Identification of a driver’s preview steering control behaviour using data from a driving simulator and a randomly curved road path

A.M.C. Odhams and D.J. Cole
Cambridge University Engineering Department

Trumpington Street
Cambridge, CB2 1PZ, UK
Phone: (+44 1223) 765201
Fax: (+44 1223) 332662
E-mail: djc13@cam.ac.uk

The paper is concerned with the identification of a preview steering control model using data obtained from driving simulator experiments. The paper adds to limited existing published work on driver steering identification. The driving task involved steering a linear vehicle along a randomly curving path. The steering control model identified from the data was based on optimal linear preview control. A direct-identification method was used, and the steering control model was identified so that the modelled steering angle matched as closely as possible, in a least squares sense, the measured steering angle of the test subject. It is shown that identification of the driver’s time delay and noise are necessary to avoid bias in identification of the controller parameters.

1. INTRODUCTION

The paper is concerned with the identification of a preview steering controller using data obtained from driving simulator experiments. The paper adds to limited existing published work on driver steering identification. Notable recent work includes that of Chen and Ulsoy [1] who identified models of steering control that used lateral position error as the input and steering angle command as output. They obtained both the steering control model and its uncertainty from driving simulator data. The model did not include preview of the road path, but the identification procedure did account for the possibility of bias arising from the closed-loop nature of the driver-simulator system. Ungoren and Peng [2] developed an adaptive lateral preview human driver model. The model made use of preview information and tunable parameters to weight lateral displacement and yaw error in the cost function. The model was tuned to fit data from drivers performing lane-change manoeuvres on a driving simulator, but details of the identification procedure were not given.

Odhams [3] completed an extensive experimental study of preview steering control behaviour of a range of drivers for a range of vehicle speeds and road widths. The work added significantly to that in [1, 2] because it identified without bias a preview steering model using data from a continuous path-following task, and because it accounted for various human characteristics such as time delays, neuromuscular bandwidth, and the driver’s learnt vehicle dynamics. The next section of the paper presents one of the steering controllers used by Odhams to identify the measured steering control behaviour. Section 3 outlines the identification procedure adopted, including validation results. The driving simulator experiments are briefly described in section 4 and identification results are presented in section 5. Conclusions are given in the final section of the paper.

2. STEERING CONTROLLER

The steering controllers identified from the driving simulator data were linear preview controllers that can be implemented as either a linear quadratic regulator (LQR) [4] or a model predictive controller (MPC) [2, 5]. Complete details of all the different steering controllers studied during the investigation are given in [6]. The present paper focuses on one of these steering controllers, the basis of which is a linear model of vehicle dynamics, specifically the simple lateral-yaw model shown in figure 1, having yaw rate \( \omega \) and lateral velocity \( \nu \) and parameterised by the mass \( M \) and yaw inertia \( I \), the front and rear cornering stiffnesses \( C_f \) and \( C_r \), and the distances \( a \) and \( b \) of the front and rear axles from the centre of mass. The forward speed \( U \) of the vehicle is constant. The handwheel angle \( \delta \) is related to the front roadwheel steer angle \( \delta_f \) by the steering gear ratio \( K = \delta/\delta_f \).
the two weights 

information on the path ahead is specified by lateral distances \( y_{pi} \) (where \( i \) is an integer) of the future road path measured at equally spaced points along the vehicle longitudinal axis, as shown in figure 2. The spacing of the measurement points is \( UT \) where \( T \) is the discrete time step of the simulation. The furthest measurement point is at the prediction horizon \( h UT \), where \( h \) is the number of measurement points.

A linear controller that minimises a least squares cost function \( J \) can be obtained by means of an LQR or MPC calculation. In both cases the controller minimises a cost function typically comprising a weighted sum of mean square lateral path following error, heading error and handwheel angle. The cost function is of the form:

\[
J = \sum_{j} q_y (y(j)^2_{error} + q_\theta (\theta(j)^2_{error} + R \delta(j)^2)) \tag{1}
\]

where: \( j \) is the prediction time step index; \( q_y \) is a weighting on the lateral displacement \( y_{error} \) of the vehicle from the target path; \( q_\theta \) is a weighting on the angular displacement \( \theta_{error} \) of the vehicle from the target path; and \( R \) is a weighting on the handwheel angle. \( R \) is set to unity since only the relative magnitudes of the three weights are significant. Thus the steering control model is parameterized by just the two weights \( q_y \) and \( q_\theta \); it is the values of these weights that will be identified from the driving simulator data.

