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A Unifying Theory of Driver Perception and Steering Control on Straight and Winding Roads

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Abstract—Novel driver support systems potentially enhance road safety by cooperating with the human driver. To optimize the design of emerging steering support systems, a profound understanding of driver steering behavior is required. This article proposes a new theory of driver steering, which unifies visual perception and control models. The theory is derived directly from measured steering data, without any a priori assumptions on driver inputs or control dynamics. Results of a human-in-the-loop simulator experiment are presented, in which drivers tracked the centerline of straight and winding roads. Multiloop frequency response function (FRF) estimates reveal how drivers use visual preview, lateral position feedback, and heading feedback for control. Classical control theory is used to model all three FRF estimates. The model has physically interpretable parameters, which indicate that drivers minimize the bearing angle to an “aim point” (located 0.25–0.75 s ahead) through simple compensatory control, both on straight and winding roads. The resulting unifying perception and control theory provides a new tool for rationalizing driver steering behavior, and for optimizing modern steering support systems.

Index Terms—Driver steering, multiloop control, preview information, system identification, visual perception.

I. INTRODUCTION

ROAD vehicles are rapidly being equipped with driver assistance systems and autopilots for temporary automatic control. Human-like and individualized automatic controllers may prove key to optimize the cooperation between the driver and an automation system [1], [2], but designing such systems requires a profound understanding of human driver behavior.

Considering steering on winding roads, the driver’s primary task is to keep the vehicle between the two lane edges. Steering in essence comprises two processes: 1) selection of perceptual feedbacks (the driver inputs), and 2) processing of the selected feedbacks into a steering output (the driver control dynamics). While drivers are known to rely strongly on visual feedback [3]–[5], over five decades of research has not led to a widely accepted theory that unifies both driver visual perception and steering control. In fact, two scientific approaches have emerged, each of which focuses on one of the two steering processes [6], [7]. The information-centered approach predominantly studies the visual cues used by drivers. Using experimental tools such as eye-trackers and visual occlusion, evidence has been provided that drivers rely on patterns of the optical flow [3], [4], [8]–[10], both “near” and “far” visual regions [10]–[13], and the road’s curvature or tangent point [14]–[16]. In contrast, the control-theoretic approach mostly ignores driver perception and focuses on understanding and modeling the driver’s control dynamics. Control theory has clarified that drivers combine feedforward (preview) control to anticipate on the road’s upcoming curves, with stabilizing feedback control to suppress disturbances such as wind gusts [17]–[21].

To accurately predict how drivers will interact with novel support technologies (e.g., in haptic-shared controllers [1], [2]), it has become clear that a unifying theory is needed that resembles both driver visual perception and control [6], [7]. For example, the currently popular two-point models [22], [23] combine state-of-the-art manual control theory [24], [25] with feedback from near and far bearing angles in the driver’s visual field [11]. Unfortunately, such models in general require assumptions on both the driver inputs and control organization, so they fail to explain—and are unsuitable for studying—how drivers adapt their perceptual feedbacks and control dynamics to task variables and novel technologies.

There is in fact a direct link between the information-centered and control-theoretic approaches, as visual cues are related to the vehicle outputs by the perspective geometry [6]. By first estimating the human’s multiloop control dynamics with system identification techniques, the perspective geometry has already revealed which visual cues humans use for control in various flying and driving tasks [17], [26]–[28]. For example, Weir and McRuer [17], [26] showed that driver steering on straight roads resembles a compensatory control strategy, based on the visual bearing angle to an “aim point” on the road centerline approximately 0.5 s ahead. To similarly estimate the visual cues used for steering on winding roads, data of the driver’s feedforward, preview response dynamics are additionally required. While the preview response dynamics have never been directly measured in driving tasks, they have recently been measured in laboratory tracking tasks using frequency-domain system identification techniques [29], [30]; these techniques may thus also reveal exactly what parts of the previewed road drivers use for steering and how.
This article aims to provide a new unified theory of driver steering on straight and winding roads, which includes both perception and control. The theory is derived directly from data obtained in a human-in-the-loop simulator experiment, without any *a priori* assumptions about the driver’s perceptual feedbacks or control dynamics. To do so, the data are analyzed with a multiloop, instrumental-variable system identification technique, yielding frequency response function (FRF) estimates of *three* driver responses, based on: 1) heading feedback, 2) lateral position feedback, and, most crucially, 3) road preview (feedforward). These estimates facilitate the formulation of a control-theoretic model that accurately captures the driver’s steering behavior. Additionally, using the perspective geometry, the model reveals the visual cues used by drivers for control. The obtained model explains driver steering and allows for predicting effects of different look-ahead times. Preliminary results of the experiment have previously been presented at the 2018 IEEE SMC conference, see [31] for details.

II. LINKING VISUAL INFORMATION TO CONTROL THEORY: PERSPECTIVE GEOMETRY

The driver’s control task is illustrated in Fig. 1. The driver follows a certain target trajectory (e.g., given by the lateral position of the road centerline \( y_\text{c} \)), by rotating the steering wheel with angle \( \delta \). External disturbances (e.g., wind gusts, \( y_\text{d} \), and \( \psi_\text{d} \)) can perturb the vehicle’s lateral position \( y \) and heading \( \psi \).

