Identification of a driver model incorporating sensory dynamics, with nonlinear vehicle dynamics and transient disturbances

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ABSTRACT
In earlier work, a driver model incorporating sensory dynamics was identified from driving simulator experiments involving random disturbances, random target paths and linear vehicle dynamics. In the present paper, the driver model and experiments are extended to include transient disturbances, discrete target paths and nonlinear vehicle dynamics. The predictions of the model are compared with measurements from the experiments. Simulator motion is found to have a significant beneficial effect on drivers’ responses, giving faster driver reaction times and more successful disturbance rejection and path following. The driver model predicts the measured responses well. The model suggests that drivers are unable to develop an accurate internal model of motion cueing filters, perceiving phase and gain distortions introduced by filtering as disturbances. Drivers are found able to account for the time-varying operating point of a nonlinear vehicle. The driver model is also able to match the behaviour of experienced drivers near the friction limit of the tyres, however, further work is necessary to understand how an inaccurate internal model impedes the performance of less experienced drivers. The findings contribute new knowledge to the fields of driver simulation and motion cueing.

1. Introduction

Most existing models of driver steering control do not consider the driver’s sensory dynamics. A review of the literature [1] demonstrated that there is significant opportunity for applying knowledge of human sensory perception to models of driver-vehicle dynamics. The development of a driver model that incorporates sensory transfer functions, noises and delays was reported in [2]. Experiments were carried out with five test subjects in a moving-base driving simulator [3]. The data from this experiment were used to identify parameter values for the driver model, and in validation tests the model was found to describe the results of the experiment well.
The model was extended in [4] to account for conflicts between visual and vestibular measurements, such as occur in a fixed-base simulator or in a moving-base simulator with limited travel. Experiments were carried out with the physical simulator motion scaled or filtered (high-pass) relative to the motion of the virtual vehicle. In general, drivers were found to develop an internal model of the motion scaling and filtering to compensate for the sensory conflicts. However, they did so less successfully when the motion was filtered rather than simply scaled. Filtering the motion results in phase and gain distortions and complicated motion discrepancies, and it is unclear whether drivers can distinguish these from the effects of external disturbances on the vehicle. One of the objectives of the present paper is to devise a procedure that addresses this question.

The target and disturbance forcing functions used in the experiments reported in [3,4] were based on stationary filtered white noise, consistent with the linear quadratic Gaussian (LQG) control strategy used in [2]. This is a reasonable representation of some target paths and disturbances which may be encountered during. However, in many situations target paths may be discrete transient manoeuvres such as a lane change or simple curve, and disturbances may be discrete transient events such as a sudden gust of wind or hitting a kerb or pothole. Previous studies investigating combined target-following and disturbance-rejection performance of drivers or pilots have generally considered random disturbances with stationary statistical properties, e.g. [5,6]. Although some research has been carried out with transient disturbances [7–11], it appears that sensory dynamics have not been considered. Therefore the second objective of the present paper is to extend the previous experiments and simulations [3,4] to include transient targets and disturbances.

In the earlier work [3,4], the experiments were performed with linear vehicle dynamics, however, in more extreme manoeuvres a vehicle may operate in the nonlinear region. Various studies have addressed this, but haven’t considered the sensory dynamics [12–15]. The final objective of the present work is to devise and perform driving simulator experiments to identify and validate the driver model [2] in the nonlinear regime of vehicle dynamics. Only constant-speed vehicles are considered at this stage, although the approach could be extended to combined lateral and longitudinal manoeuvres.

The driver-vehicle model is outlined in Section 2. The experiments and model identification procedures are described in Sections 3 and 4; results are presented and discussed in Sections 5 and 6. The conclusion is given in Section 7.

2. Driver-vehicle model

Full details of the driver-vehicle model, Figure 1, are given in [2]. A brief summary is provided here. The model consists of the plant, the driver’s internal model of the plant (which might be inaccurate), a state estimator and a controller. The plant comprises the vehicle dynamics, represented by a constant speed, two degree-of-freedom single-track model, and the driver’s neuromuscular and sensory dynamics.