If the prediction horizon is sufficiently long [4] the resulting controller is of the form:

\[
\delta(k) = k_\nu \nu(k) + k_\omega \omega(k) + \sum_{i=0}^{h} k_{pi} y_{pi}(k) \tag{2}
\]

\[
\delta(k) = K x(k) \tag{3}
\]

where \( k \) is the simulation time step index, \( K \) is an array of gains \( [k_\nu \ k_\omega \ k_{p0} \ldots k_{ph}] \) and \( x(k) \) is a vector of vehicle states and previewed lateral displacements of the road path up to the prediction horizon.

3. IDENTIFICATION

data for identifying the steering control model were obtained from human test subjects and a fixed-base driving simulator. A direct-identification method, figure 3, was used in which the road path and vehicle motion information \( x \) (assumed sensed visually by the human test subjects and operated upon by their controller gains \( K \)) were used as inputs to the candidate steering control model with gains \( K' \). The predicted steering angle \( \delta' \) from the candidate steering control model was then compared to the steering angle \( \delta \) of the human test subject, to give the prediction error \( \nu \). The steering angle \( \delta \) of the human test subject includes the effect of noise, the most significant source of which is likely to be introduced by the human sensorimotor system. In figure 3 this noise is shown as a white noise source \( w \) and a filter \( H \). The corresponding relationships are:

\[
\delta = K x + H w \tag{4}
\]

\[
\delta' = K' x \tag{5}
\]

\[
\nu = \delta - \delta' \tag{6}
\]

\[
= (K - K') x + H w \tag{7}
\]

The parameters of the steering control model \( K' \) can then in principle be iterated until the prediction error is minimised. However a potential difficulty arises when identifying a driver operating in closed-loop with a vehicle. Any noise introduced to the loop can result in a bias error of the identified steering control model parameters [7]. To reduce bias error, a noise model \( H' \) can be identified in addition to the steering control model \( K' \). The identified noise model is then used to weight the discrepancy between the measured and predicted steer angles \( \delta \) and \( \delta' \) before calculating the mean square of the weighted prediction error \( \epsilon \).

\[
\epsilon = H'^{-1} \nu \tag{8}
\]

\[
= H'^{-1}(K - K') x + H'^{-1} H w \tag{9}
\]

providing the noise model \( H' \) is identified accurately \( (H' \approx H) \) the bias error is likely to be small. An iterative procedure was adopted to identify the steering control model \( K' \) and noise model \( H' \). Initially a white noise model was assumed \( (H_0' = 1) \) and the steering control model parameters \( q_y \) and \( q_\theta \) were identified. The spectrum of the corresponding prediction error was then used to estimate a new noise model \( H_1' \). With this new noise model an improved
estimate of the steering control model parameters \( q'_\theta \) and \( q'_y \) was determined. The procedure was repeated until the parameter estimates converged (usually within ten iterations).

\[
\begin{align*}
K' & \rightarrow \tau' \rightarrow \delta' \rightarrow y \\
K & \rightarrow \tau \rightarrow \eta \rightarrow H \\
F & \rightarrow w
\end{align*}
\]

Fig. 3: Direct identification.

The identification procedure was validated using artificial test data. Seventy-five sets of artificial driver responses, each 100 s long, were generated using the preview steering controller equations (1-3) with cost function weights set to \( q'_y = 0.05 \) and \( q'_\theta = 5 \). The vehicle parameters were set to the values given in table 1. Human sensorimotor noise was represented using white noise shaped by a filter \( H = M \) having unity gain up to a corner frequency of 1 Hz, above which the gain dropped at 40 dB/decade. The vehicle speed was 20 m/s and the road path inputs were randomly curved paths.

The upper plot of figure 4 shows for each of the seventy-five sets of responses the identified cost function weight \( q'_\theta \) as a function of the standard deviation of the filtered noise \( \eta \) when the prediction error was not weighted by the filter \( (H' = 1) \). When the noise is zero the cost function weight is identified without bias. However, the plot shows that significant bias introduced as the standard deviation of the noise (degrees of hand wheel angle) increases. This result confirms that bias error is a significant risk if the true (or identified) noise filter is not used to weight the prediction error. The lower plot of figure 4 shows the identified cost function weight \( q'_\theta \) when the true noise filter is used to weight the prediction error \( (H' = M) \); the bias is much reduced. Results for the identification of cost function weight \( q'_y \) are similarly improved by the use of the true noise filter to weight the prediction error.

The identification procedure was extended to account for the possibility of time delay in the drivers’ steering control action. The hand wheel angle predicted by the candidate steering controller was delayed by a constant delay \( \tau' \) before being compared with the measured hand wheel angle, equation (9). Other simulations had shown that it was not possible to reliably identify time delay as a parameter in the iterative procedure outlined above. The correct time delay was identified by repeating the identification procedure for several different values of time delay and then selecting the time delay that gave the lowest mean square weighted prediction error. Figure 5 shows the bias in the identified value of cost function weight \( q'_\theta \) that can arise if the time delay of the true steering controller \( \tau \) is different from the time delay of the candidate controller, which in figure 5 is \( \tau' = 0.2 \) s.