Equivalently, drivers minimize the current lateral position error \( y_\text{e}(t) = y_\text{c}(t) - y(t) \). However, \( y_\text{e}(t) \) is located directly below the vehicle, see Fig. 1(c), and is thus not visible from the driver’s view through the vehicle’s front windshield. The driver must instead rely on available visual cues to obtain indirect information about \( y_\text{e}(t) \). Possible perceptual feedbacks include static optical features like the bearing and splay angles of the road edges, and dynamical cues (i.e., the optical flow) such as the rate of change of these bearing and splay angles [4], [32], [33]. Control-theoretic models typically ignore driver feedback selection; for example, see Weir and McRuer [17], [26], Donges [18], and MacAdam [34]. These models directly use the tracking error, the vehicle states, or the previewed road as inputs, which is illustrated in Fig. 1(b).

The perspective geometry provides a mathematical relation between the optical cues and the vehicle states. Fig. 1(a) shows a single perceptual variable: the bearing angle \( \eta \) to an “aim point” on the road \( T_\text{la} \) ahead of the vehicle. Using Fig. 1(c), the bearing angle \( \eta \) can be expressed as function of the vehicle and aim-point lateral positions \( y \) and \( y_\star \), and the vehicle heading \( \psi \), as follows:

\[
\eta(t + T_\text{la}) = \psi_\star(t + T_\text{la}) - \psi(t)
\]

\[
= \arcsin \left( \frac{y_\star(t + T_\text{la}) - y(t)}{D} \right) - \psi(t)
\]

\[
\approx \frac{y_\star(t + T_\text{la}) - y(t)}{U_\text{la}T_\text{la}} - \psi(t), \quad \text{for small } \psi.
\]

(1)

All symbols are defined in Fig. 1(c). Equation (1) is important, because it shows that a response to the optical bearing angle is equivalent, from a control-theoretic perspective, to *three* driver control responses with respect to \( y_\star(t + T_\text{la}) \), \( y(t) \), and \( \psi(t) \). Moreover, these three control-theoretic responses are not independent: lateral position and heading feedback are relatively weighed by a factor \( \frac{1}{U_\text{la}T_\text{la}} \) that depends on the look-ahead time \( T_\text{la} \), while the same \( T_\text{la} \) appears as a time shift in the aim point lateral position \( y_\star(t + T_\text{la}) \). As will become clear later, this “match” of \( T_\text{la} \) is key to this article. Expressions similar to (1) can be derived for other optical cues (e.g., see [6] for details), but are not further investigated here, as various researchers have suggested that the bearing angle is a key perceptual feedback.
that guides driver steering [26], [33]. Possible bearing angle aim-points are the tangent point, points on the road’s lane edge or centerline, or points on the future vehicle path [2], [10], [22], [33], [35].

III. Method

This article tests the hypothesis that drivers respond to an aim-point bearing angle. To do so, experimental human-in-the-loop data are analyzed with system identification techniques.

A. System Identification Approach

Fig. 2 shows the lumped combination of the perspective geometry and the driver as a three-channel controller in the quasi-linear framework [24]. The three linear responses are 1) a feedback $H_{a_y}$ to vehicle heading, 2) a feedback $H_{o_y}$ to vehicle lateral position, and 3) a feedforward $H_{w_y}$ to the lateral position of the previewed road centerline. Remaining nonlinearities, time-varying behavior, and injected noise are accounted for by the remnant $n(t)$. This three-channel organization provides a convenient tool for estimating the driver’s multiloop response properties, and hence for verifying whether or not drivers use an aim-point bearing angle as perceptual feedback. Nonetheless, it is not assumed that drivers are organized as the three-channel controller in Fig. 2, or even close these particular control loops. All other vehicle states (e.g., $\chi$, $\beta$, $\psi$) and tracking errors ($y_c$, $e_y$, $\psi_c$) are a (linear) combination of the $y_c$, $y$, and $\psi$ inputs, see Fig. 1(c), so responses to these signals are indirectly also captured by measuring $H_{a_y}$, $H_{o_y}$, and $H_{w_y}$.

1) FRF Estimation: With an instrument-variable, frequency-domain system identification technique, FRFs of $H_{a_y}$, $H_{o_y}$, and $H_{w_y}$ can be estimated without making a priori assumptions about their dynamics [36]. Three instrumental variables are required to disentangle the three responses. Therefore, three external forcing functions are applied in the experiment, see Fig. 2: the road $y_c$, and two disturbances $y_d$ and $\psi_d$, which appear to the driver as side-wind gusts that perturb the vehicle lateral position and heading, respectively. The use of random-appearing multisine signals, with mutually exclusive sets of input frequencies $\omega_{y_c}$, $\omega_{y_d}$, and $\omega_{\psi_d}$, guarantees that the forcing functions are uncorrelated and can serve as instrumental variables [36]. Using Fig. 2, the Fourier transform of the control output can be written as:

$$\delta(j\omega) = H_{a_y}(j\omega)Y_c(j\omega) - H_{o_y}(j\omega)\psi(j\omega) - H_{w_y}(j\omega)Y(j\omega) + N(j\omega). \quad (2)$$

