Measuring and modeling driver steering behavior
From compensatory tracking to curve driving

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Measuring and Modeling Driver Steering Behavior: From Compensatory Tracking to Curve Driving

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Abstract - *Drivers rely on a variety of cues from different modalities while steering, but which exact cues are most important and how these different cues are used is still mostly unclear. The goal of our research project is to increase understanding of driver steering behavior; through a measuring and modeling approach we aim to extend the validity of McRuer et al.'s crossover model for compensatory tracking to curve driving tasks. As part of this larger research project, this paper first analyzes the four main differences between compensatory tracking and curve driving: 1) pursuit and preview, 2) viewing perspective, 3) multiple feedback cues, and 4) boundary-avoidance strategies due to available lane width. Second, this paper introduces multiloop system identification as a method for explicitly disentangling the driver's simultaneous responses to various cues, which is subsequently applied to two sets of human-in-the-loop experimental data from a preview tracking and a curve driving experiment. The results suggest that recent human modeling advances for preview tracking can be extended to curve driving, by including the human's adaptation to viewing perspective, multiple feedback cues, and lane width. Such a model's physically interpretable parameters promise to provide unmatched insights into between-driver steering variations, and facilitate the systematic design of novel individualized driver support systems.*

Keywords: curve driving, compensatory tracking, driver modeling, preview, system identification

Introduction

Today, driving is still a manual control task that requires continuous attention and control from the human driver. Drivers manipulate the gas pedal, brakes, and gears to change the vehicle's forward velocity (longitudinal control), and they use the steering wheel to negotiate curves, change lanes, and supress disturbances like wind gusts (lateral control). To effectively design *individualized* systems for autonomous driving or driver assistance, as currently pursued [Abb11, Sal13, Gor15], it is essential to understand driver control behavior. However, humans exhibit an extremely versatile set of control skills, and it is safe to say that, today, many aspects of driver control behavior are still poorly understood. Even for lateral steering control in isolation (i.e., at constant forward velocity), a wide variety of plausible theories exist about drivers' use of preview, motion feedback, and path prediction. This is reflected by the fundamental differences in available control-theoretic models of driver steering behavior [McR77, Mac81, Hes90, Odh06, Sen09, Boe16].

Ideally, it would be desirable to have a universal model for driver steering behavior, similar to McRuer *et al.*'s crossover model for compensatory tracking tasks [McR67]. The crossover model has inputs and control dynamics that resemble those of the actual human. Its physically interpretable parameters can be intuitively adapted, or explicitly estimated from experimental data, to *predict* human behavior in new situations, to *design* human-machine interfaces, to *quantify* human skill, and to *explain* observed behavior. Unfortunately, the crossover model is only appli-cable to the extremely limited single-axis, visual compensatory tracking task (error-minimization). Drivers likely adopt a complex internal control organization, integrating a variety of cues from different modalities. Moreover, opposed to continuous error-minimization, driving is a boundary-avoidance task where, in principle, any lateral position in-between the lane markings can be considered acceptable [McR77].

A fundamental issue in understanding and modeling driver behavior is to determine which combination of cues, or even sensory modalities (e.g., visual, vestibular, proprioceptive) guide steering. Four fruitful approaches are: 1) eye-tracking to determine the driver's visual focus of attention [Lan94, Kan09]; 2) removal of cues (e.g., visual occlusion) in a simulator environment to measure driver use of the remaining cues in isolation [Don78, Lan95]; 3) theoretical assessment to rank the usefulness of available cues using control theory [Wei70] and visual field geometry [Wan00]; and 4) directly measuring the driver's control dynamics (i.e., input-output relation) using system identification [McR75, Ste11]. All these methods have their own strengths, but only multiloop system identification allows for unambiguously disentangling the driver's simultaneous lumped response to various cues, while also most directly providing an experimentally validated mathematical model. To date, multiloop system identification has never been applied to study driver steering.