Figure 6 shows the result of identification in which the steering control weights and the noise model are identified using the iterative procedure. The graph confirms that there is negligible bias in the mean values of the identified cost function weights.

4. EXPERIMENT

Experiments were performed with a fixed-base driving simulator, figure 7. The vehicle dynamics were of a linear lateral/yaw model (figure 1) having parameter values given in table 1. The vehicle was a linear lateral/yaw model with parameter values given in table 1. The test subjects steered the vehicle along a randomly curving road path projected onto a display with 180° field of view. The road path was 4 km long and either 2.5 m or 3.5 m wide. An audible warning was provided to the participants.
Fig. 5: Identified weight \( q' \) as a function of true time delay \( \tau \), with assumed time delay \( \tau' = 0.2 \) s, using artificial test data.

Fig. 6: Result of identifying cost function weights from multiple sets of simulated data and a vehicle speed of 50 m/s. Noise models were also identified.

Fig. 7: Fixed base driving simulator

Fig. 8: Prediction error against assumed time delay \( \tau' \) for subject 2.

Typical time histories of measured and predicted hand wheel angle are shown in figure 9, for a vehicle speed of 20 m/s. The graph shows good agreement. The differences in the time histories are due to noise in the experiment (most likely introduced by the human test subject) and by any mismatch in the assumed model structure and the human steering behaviour. The noise spectrum shown in the lower

5. RESULTS

Figure 8 shows the prediction error as a function of the assumed time delay. The minimum prediction error is achieved at a time delay of 0.2 s at the lowest speed of 20 m/s and 0.25 s at the highest speed of 40 m/s.

Table 1: Parameter values of vehicle model

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>mass ( M )</td>
<td>1673 kg</td>
</tr>
<tr>
<td>yaw inertia ( I )</td>
<td>2811 kgm^2</td>
</tr>
<tr>
<td>front axle distance ( a )</td>
<td>1.2 m</td>
</tr>
<tr>
<td>rear axle distance ( b )</td>
<td>1.4 m</td>
</tr>
<tr>
<td>front cornering stiffness ( C_f )</td>
<td>152386 N.rad</td>
</tr>
<tr>
<td>rear cornering stiffness ( C_r )</td>
<td>152386 N.rad</td>
</tr>
<tr>
<td>steering gear ratio ( K )</td>
<td>16</td>
</tr>
</tbody>
</table>
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graph quantifies both of these discrepancies. The dashed line in the lower graph shows that the noise model \( H' \) generated by the identification procedure fits well to the measured noise spectrum.

![Graph showing measured and predicted hand wheel angles](image)

**Fig. 9:** Upper graph: time histories of measured and predicted hand wheel angle. Lower graph: measured and identified noise spectra, standard deviation 6.8°. Test subject 2, vehicle speed 20 m/s, lane width 2.5 m.

The cost function weights identified for speeds between 20 m/s and 40 m/s are shown in figures 10 and 11. There is a significant change in weight with speed, indicating that the driver’s steering control changes to account for the speed-dependent vehicle dynamics. The weights generally reduce as the vehicle speed increases, suggesting that the driver is allowing larger path following errors relative to the handwheel inputs.

![Graph showing identified cost function weights](image)

**Fig. 10:** Identified cost function weight \( q_y' \) versus speed for subject 2, lane width 2.5 m. Vertical bars indicate one standard deviation.

![Graph showing identified cost function weights](image)

**Fig. 11:** Identified cost function weight \( q_\theta' \) versus speed for subject 2, lane width 2.5 m. Vertical bars indicate one standard deviation.

gains remain nearly constant, showing just a slight increase as the speed increases.

6. CONCLUSIONS

A direct identification technique has been applied successfully to driver preview steering control. Artificial steering data was used to show that bias-free identification could be obtained providing that a noise model was identified as part of an iterative procedure. It was also found necessary to identify the driver’s time delay. Identification results from one test subject on a driving simulator for a range of vehicle speeds showed that the driver’s preview gains reduce significantly as the vehicle speed increases. However the preview time required remains approximately constant with speed, as do the gains on the vehicle states.

REFERENCES

Fig. 12: Standard deviation of hand wheel angle prediction error versus speed for subject 2, lane width 2.5 m.

Fig. 13: Preview gain versus preview time for three speeds, corresponding to the identified cost function weights for subject 2, lane width 2.5 m.

Fig. 14: State gains (upper graph $k_\nu$, lower graph $k_\omega$) versus speed, corresponding to the identified cost function weights for subject 2, lane width 2.5 m.