The plant is shown in more detail in Figure 2. The only difference between the linear and nonlinear vehicle dynamics is nonlinear tyres, with lateral characteristics described by the ‘magic formula’ [16]. Two different nonlinear tyre characteristics were simulated, as shown in Figure 3: lateral force monotonically increasing as a function of slip angle (NI) and lateral force decreasing past the friction limit (ND). The linear (L) and nonlinear tyres have the
same cornering stiffness at zero slip angle. Two different nonlinear vehicles were simulated, one with understeering characteristics and one with oversteering characteristics.

Neuromuscular process noise is added to the output of the controller and sensory measurement noise is added to the outputs of the plant. The controller output plus process noise is filtered by the driver’s neuromuscular dynamics, giving steering angle input $\delta$ to the vehicle. The forcing signals are the target path curvature $f_\kappa$, lateral velocity disturbance $f_v$, and yaw velocity disturbance $f_\omega$.

The driver previews the upcoming target road path angles relative to the vehicle up to the preview horizon. The driver also measures the lateral path-following error $e$. The target angles $\phi_{vi}$ and path error $e_{vi}$ measured by the driver’s visual system are delayed by a visual delay $\tau_{vi}$. Vehicle lateral acceleration and angular velocity are sensed through the otoliths and semi-circular canals (SCCs), with a vestibular delay of $\tau_{ve}$ in both cases, giving perceived lateral acceleration $a_{ve}$ and angular velocity $\omega_{ve}$.

The controller and state estimator require the forcing functions to be defined as filtered white noise spectra, quantified as an RMS value and a transfer function. The three types of target path used in the experiment were a straight line (for which the RMS value is zero and
the filter is irrelevant), lane changes and smooth corners. The lane changes consist of two short impulses of curvature, for which a white noise spectrum is appropriate: \( H_{f\kappa}(s) = 1 \).

The smooth corners consist of a triangular curvature profile; an integrator transfer function \( H_{f\kappa}(s) = 1/s \) is appropriate in this case. The disturbances used in the experiment were based on impulses, therefore a white noise spectrum is appropriate: \( H_{fv}(s) = H_{f\omega}(s) = 1 \).

The RMS values of the white noise signals are denoted \( W'_{\kappa} \), \( W'_{v} \) and \( W'_{\omega} \).

The state estimator was a linear Kalman filter (LKF) for the linear vehicle and a first-order extended Kalman filter (EKF1) for the nonlinear vehicle. For the linear vehicle, the driver control is modelled as a linear quadratic regulator (LQR). The cost function \( J \) to be minimised is a weighted sum of the mean square path-following error and controller output:

\[
J = \sum_{k=0}^{\infty} \{ q_\epsilon v_\epsilon(k)^2 + q_\delta \hat{\delta}(k)^2 \}. \tag{1}
\]

For the nonlinear vehicle, five different model predictive controllers (MPC) are implemented, with varying levels of prediction accuracy:

- L0: Linearisation about zero slip angle. This gives the same result as the LQR controller (assuming the control horizon is sufficiently long).
- LP0: Linearisation about the current slip angle, and use this linearisation up to the prediction horizon.
- LPF: Linearisation at each step up to the prediction horizon \([15,17]\).
- LPF*: LPF constrained to stop the slip angles exceeding the force peak, plus a constraint on the maximum change in \( \hat{\delta} \) \([18]\).
- FNO: Full nonlinear optimisation \([19,20]\). The full nonlinear equations are used to predict the plant trajectory up to the prediction horizon.

3. Experiment

The moving-base driving simulator experiment was similar in procedure to previous experiments \([3,4]\). The longitudinal vehicle speed \( U \) was always 40 m/s, however, the
steering ratio $G$ varied depending on the conditions of the trial. The moving-base motion was set to one of four conditions: none; full (1:1); scaled; or scaled and high-pass filtered. The motion was scaled or filtered relative to the motion of the virtual vehicle to allow the drivers to follow large-angle target paths without exceeding the simulator limits (a technique employed in most moving-base driving simulators), and to investigate how drivers’ responses to transient disturbances are affected by sensory conflicts.

Lateral and/or yaw disturbances applied to the vehicle consisted of random white noise motion (also used in [3,4]) or acceleration impulses. The impulses were applied in nine different combinations (Table 1). For the nonlinear vehicle experiments only combinations I6 and I8 were used.