To solve for $H_{a_y}(j\omega)$, $H_{o_y}(j\omega)$, and $H_{w_y}(j\omega)$, three equations are required. First, (2) is evaluated only at the target signal input frequencies $\omega_{y_c}$. A second equation is obtained by interpolating the measured signals ($U$, $Y_c$, $\psi$, $Y$) in the frequency domain from the heading disturbance input frequencies $\omega_{y_d}$ to these same $\omega_{y_c}$ (denoted by $U$, $Y_c$, $\psi$, $Y$). A third equation is obtained similarly, by interpolating from $\omega_{\psi_d}$ to $\omega_{y_c}$ (denoted by $U$, $Y_c$, $\psi$, $Y$). As the remnant $N(j\omega)$ is negligibly small compared to the linear output at the input frequencies [36], the following system of equations is obtained:

$$
\begin{bmatrix}
U(j\omega_{y_c}) \\
\hat{U}(j\omega_{y_d}) \\
\hat{U}(j\omega_{\psi_d})
\end{bmatrix} =
\begin{bmatrix}
Y_c(j\omega_{y_c}) & -\psi(j\omega_{y_c}) & Y(j\omega_{y_c}) \\
\hat{Y}_c(j\omega_{y_c}) & -\hat{\psi}(j\omega_{y_c}) & \hat{Y}(j\omega_{y_c}) \\
\hat{Y}_c(j\omega_{y_d}) & -\hat{\psi}(j\omega_{y_d}) & \hat{Y}(j\omega_{y_d})
\end{bmatrix}
\times
\begin{bmatrix}
H_{a_y}(j\omega_{y_c}) \\
H_{o_y}(j\omega_{y_c}) \\
H_{w_y}(j\omega_{y_c})
\end{bmatrix}
\quad (3)
$$

which can be solved for $H_{a_y}(j\omega_{y_c})$, $H_{o_y}(j\omega_{y_c})$, and $H_{w_y}(j\omega_{y_c})$ at the frequencies $\omega_{y_c}$. After interpolating all signals to $\omega_{y_d}$ and $\omega_{\psi_d}$, (3) similarly provides FRF estimates at those frequencies. Examples of this technique’s success in estimating multiloop human control dynamics can be found, amongst others, in [29], [30], and [36].

2) Model Fitting: As the estimated FRFs reveal the driver response dynamics, they directly allow for formulating a control-theoretic model that captures all three steering responses. After proposing a model, it is fit to the data by minimizing the following least-squares criterion:

$$
\hat{\Theta} = \arg\min_{\Theta} \sum_{i=1}^{N} |E(j\omega_i|\Theta)|^2 \quad (4)
$$

$$
E(j\omega|\Theta) = \delta(j\omega) - \hat{\delta}(j\omega|\Theta) \quad (5)
$$

with $E(j\omega|\Theta)$ the modeling error at a single frequency $\omega_i$ and $N$ the total number of input frequencies of the three forcing functions combined. $\delta(j\omega)$ and $\hat{\delta}(j\omega|\Theta)$ are the measured and modeled steering wheel rotations; the latter depends on the model parameter vector $\Theta$, and is obtained by substituting the modeled $H_{a_y}(j\omega|\Theta)$, $H_{o_y}(j\omega|\Theta)$, and $H_{w_y}(j\omega|\Theta)$ into (2) (with remnant $N(j\omega)=0$). The variance accounted for (VAF) is used as a measure for the model quality-of-fit [29]:

$$
\text{VAF} = [1 - (\sigma^2_e/\sigma^2_\delta)] \times 100\% , \text{ with } \sigma^2_\delta \text{ the variance of the modeling error in (5), and } \sigma^2_e \text{ the variance of the measured control output.}
$$

B. Driving Experiment

1) Driving Task and Apparatus: The experimental setup is shown in Fig. 3. An abstract world scenery was presented which showed only the road centerline, in order to limit variability in participants’ steering behavior, and no physical motion feedback was provided. Participants were instructed to follow the
road centerline as accurately as possible (a tracking task). The centerline was 10 cm wide and was viewed from 1 m height. Visuals were presented on the simulator’s collimated projection system, which provided a 180 × 40 deg field of view. The vehicle moved at constant forward velocity $U_0 = 50$ km/h. The inner- ($\psi$) and outer-loop ($y$) vehicle dynamics, $G_\psi^o(j\omega) = \frac{133}{j\omega}$ and $G_y^o(j\omega) = \frac{U_0}{j\omega}$ in Fig. 2, were pure integrators, identical as used by Donges [18] and Land and Horwood [11]. The simulator’s left-hand side was equipped with a customized, electrically-driven passenger-car steering wheel. The steering wheel stiffness was set to 0.087 Nm/deg within 5.7 deg of the neutral position and to 0.131 Nm/deg otherwise, the damping ratio was 0.007 Nm·s/deg and inertia was 0.2 kg·m$^2$. Steering wheel rotations were limited to ±45 deg due to hardware limitations.

Participants performed four tasks: driving on straight (S, $y_c = 0$) or winding roads (W, $y_c \neq 0$), each with rotational visual feedback (tasks 1 and 2) and without (tasks 3 and 4). This article presents only the results of the natural straight and winding road driving tasks with rotational feedback; results of the other two tasks can be found in [31].

2) Road Trajectory and Disturbances: The road centerline and disturbance signals were designed to be the sum of ten sinusoids; for example, the centerline trajectory is given by

$$y_c(a) = \sum_{k=1}^{10} A_{y_c}[k] \sin(\omega_{y_c}[k]a + \phi_{y_c}[k])$$

with amplitude $A_{y_c}[k]$, frequency $\omega_{y_c}[k]$, and phase $\phi_{y_c}[k]$ of the $k$th sinusoid, and $a$ the along-track distance [37]. The longitudinal centerline coordinates are $x_c(a) = \int \cos(\psi_c(a)) da$, with the road heading given by $\psi_c(a) = \arcsin\left(\frac{dy_c(a)}{dx_c(a)}\right)$. The heading and lateral position disturbances $y_d(a)$ and $\psi_d(a)$ were defined identical to (6), and were applied directly in the vehicle body reference frame. All forcing function parameters can be found in [31]. To avoid spectral leakage, all frequencies $\omega[k]$ were selected to be integer multiples of the fundamental measurement frequency ($\frac{2\pi}{1800} = 0.0045$ rad/m), with 1389 m the centerline track length. The total track length driven by participants per measurement run was 1806 m; the first 278 m (run-in) and last 139 m (run-out) were not analyzed. The forcing function amplitudes $A[k]$ were scaled to obtain a realistic driving task, see Fig. 4(a) for their spectra. An example of measured control outputs is shown in Fig. 4(b), to illustrate that participants steered predominantly at the forcing function input frequencies (the peaks in the spectrum), and above all at the centerline frequencies $\omega_{y_c}$, so the task predominantly involved road following.