The goal of our research project is to obtain the much needed fundamental insight into driver steering behavior, using a combination of all the four mentioned approaches. We aim to quantify these new insights

in a structurally-isomorphic model that extends the validity of McRuer *et al.*'s crossover model to curve driving tasks. As part of this larger research project, in this paper we will explain the differences between compensatory tracking and curve driving, and demonstrate the strength of multiloop system identification for studying driver steering behavior.

First, we review McRuer *et al.*'s crossover model, together with the system identification techniques that were used to obtain that model. Second, we explain how we plan to move from compensatory tracking to curve driving tasks, by stepwise introducing preview, perspective viewing, visual rotational cues, optic flow, vestibular motion, and two lane boundaries (opposed to line-tracking). Next, we introduce a multiloop system identification technique, which is required to separately measure the multiple, simultaneously present human responses in these more elaborate tasks. Finally, we present experimental data from two tasks with various preview times, to demonstrate the new, fundamental insight that our approach can provide about driving. The first task involved preview tracking, and the second task involved full field-of-view visual curve driving.

Measuring and Modeling Compensatory Tracking Behavior

The Crossover Model

In compensatory tracking tasks, only a single task-specific, instantaneous error is available to the human, for example representing the difference between a vehicle's desired and actual lateral position. When the desired trajectory is unpredictable, humans can only adopt a single-loop control organization, known as compensatory tracking behavior [McR67], see Fig. 1 and Fig. 2. In compensatory tasks, the human's control dynamics can be approximated with a simple linear time-invariant model; nonlinear and time-varying contributions are relatively small, and are accounted for by a remnant "signal" (n in Fig. 1). The crossover model is given by [McR67]:

$$H_{o_e}(j\omega)H_{ce}(j\omega) = \frac{\omega_c}{j\omega}e^{-j\omega\tau_e}, \qquad (1)$$

and states that the human and vehicle dynamics (H_{o_e} and H_{ce}, respectively) combined resemble an integrator with a time delay τ_e around the crossover frequency ω_c. A set of "Verbal Adjustment Rules" quantifies the adaptation of the crossover model's variables, τ_e and ω_c, to task variables like the vehicle dynamics and the forcing functions' bandwidth [McR67]. From Eq. 1 it follows that the human's control dynamics in the crossover region are:

$$H_{o_e}(j\omega) = K_e \frac{1 + T_{L,e}j\omega}{1 + T_{l,e}j\omega}e^{-j\omega\tau_e}, \qquad (2)$$

with K_e humans' control gain, and $T_{L,e}$ and $T_{l,e}$ their lead and lag equalization time constants, respectively, which are adapted to achieve the crossover model's integrator dynamics around the crossover frequency. Extensions of the crossover model to lower and higher frequency ranges typically include a separate model for the neuromuscular system dynamics [McR68, Hes80]. The model parameters are

physically interpretable, which facilitates their intuitive adaptation to predict behavior in new situations. Moreover, the crossover model provides explicit quantitative insights into human adaptation and skill development. Since its development in the 1960's, the crossover model has become an essential tool in the research, design, and evaluation of human-machine systems (e.g., see [McR69, Hes90, Poo16]).

System Identification

Measuring the human's control dynamics in compensatory tracking tasks is relatively straightforward, because the human is organized as a single input (the visual error) and single output (the steering wheel rotations) controller. McRuer *et al.* [McR67] used an instrumental variable, frequency-domain system identification method to estimate the linear part of the human's control dynamics. This method relies on a multisine external input signal (or forcing function), the instrumental variable, which consists of a limited number N (typically around 10) sine waves:

$$f_t(t) = \sum_{i=1}^{N} A_i \sin(\omega_i t + \phi_i), \qquad (3)$$

with A_i the amplitude, ω_i the frequency, and ϕ_i the phase of the ith sinusoid. f_t corresponds to the desired trajectory forcing function in Fig. 1, which can be thought of as the road's trajectory to be followed in driving tasks. Alternatively, it is also possible to use a multisine disturbance signal f_d, which may resemble wind gusts. At the input frequencies ω_i, remnant is negligibly small compared to the human's response to the forcing function, and the human's linear control dynamics can be approximated with:

$$\hat{H}_{o_e}(j\omega_i) = \frac{S_{f_t u}(j\omega_i)}{S_{f_t e}(j\omega_i)}, \qquad (4)$$

with S the cross-power spectral density estimate of the respective subscripted signals. The N estimated Fourier coefficients $\hat{H}_{o_e}(j\omega_i)$ allowed for an explicit look into the H_{o_e} block in Fig. 1, and enabled McRuer *et al.* [McR67] to propose the crossover model.

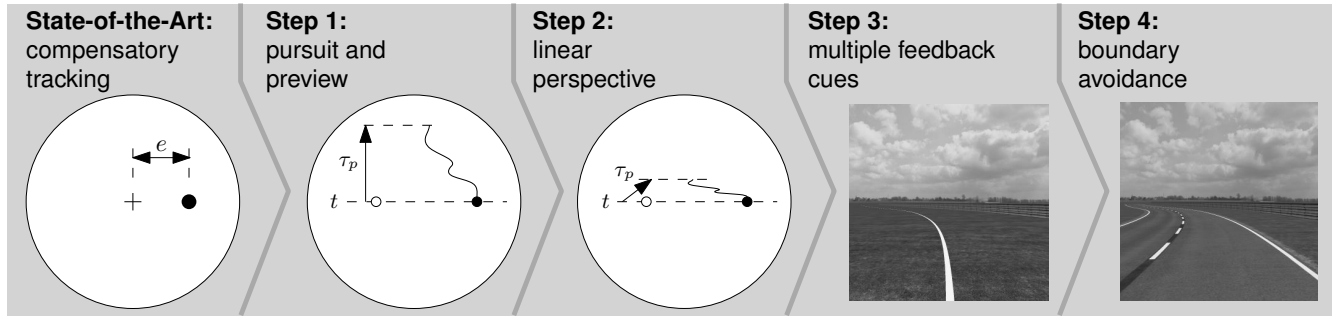# From Compensatory Tracking to Curve Driving

McRuer *et al.*'s [McR67] single-axis, visual compensatory tracking task is equivalent to a driving task from which only the current lateral position error with respect to the road's center-line is perceived by the driver. Clearly, drivers may additionally respond to many other cues while negotiating curves. In our research project we will stepwise introduce elements from a curve driving task into the compensatory tracking task, which is schematically shown in Fig. 2. The four main differences between compensatory tracking and curve driving will be discussed in detail in this section: 1) pursuit and preview, 2) perspective viewing, 3) multiple feedback cues, and 4) boundary avoidance.

Step 1: Pursuit and Preview

In contrast with compensatory tracking tasks, drivers that negotiate curves perceive cues that contain
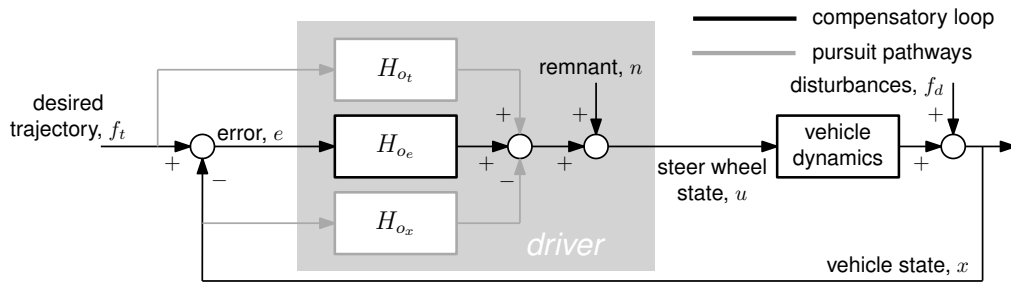
Figure 1: Driver-vehicle control diagram that illustrates the possible driver responses, based on [McR67]. The single-loop compensatory control organization is shown in black, while additional pursuit pathways are shown in gray. The driver's possible (proprioceptive) pursuit response on the steering wheel state u is not shown, because it is not considered in this paper.