It was hypothesised that scaled vehicle motion (lateral and yaw motion of the vehicle multiplied by constant gains of between 0 and 1 before being cued by the moving base of the simulator) might be easily interpreted and used by the driver. However, a possible disadvantage of scaling motion to accommodate the physical motion constraints of the moving base is that high frequency components of the motion would be unnecessarily reduced in amplitude. High frequency components of vehicle motion typically have small amplitude, well within the capability of the moving base, but might become undetectable by the driver if scaled down.

Therefore an alternative strategy is to high-pass filter the vehicle motion, so that large amplitude low frequency components are reduced in amplitude to satisfy the physical constraints of the moving base, while higher frequency components are cued at their true amplitude. A potential difficulty of high-pass motion filtering is that the driver might find it difficult to interpret and use the filtered motion, due to the frequency-dependent gain and phase effects of the filter. One of the objectives of the experiment was therefore to determine the extent to which drivers can detect the difference between motion caused by the phase and gain distortions of the motion cueing filters, and motion caused by disturbances on the vehicle. If a driver cannot detect the difference, this might put into question the suitability of the motion cueing filters.

For the linear vehicle experiments, ‘shaped’ disturbances were created, as illustrated conceptually in Figure 4. In the top left graph is a trial with full (not filtered or scaled) motion; the virtual vehicle (car) undergoes some motion (a rectangular lateral displacement function in this example), which may result from either a disturbance on the vehicle or from driver steering action, and the motion of the physical simulator is the same. The top right graph is the same trial, except that the motion of the virtual vehicle is filtered before being sent to the physical simulator. In the bottom left graph, a shaped disturbance is applied to the virtual vehicle but the motion is not filtered before being sent to the physical simulator. The disturbance is shaped so that the motion of the virtual vehicle (and of the physical simulator) is the same as the filtered motion in the top right graph. The question is, can a test subject detect that the simulator motion in the bottom left graph was caused by a disturbance on the vehicle, and that the identical simulator motion in the top right

| Impulse combination number | I1 | I2 | I3 | I4 | I5 | I6 | I7 | I8 | I9 |
|----------------------------|----|----|----|----|----|----|----|----|----|
| Sign of $f_v$              | 0  | 0  | 0  | 1  | 1  | 1  | -1 | -1 | -1 |
| Sign of $f_\omega$         | 0  | -1 | 1  | 0  | -1 | 1  | 0  | -1 | 1  |

Table 1. Possible combinations of signs of $f_v$ and $f_\omega$ impulse disturbances.
Figure 4. Design of shaped transient disturbances. Vehicle (car) and simulator motion is compared using motion cueing filters and/or shaped disturbances.

The conditions of the 15 trials performed with the linear vehicle are summarised in Table 2. When the driver’s internal plant model is equal to the real plant, the driving simulator’s motion cueing filters $H_{\text{HP}}(s)$ and gains correspond to the motion cueing filter blocks $H_{\text{ma}}(s)$ and $H_{\text{mu}}(s)$ in the plant model of Figure 2. Trials T1–T5 were carried out with a straight line target path to measure the feedback component of driver steering control. Four out of the nine impulse disturbances given in Table 1 were used: I3, I4, I5 and I6. The corresponding shaped disturbances were also tested. An example of the disturbances from trial T2 is given in Figure 5. Trials T6–T9 were carried out with a target consisting of successive lane changes as shown in Figure 6(a). The direction of the lane change alternated, and the disturbances were added at the onset of the lane change. For trials T10–T15 the target path consisted of smooth corners (all with minimum radius of curvature 50 m) connected by straights, Figure 6(b). Only the impulse disturbances were used, and they were placed either at corner entry or mid-corner.

The conditions of the 16 trials performed with the nonlinear vehicle are summarised in Table 3. Two types of target path were used: a circle of constant radius, either 70 m or 140 m; and a circuit consisting of four corners, the minimum radius for each successive corner being: 78 m, 65 m, 71.5 m and 58.5 m.