3) Participants and Procedures: Eight motivated volunteers participated in the experiment, all students or staff from TU Delft. Participants signed for informed consent prior to the experiment. First, a single run of each condition was performed to familiarize participants with the steering wheel, the vehicle dynamics, and the display. Then, the four experimental conditions were performed in an order randomized over sets of four participants according to a balanced Latin-square design. A condition was performed at least until tracking performance (rms($y_c$)) and control activity (rms($\delta$)) were approximately constant in five consecutive runs, which were then used for analysis. The applied steering wheel rotations $\delta(t)$ and the vehicle lateral position $y(t)$ and heading $\psi(t)$ were recorded at 100 Hz.

4) Data Analysis: The collected data were interpolated offline to constant along-track distance intervals $\Delta a = 0.1389$ m, to facilitate the frequency-domain analysis without leakage. All signals were averaged over the five measurement runs in the frequency domain to reduce effects of remnant noise on the FRF and model parameter estimates. Final results are presented as function of the temporal frequency (i.e., in rad/s), which is obtained by multiplying the spatial, along-track distance frequency (in rad/s) with the forward velocity $U_0$. This facilitates comparisons with manual control data in the literature (e.g., [17], [26], and [29]), and is a good approximation, as participants completed the 1389 m measurement part of the track always well within 0.5% of the nominal time (100.05 s, the time required to exactly follow the centerline).

IV. IDENTIFICATION AND MODELING RESULTS

A. Multiloop FRF Estimates

Fig. 5 shows Bode plots of estimated driver heading, lateral position, and preview response dynamics. No preview response dynamics were estimated in straight road tasks, as $y_c = 0$. The cross markers in Fig. 5 indicate the FRF estimates.

1) Heading Response Dynamics: Fig. 5(a) shows that the $H_{\phi_{y_c}}(j\omega)$ FRF estimates approximate gain dynamics at low frequencies and differentiator dynamics at higher frequencies, both in straight and winding road tasks. This can be interpreted.
as responses proportional to the vehicle’s heading angle and rate. Furthermore, notable phase lag is visible in Fig. 5(d), with a characteristic roll-off at higher frequencies that reflects the driver’s response time delay. No evidence of the driver’s neuromuscular system dynamics is visible in Fig. 5(a) and (d), suggesting that the neuromuscular bandwidth was higher than the highest forcing function input frequency (11.5 rad/s).

At low frequencies, the gain $H_o\psi(j\omega)$ dynamics equalize the vehicle yaw dynamics $G_\psi\delta(j\omega)=1/33j\omega$ to integrator open-loop dynamics $H_o\psi(j\omega)$, in agreement with the crossover-model theory [24]. Consequently, the driver’s heading response dynamics can be modeled as a compensatory control response, identical to McRuer’s simplified precision model [24]

$$\psi_o(j\omega) = H_{cmp}(j\omega) = K_{e\psi}(1+T_{L,e\psi}j\omega)e^{-\tau_{e\psi}j\omega} \quad (7)$$

with gain $K_{e\psi}$, lead time-constant $T_{L,e\psi}$, and time delay $\tau_{e\psi}$.

2) Lateral Position Response Dynamics: Fig. 5(b) and (e) shows that the $H_o\gamma(j\omega)$ FRF estimates have a shape that is identical to $H_o\psi(j\omega)\Theta_\delta(j\omega)$, in agreement with the crossover-model theory [24]. Consequently, the driver’s heading response dynamics can be modeled as a compensatory control response, identical to McRuer’s simplified precision model [24]

$$\gamma_o(j\omega) = H_{cmp}\gamma(j\omega) = K_{e\gamma}(1+T_{L,e\gamma}j\omega)e^{-\tau_{e\gamma}j\omega} \quad (8)$$

with $H_{cmp}(j\omega)$ defined by (7) and $K_{e\gamma}$ the driver’s weighing of heading and lateral position feedback. The observed lateral position and heading feedback dynamics combined, modeled by (7) and (8), are consistent with general theories of multiloop manual control [24], [38]: humans close the inner loop (heading) with dynamics that equalize the open-loop dynamics to an integrator, such that the outer loop (lateral position) can be closed with straightforward proportional control (gain $K_{e\gamma}$).

3) Preview Response Dynamics: In winding road tasks, drivers additionally mechanize the feedforward preview response $H_{oyc}(j\omega)$. The magnitude of the $H_{oyc}(j\omega)$ FRF estimates in Fig. 5(c) approximates gain dynamics at low frequencies, while the reduced magnitude at higher frequencies points to integrator dynamics. This suggests that drivers adopt responses proportional to the centerline lateral position ahead. The phase of the preview response in Fig. 5(f) reveals phase lead, which increases towards higher frequencies. This behavior resembles a negative time delay and can be interpreted as a response to the previewed centerline ahead.