Figure 2: Stepwise introduction of elements from a curve driving task (far right) into a compensatory tracking task (far left).

information about the desired trajectory f_t and the vehicle states x. Drivers can directly respond to these signals, which is reflected by the H_{o_t} and H_{o_x} blocks in Fig. 1, and which is known as *pursuit* tracking [All79, Hes81]. Moreover, drivers can typically preview the road for some part ahead, yielding information about the future desired trajectory $f_t([t, t + \tau_p])$, up to a certain preview time τ_p. The additional information allows for an extremely wide variety of acceptable steering behaviors, which is an important reason why driver behavior is still poorly understood.

First, with *preview*, drivers can anticipate the desired trajectory, which allows them to compensate for both their own response delays and other lags, like those of the vehicle dynamics [Ito75, El17]. In fact, with sufficient preview, drivers follow a desired trajectory nearly perfectly [McL73, Mil76]. However, how drivers exactly use preview has long remained unclear, which is reflected by the many fundamentally different ways in which driver models incorporate preview. Well-known driver models use either one [McR77, Don78, Mac81], two [Sal04, Sal13], or many [Mac81, Odh06] points from the previewed trajectory ahead as input, together with any function (e.g., lateral position, heading, or curvature) of that desired trajectory.

Second, in pursuit tasks, drivers can also *predict* their vehicle's trajectory, because they have knowledge of both the vehicle's states and their own control inputs [Mac81, Odh06]. Similar as for driver use of preview, it is yet unclear if, and how, drivers predict their vehicle's trajectory, which is again reflected by the many different prediction mechanisms incorporated in current driver models. Proposed driver prediction mechanisms range from simple linear extrapolation [Kon68, Wei70, Hes90] to elaborate optimization of

the driver's own control inputs over a certain future time span, using a model of the vehicle's dynamics [Mac81, Odh06].

In the first step of our research project, we investigate pursuit and preview control behavior in laboratory tracking tasks that closely resemble compensatory tracking (see Fig. 2, **Step 1**). A plan-view of the previewed trajectory is shown together with the vehicle's lateral position. Using multiloop system identification (explained in the next section), we estimate the human's H_{o_t} and H_{o_x} blocks; H_{o_t} shows how humans use preview, while H_{o_x} reveals if and how humans predict the vehicle's trajectory. Experimental results of this task were recently published in [El16b, El17], and will be reviewed in the final section of this paper.

Step 2: Perspective Viewing

The viewing perspective in normal driving tasks differs markedly from the plan-view preview tracking task (Step 1). In driving, linear perspective introduces a *nonlinear* mapping between the visual cues on the one hand, and the vehicle states and the desired trajectory on the other hand; a plan-view display (orthographic projection) only involves a linear scaling, or "gain". This has two important consequences. First, due to linear perspective the previewed trajectory in driving tasks appears smaller with increasing distance ahead (see Fig. 2, **Step 2**), such that tracking errors close ahead are visually emphasized. It has never been explicitly investigated if and how linear perspective evokes adaptations in human preview control behavior, because this first requires a better understanding of human preview control (Step 1).

Second, while the vehicle state (lateral position) is explicitly visible on the display in the plan-view tracking
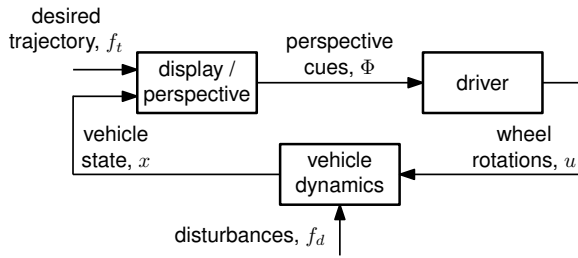
Figure 3: Illustration of steering with perspective viewing.