There were five test subjects in total. All five possessed driving licences and had at least 6 years experience driving cars on public roads. Drivers 1–4 all had a small amount of
**Table 2.** Conditions of each trial for the linear vehicle experiment.

| Trial | Target       | Disturbances        | Motion cueing filters | Steer ratio |
|-------|--------------|---------------------|-----------------------|-------------|
| T1    | Straight line| White noise         | \( H_{ma}(s) \)       |            |
| T2    | Straight line| Transient           | \( H_{ma}(s) \)       | 0.2         |
| T3    | Straight line| Transient           | \( H_{ma}(s) \)       | 0.2         |
| T4    | Straight line| Transient           | \( H_{ma}(s) \)       | 0.4         |
| T5    | Straight line| Transient           | \( H_{ma}(s) \)       | 0.2         |
| T6    | Lane change  | Transient           | \( H_{ma}(s) \)       | 0.2         |
| T7    | Lane change  | Transient           | \( H_{ma}(s) \)       | 0.2         |
| T8    | Lane change  | Transient           | \( H_{ma}(s) \)       | 0.3         |
| T9    | Lane change  | Transient           | \( H_{ma}(s) \)       | 0.3         |
| T10   | Corners      | White noise         | \( H_{ma}(s) \)       | 0           |
| T11   | Corners      | White noise         | \( H_{ma}(s) \)       | 0.1         |
| T12   | Corners      | Transient           | \( H_{ma}(s) \)       | 0           |
| T13   | Corners      | Transient           | \( H_{ma}(s) \)       | 0           |
| T14   | Corners      | Transient           | \( H_{ma}(s) \)       | 0.1         |
| T15   | Corners      | Transient           | \( H_{ma}(s) \)       | 0.1         |

Note: High-pass filters \( H_{HP}(s) \) had a cutoff frequency of 5 rad/s.

**Figure 5.** Disturbance signals for trial T2, with a straight line target path and full motion.

**Figure 6.** Lane change and corner targets for the linear vehicle experiments: (a) Lane change and (b) Corner.

experience driving in a simulator. Driver 5 was a professional test driver with a great deal of experience driving simulated and real cars. Drivers 1, 4 and 5 were the same as those who carried out the experiments in [3,4], however, drivers 2 and 3 were new test subjects. The
Table 3. Conditions of each trial for the nonlinear vehicle experiment.

| Trial | Target     | Disturbance | Motion | Vehicle   | Tyre |
|-------|------------|-------------|--------|-----------|------|
| NL1   | Circle R140 m | White noise | Filtered | Understeering | L    |
| NL2   | Circle R140 m | White noise | None   | Understeering | L    |
| NL3   | Circle R140 m | White noise | Filtered | Understeering | NI   |
| NL4   | Circle R140 m | White noise | None   | Understeering | NI   |
| NL5   | Circle R70 m  | White noise | Filtered | Understeering | NI   |
| NL6   | Circle R70 m  | White noise | None   | Understeering | NI   |
| NL7   | Circle R70 m  | White noise | Filtered | Understeering | ND   |
| NL8   | Circle R70 m  | White noise | None   | Understeering | ND   |
| NL9   | Corners     | White noise | Filtered | Understeering | NI   |
| NL10  | Corners     | White noise | None   | Understeering | NI   |
| NL11  | Corners     | Transient   | Filtered | Understeering | NI   |
| NL12  | Corners     | Transient   | None   | Understeering | NI   |
| NL13  | Corners     | White noise | Filtered | Oversteering | NI   |
| NL14  | Corners     | White noise | None   | Oversteering | NI   |
| NL15  | Corners     | Transient   | Filtered | Oversteering | NI   |
| NL16  | Corners     | Transient   | None   | Oversteering | NI   |

Note: Moving-base motion was high-pass filtered and multiplied by scaling factors of 0.2 for sway and 0.5 for yaw. For the cornering trials, the cutoff frequency was 4 rad/s. For the circular trials, the cutoff frequency was 0.2 rad/s.

number and demographic range of test subjects was not sufficient to quantify the steering control behaviour of the general population of drivers. However, this was not an objective of the experiments. The driver model is primarily intended to predict the behaviour of individual drivers.

