miscues are linked, and this will be explored further with the longitudinal filter for example.

The longitudinal direction contains the largest magnitude accelerations and thus requires a low-gain filter. The filters designed by the two alternative methods are shown in Figure 8. As anticipated, the filters are both high pass, as sustained low-frequency accelerations will cause large displacements and thus associated workspace usage. The cut-off frequency of the filters are both at approximately 2 rad/s, but the low- and high-frequency filter gains differ, with the LQG filter reaching a higher high-frequency gain as well as increasing the attenuation of the lower frequency signals. The results of the filtering of the two cueing approaches are shown in Figure 9. The optimal control approach yields a stronger onset cue, i.e. the initial acceleration is larger, however it then produces a larger miscue. The relationship between the magnitude of the onset and miscue arises from simple physics. If the platform undergoes an acceleration, it will also need to be decelerated in order to remain within the workspace. Hence, the larger the acceleration, the larger the subsequent miscue.

Periods of lateral accelerations tend to be sustained for longer periods than longitudinal braking and acceleration. The lateral cueing filters are shown in Figure 10 with the associated responses given in Figure 11. In the case of lateral accelerations an onset cue is again produced which increases with the LQG filter reaching a higher high-frequency gain as well as increasing the attenuation of the lower frequency signals. The results of the filtering of the two cueing approaches are shown in Figure 9. The optimal control approach yields a stronger onset cue, i.e. the initial acceleration is larger, however it then produces a larger miscue. The relationship between the magnitude of the onset and miscue arises from simple physics. If the platform undergoes an acceleration, it will also need to be decelerated in order to remain within the workspace. Hence, the larger the acceleration, the larger the subsequent miscue.
... signal (Figure 9). Before a braking manoeuvre the platform is accelerated in the “wrong direction, which...
allows the system to produce a larger and more sustained acceleration signal; initially to slow the platform down, and then to move it backwards. In addition, there is no washout of the platform to a neutral position, which is common in motion cueing strategies, because the performance index as defined does not call for this type of behaviour. The inclusion of a velocity term in the performance index reduces the magnitude of the false cue that occurs ahead of a manoeuvre, but necessarily also reduces the magnitude of the onset cue. The advantage of this strategy is that the velocity-related term in $J_2$ provides a method of shaping the cueing signal. Unfortunately open-loop feed-forward cueing cannot be implemented in a practice, because there needs to be some form of feedback response from the driver’s. However, these calculations are useful in terms of analysing workspace usage, and examining the feasible accelerations for a given platform.

6. CONCLUSION

We have introduced the use of numerical optimal control techniques into the design of linear filters for race car motion cueing strategies. Numerical optimal control techniques can also be used to assess the capabilities and achievable performance of any simulator motion platform. This approach is able to recognise explicitly the kinematic constraints of the workspace and reduce the need for iterative tuning. An additional benefit comes from the use of real acceleration data rather than coloured noise realisations that are unlikely to be representative of real car behaviour. In the open-loop case, changes to the performance index, such as the introduction of velocity penalties, can be used to alter the characteristics of the resulting cues. The nonlinear programming framework facilitates the extension of the optimal control computations to non-quadratic cost functions. This is a key advantage of this approach and makes it possible to penalise the simulator motion in a nonlinear manner. In this way we hope to take advantage of the nonlinear characteristics of the problem and of human motion perception. This work also has the potential to be developed further to include all six degrees of freedom for use with a 3D car model. The use of optimal-control ideas in a closed-loop system, that does not just use linear filters, also needs to be explored so that the useful characteristics of the open-loop system can be exploited. Finally, the use of non-quadratic performance indices (norms) deserves further attention.

REFERENCES