Figure 4: Illustration of a multiloop control organization.

tasks, a driver's perspective view only shows this information, through the scenery ahead (like in Step 3 in Fig. 2). Drivers must cognitively reconstruct the vehicle's lateral position relative to the road using the perspective visual cues from the scenery ahead, or, alternatively, directly use certain perspective visual cues to control their vehicle. For example, a straight road's perspective splay angle is directly related to the vehicle's lateral deviation from the centerline [Don78, Mul05]. For small deviations this relation is approximately proportional, so the splay angle simply replaces the explicit lateral position cue that is shown on the pursuit display in Step 1. For large deviations, or on curved roads, the relation between visual cues and the vehicle's states is strongly nonlinear [Mul04].

In perspective tasks, the assumption in Fig. 1 that drivers respond directly to the vehicle states and the desired trajectory is thus not necessarily valid. Instead, cues from the perspective visual scene are the input to the human, and these are related to the vehicle states by a (nonlinear) perspective transformation [Mul04, Mul05], see Fig. 3. Multiloop system identification can still be applied to estimate the H_{o_t} and H_{o_x} blocks in Fig. 1, but yields the lumped dynamics of the human and the perspective transformation together. The estimated lumped dynamics may reveal which perspective cues are used by the human, as was shown in piloting tasks [Swe99]. Additional measurements (e.g., eye-tracking) can provide supporting evidence for the actual inputs and control organization adopted by the driver.

In the second step of our research project, we will only investigate the effects of linear perspective on human use of preview information. To do so, we will perform the same preview tracking task as in Step 1, but with a perspectively transformed previewed trajectory (see Fig. 2, **Step 2**). In our research project we will thus not pinpoint which perspective cues (like splay angle) are actually used by the human; instead, we will consider the lumped human and perspective transformation dynamics together, essentially assuming that humans have direct knowledge of the vehicle states.

Step 3: Multiple Feedback Cues

The tasks discussed in Steps 1 and 2 involved only visual lateral position feedback. Indeed, lateral position in the lane is a likely cue that guides steering during curve driving [Wei70, Lan95]. However, most road vehicles have dynamics – from steering input to lateral position – that consist of more than two integrators [Raj11], such that continuous stabilizing control is required from the human, through lead
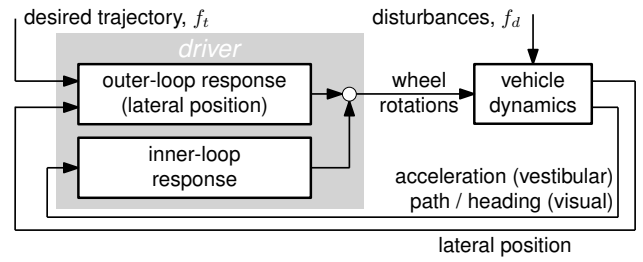
equalization [McR67]. Weir and McRuer [Wei70] showed that the human can, and will, close an additional inner-loop to ease the (lead equalization) requirements on the lateral-position outer-loop (see Fig. 4 for an illustration). Any cue that includes information about the vehicle's lateral velocity (i.e., lead on the lateral position) or acceleration can be used as inner-loop. Vestibular, proprioceptive, auditory and rotational visual cues (e.g., path/heading angle and rate) all contain such lead information. Note that none of these cues are present in the tasks in Steps 1 and 2.

With multiloop system identification (see the next section), the driver's inner- and outer-loop control dynamics can in theory be explicitly measured and disentangled, but this has never been done to date. As such, in curve driving tasks, the exact roles of visual cues like path and heading angle, and of non-visual cues like motion feedback, are still poorly understood. In the third step of our research project, we investigate three situations that possibly evoke drivers to close additional inner loops: 1) presence of physical motion feedback in the lateral position, plan-view preview tracking task from Step 1; 2) introduce "camera" rotations that correspond to the vehicle's heading changes, yielding visual heading and path cues (see Fig. 2, **Step 3**); 3) increase the strength of the path cues by increasing the visual flow (i.e., the texture density) to a level similar as in real driving tasks.