4. Parameter identification

The identification procedure described in [3,4] was used to find parameter values that minimise the mean square difference of the modelled and measured steering angles. The agreement between the model and the experiment is quantified as the Variance Accounted For (VAF), which says what percentage of the measured steering angle response is accounted for by the model [3]. The difference between VAF and 100% is due to modelling error or noise in the experiment (driver, simulator, instrumentation). Box–Jenkins models are also identified, which provides an indication of the upper bound on VAF achievable with a linear model. Although the number of test subjects was relatively small, each subject completed a large number of trials, and simulation of the identification procedure has confirmed reliability of the procedure [3]. For the linear vehicle experiments the response time histories of all five drivers were averaged to give less noise than the responses from the individual drivers. For the nonlinear vehicle experiments, the parameter values are identified separately for each trial and driver because the nonlinearity makes averaging inappropriate.

For the linear model, many of the parameter values were set to constant values, as identified in [4]. However, various additional parameters are introduced for trials with transient target or disturbance profiles. These are:

- Target and disturbance equivalent RMS values $W'_x$, $W'_y$ and $W'_\omega$.
- Sensory signal equivalent RMS values $M_o$, $M_\omega$, $M_\phi$ and $M_e$.
- Cost function weight $q_\delta$. 
In [4], several variations of the driver model are presented based on possible differences between the driver’s internal model of the motion scaling or filtering and the real system. In model M0, the driver assumes there is no physical motion, and in model M1 the driver assumes the physical motion is at full scale. In model M2, the driver’s internal model matches the actual motion scaling factors or filters, and in model M3 optimal internal model yaw and lateral motion scaling factors are identified to fit the measured results as closely as possible.

The nonlinear model takes much longer to simulate than the linear model, so it is not practical to identify a large number of parameter values. Wherever possible, parameter values are identified from the linear experiments [3,4]. The parameters remaining to be identified are: equivalent RMS values $M$ for the steering angle and each sensory measurement; equivalent forcing function RMS values $W_e'$, $W_v'$ and $W_\omega'$ used in the driver’s internal model; and the steering cost weight $q_\delta$. For a trial with a large-angle transient target and white noise disturbances, the equivalent RMS values for most signals can be set equal to their measured RMS values, although a suitable equivalent target path RMS value $W_e'$ must still be identified. Controller LPF* and an extended Kalman filter EKF1 are used in the nonlinear driver model for the identification procedure. While these minimise the cost function successfully, real drivers may be unaware of the full nonlinear dynamics or may use simplifications to reduce their mental load, resulting in a sub-optimal control performance. To test this hypothesis, parameter values are also identified for controller LP0 and for a combination of controller L0 with a linear Kalman filter (LKF).

5. Results – linear vehicle

5.1. Driver performance comparison

Figure 7 plots the RMS path-following error $e$ against the RMS steering angle $\delta$ for each driver and trial. The values for each trial are given by the small markers, with the average values for each driver given by large markers. The results for each trial appear in three distinct groups: the straight line trials around 0.05 and 0.1 rad; the lane change trials around 0.1 and 0.3 rad; and the cornering trials, which required a large amplitude low-frequency steering, resulting in much larger RMS steering angles.

A surprising result seen in Figure 7 is that, when averaged across all trials, the drivers who steered the least also achieved the lowest path-following errors. This is the opposite to what might be expected from LQR control, where the form of the cost function implies a trade-off between steering activity and path-following performance. This discrepancy may be a result of differences in the experience of the drivers, with more experienced drivers able to achieve a lower path-following error while also minimising steering activity. The best driver in Figure 7 is driver 5, who is a professional test driver.

5.2. Transient disturbances

The steering responses (averaged across drivers) to one of the impulse combinations (I4) in the straight line trials are plotted in Figure 8(a), and the corresponding path-following errors are shown in Figure 8(b). It should be noted that the disturbance magnitudes were identical in trails T3–T5, but they were smaller in trial T2.
Figure 7. Performance of each driver in each trial of the transient experiment. Average values across all trials are shown by large markers.

Figure 8. Measured responses to impulse disturbances in straight line trials, for impulse combination I4 with various motion conditions. The same disturbance amplitudes were used with scaled, filtered and no motion. Smaller amplitude disturbances were used with full motion. (a) Steering angle and (b) Path-following error.