Comparable preview response dynamics have been measured in single-loop preview tracking tasks (e.g., see [29] and [30]), and were modeled with a target prefilter $H_{of}(j\omega)$

$$\gamma_o(j\omega) = H_{of}(j\omega)H_{o\gamma}(j\omega) \quad (9)$$

The reason for including the lateral position response model ($H_{o\gamma}$) in the preview response dynamics, is that their FRF estimates are near-identical at the lowest frequencies [compare Fig. 5(b) with (c), and (e) with (f)], which suggests that identical (inner-loop) dynamics are visible in both estimates. The following prefilter dynamics are consistent with the estimated FRFs in
Fig. 5, and are identical to the preview model of [29], [30]:

\[ H_{yf}(j\omega) = K_f \frac{1}{1 + T_{tf}j\omega} e^{T_{tf}j\omega} \]  (10)

with \( K_f \) the scaling gain, \( T_{tf} \) the low-pass (smoothing) filter time-constant, and \( \tau_f \) the look-ahead time.

B. Control-Theoretic Model

1) Model Synthesis: In contrast with the parallel multiloop organization in Fig. 2, the FRF estimates suggest that drivers are organized as series multiloop controller. The heading response is the innermost loop, because its dynamics \((H_{o,m}^e)\) also appear in the lateral position and preview responses, and can thus be moved to the right of the summation point in Fig. 2. Similarly, it follows that lateral position feedback constitutes the middle loop, and preview feedforward the outer loop. Substituting (7)–(9) in (2) yields for the full model

\[ \delta(j\omega) = H_{o,m}^e(j\omega)E^*(j\omega) + N(j\omega) \]  (11)

\[ E^*(j\omega) = K_y^* [H_{o,j}(j\omega)Y_{c,j}(j\omega) - Y(j\omega)] - \psi(j\omega). \]  (12)

The parameter vector, \( \Theta = [K_{e,c}, T_{Le,c}, \tau_{e,c}, K_y^e, K_f, \tau_f, T_{tf}]^T \), has seven parameters. In straight road driving \((y_t = 0)\), \( K_f, \tau_f, \) and \( T_{tf} \) are redundant, yielding a four-parameter model.

2) Model Fits: The dynamics of the fitted model are shown in the Bode plots in Fig. 5, together with the FRF estimates. The FRF estimates of the driver’s lateral position, heading, and preview response dynamics are all captured well by the model, both in straight and winding road driving tasks. This result is not trivial, given that the model was fit by minimizing the error in steering output, see (4), and not in each of the estimated multiloop response dynamics separately. There is a small discrepancy between the model and the FRF estimates at the very lowest and highest input frequencies, because, here, several FRF components are poorly estimated (which is clear from the large errorbars in Fig. 5) and possibly also because the driver’s neuromuscular system dynamics were not explicitly modeled. The model also closely matches participants’ steering output, with VAFs that are well above 90% for all eight participants (see Tables I and II).

3) Parameters Estimates: Estimated model parameters, given in Tables I and II, are comparable to values found in other manual control experiments. For example, the response time delay \( \tau_{e,c} \) is between 0.3 and 0.4 s for all participants, while values between 0.25 and 0.6 s are typically reported in the literature [18], [26]. The farthest point of the previewed centerline trajectory that is used for control in winding road tasks, characterized by \( \tau_f \), is on average positioned around 0.9 s ahead, comparable to preview tracking tasks [30], and almost identical to the position of the “far point” (0.93 s) measured by Land and Horwood [11] in their visual occlusion driving experiment.

Tables I and II show that participants generated more lead (higher \( T_{Le,c} \)), and relied relatively less on heading feedback (lower \( K_{e,c} \), higher \( K_y^e \)) in straight road tasks, as compared to winding road tasks. Table II further shows that the estimate of \( K_f \) equals exactly one for all eight participants, so this parameter can be dropped from the model. Consequently, only six parameters are required to capture all characteristic dynamics of driver steering on winding road.

C. From Control Theory to Visual Cues

1) Physical Interpretation of Modeled Behavior: The derived model, given by (11) and (12), suggests that drivers minimize a certain error variable \( e^* \) through compensatory control; the key question then is which error. In Section II, it was explained that the perspective geometry connects control theory to visual cues. Comparison of (12), the modeled error \( e^* \), with the Fourier transform of the aim-point bearing angle \( \eta \) in (1), reveals that \( e^* = \eta \) when

\[ \text{feedforward: } H_{o,j}(j\omega)Y_{c,j}(j\omega) = Y_{c,j}(j\omega)e^{T_{tf}j\omega} \]  (13)

\[ \text{feedback: } K_y^e = \frac{1}{U_{o,c}T_{la}}. \]  (14)

The first equality, (13), essentially states that the preview filter \( H_{o,j}(j\omega) \) should output a single aim-point \( T_{tf} \) s ahead. Evaluating the modeled filter in the time domain, as done in Fig. 6, yields the convolution of the filter’s impulse response with the previewed trajectory ahead (up to \( \tau_f \)), which output can indeed be considered as a single aim point. The position of the aim point ahead can be approximated by \( \tau_f - T_{tf} \), as

---

1Alternatively, the observed high-frequency smoothing behavior can be modeled by taking the (weighed) average of two viewpoints, much like in recent two-point driver models [2], [22]. However, here, a low-pass filter is chosen because this captures the centerline smoothing behavior with a single parameter \( (T_{tf}) \) and because the shape of the FRF phase in Fig. 5(f) reflects the behavior of a single negative time delay.
explained in Fig. 6, such that the equality in (13) simplifies to \( \tau_f - T_{1,f} = T_{la} \).