Step 4: Boundary Avoidance

The tasks up to Step 3 all required the human to follow a well-defined signal, which is called tracking. Drivers do not typically aim to continuously keep their vehicle on the lane's center-line, but instead steer only when the vehicle laterally approaches the road's edges [God86, Boe16]. This is called boundary avoidance, and is known to evoke less aggressive and intermittent (or "satisficing") driver steering behavior [McR77, Boe16]. In the final step of our research project we will extend the multiloop, perspective preview tracking task from Step 3 to a boundary-avoidance, curve driving task (see Fig. 2, **Step 4**. Due to drivers' possibly intermittent steering behavior, multiloop system identification (which assumes time-invariant behavior) alone may not suffice to reveal all the subtle differences between tracking and boundary-avoidance behavior. We intent to perform additional time-domain analyses, and to take advantage of recent advances in the modeling of intermittent human steering behavior [Mar17].

Multiloop System Identification

The introduction of elements from curve driving tasks allows humans to respond to multiple cues, or signals, instead of the single error signal in compensatory tracking tasks. To separately estimate the dynamics of multiple, simultaneously active human response blocks, the single-loop system identification technique, used by McRuer *et al.* [McR67] to derive the crossover model, has been extended to multiloop applications [Sta67, Paa98]. The maximum number of human response blocks that can be estimated is equal to the number of uncorrelated external forcing functions. For example, to estimate both the human's H_{o_t} and H_{o_x} pursuit blocks, two forcing functions are needed. Realistic forcing functions can be a desired trajectory f_t (e.g., a winding road) and disturbances f_d (e.g., wind gusts). The correlation between the driver's steering output and each uncorrelated forcing function then allows for disentangling the two driver response blocks. Two forcing functions can be constructed to be uncorrelated by using multisines (see Eq. 3) with mutually exclusive frequencies components ω_i [Sta67, Paa98].

Consider the scheme in Fig. 1, but without the driver's possibly active H_{o_e} response (at the end of this section we explain why this simplification poses no assumption on the actual driver's behavior). The resulting control diagram is given in Fig. 5. Neglecting the human remnant at the multisine forcing function input frequencies, we can write:

$$U(j\omega_i) = H_{o_t}(j\omega_i)F_t(j\omega_i) - H_{o_x}(j\omega_i)X(j\omega_i), \quad (5)$$

with capitals indicating the Fourier transform of the respective signals. A second equation is needed to solve Eq. 5 for the two unknown dynamics $H_{o_t}(j\omega_i)$ and $H_{o_x}(j\omega_i)$. First, evaluate Eq. 5 only at the desired trajectory's input frequencies, ω_t. Then, interpolate the signals $U(j\omega_d)$, $F_t(j\omega_d)$, and $X(j\omega_d)$ in the frequency domain from the neighboring disturbance signal input frequencies ω_d to ω_t, yielding $\tilde{U}(j\omega_t)$, $\tilde{F}_t(j\omega_t)$, and $\tilde{X}(j\omega_t)$, to obtain the following set of equations:

$$\begin{bmatrix} U(j\omega_t) \\ \tilde{U}(j\omega_t) \end{bmatrix} = \begin{bmatrix} F_t(j\omega_t) & -X(j\omega_t) \\ \tilde{F}_t(j\omega_t) & -\tilde{X}(j\omega_t) \end{bmatrix} \begin{bmatrix} H_{o_t}(j\omega_t) \\ H_{o_x}(j\omega_t) \end{bmatrix}, \quad (6)$$

which can be solved for $H_{o_t}(j\omega_t)$ and $H_{o_x}(j\omega_t)$. Similarly, after interpolating all signals from ω_t to ω_d, Eq. 6 can also be evaluated at the disturbance signal input frequencies to obtain $H_{o_t}(j\omega_d)$ and $H_{o_x}(j\omega_d)$. Example multiloop system identification results are shown in Fig. 5 and will be discussed in the next section.