Figure 8(a) shows that the response time was similar for the three conditions with motion, however, the drivers steered later and at a lower initial steering rate without motion. This indicates that physical motion information reduces drivers’ reaction times to disturbances, even if the motion is scaled or filtered. Comparison of the scaled motion and filtered motion results shows that drivers steered more in their initial response and returned to zero steering angle earlier with scaled motion, with a similar amount of path overshoot in both conditions.

The effects of the motion conditions on the path-following error $e$ can be seen in Figure 8(b). The error was smallest for the full motion trial, where the disturbance amplitudes were smaller. The vehicle returned to the line slightly earlier with scaled rather than filtered motion. The path-following error was much larger with no motion, indicating that physical motion information allows drivers to respond to impulse disturbances more effectively.
Similar plots for the two lane change trials with I4, with scaled motion and filtered motion, are shown in Figure 9. The steering angles plotted in Figure 9(a) show that differences between the two motion conditions are small for the initial steering action. However, the return phase was carried out significantly later with filtered motion and often required an additional small correction. The path-following errors plotted in Figure 9(b) show that, for the I4 case where the disturbance acts in the direction of the lane change, this delayed steering action with filtered motion caused the vehicle to overshoot the target. These responses, and the responses for the other transient disturbances, indicate that drivers are able to respond to disturbances during lane changes better when the motion is scaled rather than filtered.

Comparison of the steering angles and path-following errors for the cornering trials with transient disturbances (T12–T15) did not reveal clear differences between trials with filtered motion and no motion. This could be because the task was dominated by the feedforward component of steering action, and therefore any benefit to the feedback component of steering control provided by physical motion was difficult to detect.

The identification procedure was used to fit the driver model to the measurements. The resulting VAFs using internal models M0, M1, M2 and M3 are plotted in Figure 10. In general the VAF values are high, with model M3 fitting best as expected. VAF values are higher for the lane-change trials than the straight-line trials, and much higher for the cornering trials. This is because the low-frequency components associated with following the target paths dominate the measured steering angles in these trials. Model M2 fits the results well for many of the trials, however, model M1 fits better for trials T8 and T9 which had filtered motion. Model M2 fits worse than model M3 for trial T4, which also had filtered motion. This indicates that the drivers had difficulty learning accurate internal models of the motion cueing filters, which is consistent with the result found in [4] for random disturbances.

5.3. Shaped disturbances

Trials T2–T9 contained shaped impulsive disturbances which were designed to imitate distortions resulting from filtering the vehicle motion. The objective was to investigate the extent to which drivers can distinguish between disturbances and motion cueing filtering distortions. This question can be approached from two directions: first, will a driver react to a shaped disturbance as if it were a filtering distortion? Second, will a driver react to a
filtering distortion as if it were a disturbance? These questions are addressed by comparing simulations using the driver model with results measured in the experiment. A new variation of the driver’s internal model, M5, is defined, in which the driver’s internal model of the motion cueing filters $H'_{ma}(s)$ and $H'_{mo}(s)$ is equal to $H_{HP}(s)$, multiplied by additional scaling factors $K'_{ma}$ and $K'_{mo}$, which are optimised during the identification procedure in a similar way to model M3:

$$H'_{ma}(s) = K'_{ma}H_{HP}(s) \quad (2)$$

$$H'_{mo}(s) = K'_{mo}H_{HP}(s) \quad (3)$$

This model variation represents a driver who believes that the motion is filtered, which would be an erroneous assumption if the motion arises from shaped disturbances. The identification procedure is run using this model for all trials with transient disturbances. The resulting VAFs are compared with models M2 and M3 in Figure 11. The important trials for the first question are trials T3, T6 and T7, which had scaled motion and included shaped disturbances. Model M5 fits the measurements worse than models M3 and M2 for these trials, indicating that the shaped disturbances did not make the drivers believe the motion was filtered.

The second question can also be answered by looking at the results shown in Figure 11. Model M3 represents a driver who believes that the motion is scaled, which implies that any distortions caused by filtering of the motion are perceived as disturbances. This can be compared with model M2, in which the driver is aware of the correct filtering, and model M5, which allows for the driver misidentifying the motion gains while still being aware of the filtered motion. The important trials for this question are T4, T8 and T9, which had filtered motion. In trial T4, differences between the models are small, however, model M3 fits the results best. In trials T8 and T9, model M3 fits much better than models M2 and
Figure 11. VAF values using model M5 for trials with transient disturbances, compared with models M2 and M3 and the Box–Jenkins upper bound.