The second equality, (14), reflects that the control-theoretic model gain \( \frac{1}{K_{y}} \), the driver’s relative weighing of lateral position and heading feedback, can also be interpreted as a look-ahead time. “Looking” closer ahead (lower \( T_{la} \)) corresponds to a stronger reliance on lateral position feedback (higher \( \frac{1}{K_{y}} \)), and vice versa.

2) Evidence of Bearing Angle Control on Winding Roads:

The crucial point of (13) and (14) is that together, they allow for testing whether drivers use the aim-point bearing angle as perceptual feedback in winding road driving tasks. This is the case when \( \tau_f - T_{1,f} = \frac{1}{K_{\psi}} \), that is, when the estimated feedback and feedforward responses correspond to the same look-ahead time. Fig. 7 shows that, indeed, all eight participants tuned their feedback and feedforward control dynamics to correspond to the same look-ahead time. To better appreciate this striking equality, note that from a control-theoretical perspective, the two look-ahead times emerge from two fully independent processes.

1) The driver’s relative weighing of heading and lateral position feedback (\( \frac{1}{K_{y}} \)) manifests as the difference in magnitude between the FRF estimates in Fig. 5(a) and (b).

2) The driver’s feedforward, the processing of the previewed trajectory \( H_{o,y} \) into an aim point shifted \( \tau_f - T_{1,f} \) s ahead, manifests as the characteristic increase in phase towards higher frequencies of the preview response FRF estimates, in Fig. 5(f).

This confirms the main hypothesis of this article: drivers use the aim-point bearing angle \( \eta \) as perceptual feedback for steering, as illustrated in Fig. 1(a). Estimated aim-point look-ahead times are between 0.5 and 0.75 s for all participants, as illustrated in Fig. 7(b). Substituting \( T_{la} \) for both \( \tau_f - T_{1,f} \) and \( \frac{1}{K_{\psi}} \) in the model means that only five parameters are required to capture the driver’s control output, control dynamics, and selection of visual feedbacks in winding road tasks. A control diagram of the final model is given in Fig. 8.

3) Bearing Angle Control on Straight Roads: It is impossible to validate the equality of (13) and (14) in straight road tasks, where drivers lack a preview response. As has been explained in the literature (e.g., [38] and [33]), the driver’s weighing of heading and lateral position feedback on straight roads can equally be the result of separate responses to the road’s vanishing point (heading information) and splay angle (lateral position information), as by a single aim-point bearing angle response. Nonetheless, assuming that drivers use comparable perception and control strategies on straight and winding roads, it follows that the aim-point bearing angle is also the driver’s main perceptual feedback on straight roads. Using (14) to estimate the aim-point look-ahead times in straight road tasks yields values between 0.25 and 0.55 s for the eight participants, see Fig. 7(c). Note that for straight road driving, the exact same aim-point model was previously proposed by Weir and McRuer [17], [26].

V. MODEL ANALYSIS

With the main hypothesis of this article confirmed, the new unified perception and control model will be used to rationalize and predict (adaptations of) driver steering behavior.

A. Feedforward Control: Preview Prefilter

First, it is investigated why equalizing the feedback (\( \frac{1}{\frac{T_{la}K_{y}}{U_0}} \)) and feedforward (\( \tau_f - T_{1,f} \)) look-ahead times is a particularly “good” control strategy, not only because it is perceptually convenient, but also from a performance perspective. To do so, the originally proposed seven-parameter model is used.

1) Perfect Target-Tracking Dynamics: Drivers follow a road centerline perfectly when \( y_c(t) = 0 \), or equivalently, when
y(t) = y_c(t). From Fig. 2, it follows that the closed-loop dynamics due to \( y_c \) (neglecting \( y_d, \psi_d, \) and \( n \)) are given by

\[
Y(j\omega) = \frac{G^y(j\omega)H_{o_{yc}}(j\omega)}{G^y(j\omega)H_{o_{yc}}(j\omega) + G^\psi(j\omega)H_{o_{yc}}(j\omega) + 1}.
\] (15)

After substituting \( Y(j\omega) = Y_c(j\omega) \), together with the modeled driver control dynamics from (7)–(9) and the vehicle dynamics, the following expression can be obtained for the “perfect” prefilter dynamics that yield \( y_c(t) = 0 \):

\[
H^P_{o_{yc}}(j\omega) = \frac{1}{G^y(j\omega)H_{o_{yc}}(j\omega) + 1}.
\] (16)

This equation shows that perfect centerline tracking requires a direct unfiltered response to the centerline’s lateral position \( y_c \) at low frequencies, and responses to the derivative (heading) and second derivative (curvature) at increasingly higher frequencies. Example \( H^P_{o_{yc}}(j\omega) \) dynamics are shown in Bode plots in Fig. 9.

The strict separation between frequency regions suggested by (16) is not visible in practice, because the three terms partially cancel each other due to phase differences. Fig. 9 reveals that drivers who adopt prefilter dynamics that approximate a gain in low frequencies and responses to the derivative (heading) and second derivative (curvature) at increasingly higher frequencies. Example \( H^P_{o_{yc}}(j\omega) \) dynamics are shown in Bode plots in Fig. 9.