M5. This indicates that in trials with filtered motion the drivers steered as if the motion was scaled, implying that any phase and gain distortions caused by the filtering were perceived as disturbances.

These findings are consistent with the conclusion in Section 5.2, that drivers had difficulty learning accurate internal models of the motion cueing filters, but were able to identify motion scaling.

6. Results – nonlinear vehicle

6.1. Driver steering performance

Eight pairs of identical trials were carried out with and without physical motion feedback. As an example, Figure 12 shows a short section of trial NL7, and the identical trial NL8 with no physical motion feedback, where the random disturbances pushed the vehicle near the friction limit of the tyres. The percentage change in RMS steering angle and path-following error when motion feedback was provided is shown for all the trials in Figure 13. The percentages are found with respect to the largest RMS value within each pair, giving a symmetric percentage difference between $-100\%$ and $100\%$. The median value over the five drivers for each pair of trials is also shown in Figure 13, chosen instead of the mean due to outliers caused by accidental spins or skids in some of the trials. Figure 13 shows that the addition of physical motion allowed the drivers to control the vehicle better. With physical motion drivers were able to steer less while also following the target line more closely. These results agree with the findings from the linear vehicle experiments, Section 5.1.

6.2. Driver model identification

The simulated responses of various combinations of controller and state estimator are compared with the experimental data to determine which combination best describes the
control behaviour of a human driver. VAF values are plotted in Figure 14. In general, the VAF values are high. This is partly due to the large low-frequency target-following components which dominate the steering response, however, it also shows that all the controller/state estimator combinations can predict the measured driver steering behaviour. There is a large variation in VAFs between drivers, showing that the control of some drivers is more predictable than others, which could result from different levels of experience. VAFs are largest for drivers 2 and 5, who were also found to be the better-performing drivers in terms of RMS steering angle and RMS path-following error. Low VAFs are seen for trial NL16 with driver 2, due to the car undergoing a large skid during the trial, however apart from this the model fits the results of driver 2 well.
Differences between models are difficult to see in Figure 14 due to the large VAFs, therefore the VAFs of L0/LKF and LP0/EKF1, expressed as percentage difference from the VAFs of LPF*/EKF1, are plotted in Figure 15. For trials NL1 to NL4 (with the large radius circular target) all models fit the results similarly, indicating that for low-slip manoeuvres it is not necessary to consider the varying operating point of the nonlinear tyres. However, for the other trials significant differences are seen between models. The largest VAFs are for LPF*/EKF1, indicating that drivers are able to consider the nonlinear operating point of the vehicle, including how it might vary up to the prediction horizon. In many cases this model is seen in Figure 14 to fit better than the Box–Jenkins model, indicating that a linear model cannot be expected to fully capture the behaviour of the drivers controlling a nonlinear vehicle.

The preview time $T_p$ is identified in [4] was 0.87 s. However, the LQR controller has an infinite control horizon and uses an internal model of the target spectrum to predict future values of the target ahead of the prediction horizon. In the nonlinear model, the control horizon is equal to the prediction horizon, therefore it may be necessary to use a larger value of $T_p$. One possible value is 1 s, since eye-tracking studies have measured that drivers focus on a point on the road around 1 s ahead of them [21–24]. Alternatively, a preview time of 2 s allows the simulated driver to account for vehicle behaviour twice as far into the future. The identification procedure was run with values of $T_p = 0.87$ s, 1 s and 2 s to investigate which value best describes the behaviour of real drivers.

The differences between the VAFs found for each preview time and the results found for $T_p = 0.87$ s are plotted in Figure 16. Some variation can be seen between the drivers. For drivers 1, 3 and 4 the shorter preview times generally fit the results better. For drivers 2 and 5, who had larger overall VAF values in Figure 14, the longer preview times fit better for the circular trials and the shortest preview time fits best for the cornering trials. There is
Figure 15. VAFs of L0/LKF and LP0/EKF1, expressed as percentage difference from the VAFs of LPF*/EKF1. Preview time is $T_p = 1$ s.