2) Analysis of Measured Prefilter Dynamics: Measured driver prefilter dynamics \( H_{o_{yc}}(j\omega) \) match the phase required for perfect target-tracking well, see Fig. 9(b). However, the magnitude of the measured \( H_{o_{yc}}(j\omega) \) dynamics reveals explicit lag behavior (centerline smoothing) at higher frequencies, as opposed to the lead dynamics required for perfect target-tracking, see Fig. 9(a). Together, this indicates that drivers synchronize the vehicle’s lateral position movements well with the changes in centerline lateral position, while cutting corners at high frequencies.\(^2\) For the data in Fig. 9, the standard deviation of the vehicle’s lateral position deviation from the centerline \( \sigma_{y_c} \approx 0.1 \) m, which is sufficiently low for safe lane keeping on most roads; measured deviations on real roads are typically higher [10], because the current model analysis lacks external disturbances (\( y_d, \psi_d \)) and human remnant (\( n \)).

3) Optimal Feedforward Look-Ahead Time: The measured driver preview prefiltering dynamics are suboptimal, as \( \sigma_{y_c} > 0 \) m. However, Fig. 9(b) clearly shows that the effective feedforward look-ahead time \( \tau_f \) is optimal, and that \( y_c \) increases sharply when, for example, only \( \tau_f \) is changed [see Fig. 9(c)]. A \( \tau_f \) that is just 0.3 s away from the optimum yields a striking ten-fold increase in the lateral deviations.

\(^2\)In preview tracking tasks, human controllers occasionally adopt a high-frequency, open-loop response in parallel to the control response observed here. The additional, fast open-loop response allows for matching \( H^P_{o_{yc}} \) also at high frequencies and leads to improved target tracking. However, such a high-frequency response comes at the cost of substantial control effort, and appears to be mechanized only by experienced controllers in tasks with high-frequency target signals and first-order (or lower) vehicle dynamics [40], [41].
From the perfect target-tracking dynamics in (16), an expression can be derived for the optimal feedforward look-ahead time. The best match with the phase of $H_{0,0}^f(j\omega)$ at low and middle frequencies is obtained when the effective feedforward look-ahead time $\tau_f - T_{f,0}$ of the driver's prefilter $H_{0f}$ approximates the highest time constant in (16), which, remarkably, is $1/K_y U_0$. This is the exact same equality that indicated a response to the aim-point bearing angle, and was shown to be perfectly satisfied by all eight participants, see Fig. 7. The severe performance penalty for poorly tuned look-ahead times explains why bearing angle control is not only perceptually feasible, but also desirable for performance. It explains the near-perfect statistical correlation between $\tau_f - T_{f,0}$ and $\frac{1}{K_y U_0}$ in Fig. 7.

B. Aim-Point Dynamics and Look-Ahead Time

After dropping $K_y$ and substitution of $T_{la}$, the model in Fig. 8 was obtained, which reflects that drivers adopt a compensatory control strategy, with the aim-point bearing angle $\eta$ as error-feedback variable. The driver’s selection of an aim-point and the driver’s response dynamics therefore determine the attained driving performance and stability.

1) Aim-Point Dynamics: As drivers do not respond directly to the vehicle outputs (e.g., $y$, $\psi$), but to the selected visual feedbacks, the apparent control task as perceived by the driver is defined by the visual cue dynamics, and not the vehicle dynamics [6], [27]. Visual cue dynamics are the combination of the vehicle dynamics and the perspective geometry, and characterize the movement of the considered visual cue within the driver’s visual field due to steering inputs. The dynamics of the aim-point bearing angle $\eta$ are obtained by dividing the Fourier transform of (1) by $\delta(j\omega)$, yielding

$$G_\eta^y(j\omega,T_{la}) = \frac{\eta(j\omega)}{\delta(j\omega)} = \frac{-G_\delta^y(j\omega)}{U_0 T_{la}} - G_\delta^y(j\omega).$$

The aim-point dynamics thus depend explicitly on the look-ahead time $T_{la}$ selected by the driver. Fig. 10(a) shows a Bode magnitude plot of the aim-point dynamics for various look-ahead times. $G_\eta^y(j\omega,T_{la})$ resembles the vehicle’s lateral position dynamics (here, a double integrator) at low frequencies, and the vehicle’s heading dynamics (here, a single integrator) at high frequencies. By substituting the vehicle dynamics into (17), it follows that the break frequency is $1/T_{la}$ rad/s.

Selecting an aim point close ahead thus predominantly yields a double integrator control task, and requires explicit lead equalization from the driver in $H_{0,0}^{cmp}(j\omega)$, according to the crossover model [24]. An aim point far ahead, on the contrary, effectively yields a single integrator control task, in which proportional compensatory control suffices. For the performed experiment, Fig. 10(b) shows that the measured crossover frequencies $\omega_\eta$ of the open-loop dynamics $G_\eta^y(j\omega,T_{la})H_{0,0}^{cmp}(j\omega)$ are in general higher than $1/T_{la}$ rad/s. This indicates that crossover occurs at a frequency where the bearing angle open-loop resembles integrator dynamics.

2) Aim-Point Look-Ahead Time: The effects of varying the aim-point look-ahead time $T_{la}$ are also investigated in closed-loop model simulations, identical to those for $\tau_f$ variations in Fig. 9. Here, however, the final five-parameter bearing-angle model is used, and the experimental disturbances $y_d$ and $U_d$ are additionally included. All model parameters (except $T_{la}$) are fixed at the values listed in Fig. 9(b).