Figure 16. Difference between VAF values with various preview times and with $T_p = 0.87$ s, using EKF1 and LPF*.
Figure 17. Predicted change in RMS steering angle and path-following error with physical motion, calculated using simulations of the nonlinear driver model with LKF* and EKF1. (a) Steering angle $\delta$ and (b) Path-following error $e$.

little difference between preview times of 0.87 s and 1 s (which is expected as the values are similar), however, the VAFs are significantly lower in many trials for a preview time of 2 s. Therefore a preview time of around 1 s is an appropriate choice to match observed steering behaviour. This is consistent with results from eye-tracking studies [21–24], indicating that drivers do not predict the motion of the vehicle past the point at which they direct their gaze.

Simulations were also run with controller FNO, using the parameter values identified for LPF*. The resulting steering angles were almost identical, showing that in the conditions tested LPF* is able to find the optimal nonlinear control action.

6.3. Predicted effects of physical motion

The experimental results showed that the provision of physical motion allowed drivers to steer less and follow the target path more accurately on average. The simulated percentage differences in RMS steering angle and path-following error with the provision of physical motion are plotted in Figure 17. These can be compared with the experimental results shown in Figure 13. In general, the percentage differences are smaller in magnitude for the simulations in Figure 17 than the experimental results in Figure 13. This may be a result of driver noise or internal model discrepancies in the measured results. However, the overall trends are the same, with the addition of physical motion predicted to allow the driver to steer less and follow the target path more closely. One of the reasons for smaller reductions in RMS steering angle compared to RMS path error may be that the large amplitude low frequency components of steering angle necessary to perform the circle and corner manoeuvres are less likely to be affected by the motion feedback condition. It is also apparent that the RMS path error reduction tends to be larger for the circle trials (NL1–8) than for the corner trials (NL9–16). This might be because the high-pass cut-off frequency was
0.2 rad/s for the circles and 4 rad/s for the corners, thus providing the drivers with more motion feedback in the circle trials.

7. Conclusion

Moving-base driving simulator experiments were performed to identify a driver model with sensory dynamics [2]. An objective of the present work was to extend the experiments and simulations of earlier work [3,4] to include targets and disturbances with transient rather than random characteristics.

Driver performance was found to depend on the physical motion feedback, with smaller reaction times and more accurate disturbance rejection and path-following achieved when physical motion feedback was present. Furthermore, drivers were found to respond to disturbances more accurately when the physical motion was scaled rather than filtered. These measured effects were matched by predictions made by the identified driver model. These findings confirm, within the constraints of the experiment, the conclusions reached in the earlier work on random target and disturbance signals, and thus extend the understanding to a wider range of vehicle operating conditions.

Filtering the vehicle motion before presenting it to the driver as a physical cue results in phase and gain distortions and complicated motion discrepancies, and it was unclear from the earlier work whether drivers can distinguish these from the effects of external disturbances on the vehicle. An objective of the present paper was to use the identified model to address this question. The identification results indicate that drivers are generally able to develop an accurate internal model of scaled physical motion, however, when the motion is filtered drivers are found to rely on a simplified internal model such as equivalent scaling factors, with any phase and gain distortions caused by motion cueing filtering perceived as disturbances. This finding has implications for the design of motion cueing algorithms in moving-base driving simulators.

The final objective of the present work was to devise and perform driving simulator experiments to identify and validate the driver model in the nonlinear regime of vehicle dynamics; the earlier work had considered only linear vehicle dynamics. For manoeuvres involving large slip angles of the nonlinear vehicle, a nonlinear driver model accounting for the time-varying nonlinear operating point fitted the measured results best, particularly for more experienced drivers. The model was also able to predict correctly the beneficial effect of adding motion feedback and the performance of more experienced drivers near the limit of friction.

It is believed that these conclusions contribute new understanding of the effect of physical motion on driver steering control. Further work is desirable to understand the cognitive process involved in learning the internal model, and to understand how inaccurately learnt internal models affect the control strategy of less experienced drivers, for both linear and nonlinear vehicle dynamics. Further work is also desirable to develop driving simulator motion cueing filters that account for drivers’ ability to learn (or not) an internal model of the filter.

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