Fig. 11 shows that the driver-vehicle system becomes unstable when the look-ahead time $T_{la}$ is reduced to below approximately 0.3 s, which is a direct consequence of the bearing angle dynamics that converge to a double integrator and become less stable [see Fig. 10(a)]. Increasing the look-ahead time $T_{la}$ beyond the optimal value (0.5–1 s ahead) in general leads to larger deviations from the centerline [$\sigma_y$, Fig. 11(a)]. A larger look-ahead time further yields smoother control outputs [lower $\sigma_\delta$, Fig. 11(b)], while more aggressive steering corrections are predicted for smaller look-ahead times. These model predictions correspond to the behavioral trends measured by Land and Horwood [11] for different look-ahead times in their visual occlusion driving experiment.

Fig. 11 also illustrates the interaction between the driver’s two key processes (feedback selection and control). When a compensatory control strategy with a lower response gain $K_y$ is adopted (dotted lines in Fig. 11), a higher look-ahead time $T_{la}$ is required to achieve optimal performance, as the minimum in $\sigma_y$, in Fig. 11(a) moves to the right. Equivalently, drivers that select an aim point farther ahead (higher $T_{la}$) should in general...
minimize the bearing angle with a lower response gain $K_{e,*}$ to achieve optimal performance.

VI. DISCUSSION

This article presented a new, unifying theory of driver perception and control through an empirical, data-driven approach. Based on steering data, collected in a human-in-the-loop simulator experiment with three uncorrelated forcing functions, multiloop FRF measurements of drivers’ steering dynamics were obtained. These FRF estimates, in particular of the driver’s preview, feedforward response in winding road tasks, provided strong evidence that the visual bearing angle between the vehicle heading and an aim point ahead is the main perceptual feedback that guides steering. Moreover, the FRF estimates showed that the bearing angle is minimized through straight and simple compensatory control.

The resulting unifying theory of driver perception and control applies to steering on both straight and winding roads. Drivers select an aim point on the centerline ahead on straight roads [17], [26], while the aim point on winding roads is obtained by smoothing a portion of the centerline ahead. Because the resulting bearing-angle error is minimized through a compensatory control strategy, a unifying framework emerges for manual control behavior that spans tasks as different as compensatory display tracking and steering on winding roads. The derived driver model directly extends the widely-accepted crossover model theory [24] for compensatory tracking, and shows that the key difference is which error is being minimized by the human controller.

The driver’s main, low-frequency control response can be characterized by only two processes: first, selection of an aim point in the visual scene at a look-ahead time $T_{ia}$ ahead of the vehicle, and second, minimization of the visual bearing angle between the vehicle heading and the aim point through proportional control (gain $K_{e,*}$) with a response time delay $\tau_{e,*}$. Such compensatory control based on a future target point is also known as prospective control [7], [42]. Additional research is required to establish the range of driving velocities, vehicle dynamics, road widths, and geometries, for which a simple bearing-angle minimization strategy is adequate. Driver lead generation ($T_{l,e,*}$) and centerline smoothing ($T_{l,f}$) are auxiliary high-frequency behaviors, at least for the task performed here, and help to improve on performance, stability, and control effort objectives.

In theory, the baseline, low-frequency control strategy requires visibility of only an aim point. This is consistent with the seminal experiment of Land and Horwood [11], in which drivers could follow a road adequately at low driving velocities (i.e., low-frequency control) when only a single one-deg vertical portion of the visual field was available. For accurate steering at higher velocities (comparable to the driving task performed here, with higher frequencies in the forcing functions), Land and Horwood [11] showed that multiple portions of the visual field are required (i.e., “near” and “far” points). Indeed, for the measured high-frequency lead behavior ($T_{l,e,*}$), drivers may need feedback of the global optical flow to obtain heading rate information [8], [38]. Moreover, for smoothing the centerline’s higher frequency oscillations, visual preview of a substantial portion of that centerline seems essential [30]. To truly connect the steering behavior measured here with the literature, results of a visual occlusion experiment (e.g., Land and Horwood [11]) should be analyzed with the system identification techniques from this article.

The proposed unified perception and control theory provides a potentially crucial new analytic tool for researchers and engineers. For the first time, it is possible to quantitatively predict the effects of different perceptual feedback selection strategies, which determine closed-loop performance and stability together with the driver’s control dynamics. The model furthermore allows for predicting exactly how much preview drivers need (model parameter $\tau_f$ or $T_{ia} + T_{l,f}$), and how this depends on the given driving task, such as the driving velocity, vehicle dynamics, and road width and curvature. With proper extensions, the model may be used in future work for quantifying effects of other sensory feedbacks, to assess the fidelity of physical motion feedback provided in driving simulators, or the effects of novel steering support systems with haptic interfaces [1], [2].

VII. CONCLUSION

This article studied driver steering behavior by measuring and modeling the driver’s multiloop response properties. FRF estimates revealed how drivers use visual preview of the road ahead for control, and facilitated the formulation of the first data-driven classical control model that unifies driver perception and control. Perspective geometrical relations suggest that drivers are organized as series controllers. Both on straight and winding roads, drivers minimize the bearing angle to an “aim point” (located 0.25–0.75 s ahead) through compensatory control. Such bearing angle control yields adequate, yet suboptimal centerline-tracking performance, as well as corner-cutting behavior. Extending previous models such as the seminal crossover model, a single framework is now available for analyzing manual control behavior in tasks that range from single-loop compensatory tracking to driver steering on straight and winding roads. The proposed model provides a tool for predicting adaptations in driver control dynamics and, for the first time, also in driver visual feedback selection. The model can thereby be instrumental for rationalizing between-driver variability and for optimizing the design of human-like or individualized steering support systems in modern road vehicles.

REFERENCES