There are three situations in which not all driver response pathways can be disentangled with multiloop system identification. First, because the number of meaningful forcing functions that can be defined is limited, the number of driver response blocks that can be separated is also limited. Second, blocks that have the same input can never be disentangled; for example, a simultaneous visual and vestibular response to (derivatives of) the vehicle's lateral position can only be estimated together, as a lumped response. Finally, due to the interdependency between e, f_t and x ($e = f_t - x$), it is never possible to simultaneously estimate all three response blocks, H_{o_t}, H_{o_x}, and H_{o_e}. In any of these situations, more driver pathways are active than can be disentangled, and the
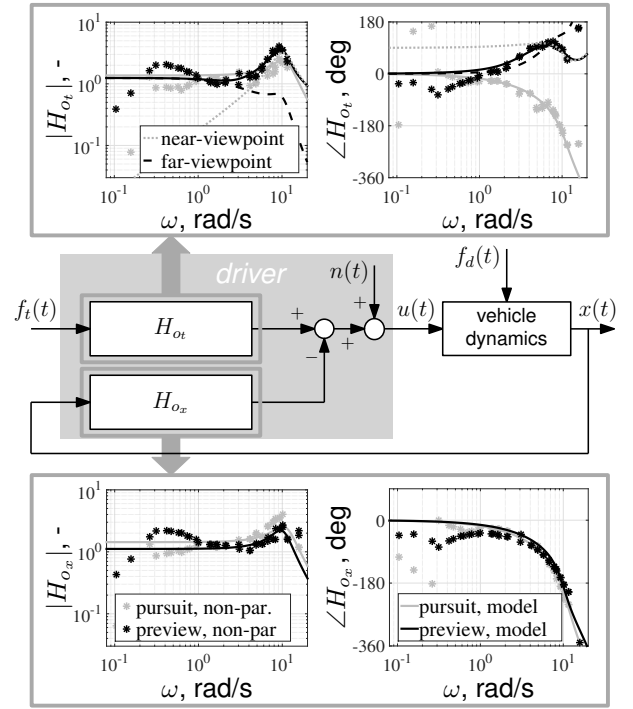
Figure 5: Illustration of estimated multiloop human controller dynamics for a single subject in pursuit and preview tracking tasks (gray/black markers), together with the fitted preview model (solid lines), adapted from [El16b].

estimated driver dynamics will be lumped combinations of all the actually active driver response blocks. The active pathways that are not present in the identified model structure are not assumed to be absent, but instead appear as "contamination" in the estimated control dynamics. As we will see in the next section, this limitation is not always problematic, because the lumped estimate of the driver's response dynamics may reveal which modality, or pathway, was active or dominant. Moreover, by our stepwise introduction of driving-task elements into a compensatory task, additional driver responses occur only gradually, which facilitates the study of many separate driver responses in isolation.

Results

In this section, we demonstrate the usefulness of multiloop system identification for studying driver steering behavior. First, we review results of a pursuit and preview tracking experiment (Step 1), which were recently published in [El16b]. Second, we present our first data from a simulator-based curve driving experiment (Step 4).

Preview Tracking (Step 1)

Only recently, multiloop system identification was applied for the very first time to measure the human's $H_{o_t}(j\omega)$ and $H_{o_x}(j\omega)$ control dynamics in pursuit and preview tracking tasks [El16b]. Subjects were presented with the display in Fig. 2, Step 1 (10 cm outer radius), on a screen directly in front of them, while control inputs were given with a side stick. Tasks involved 0 s (pursuit) and 1 s of preview, both of
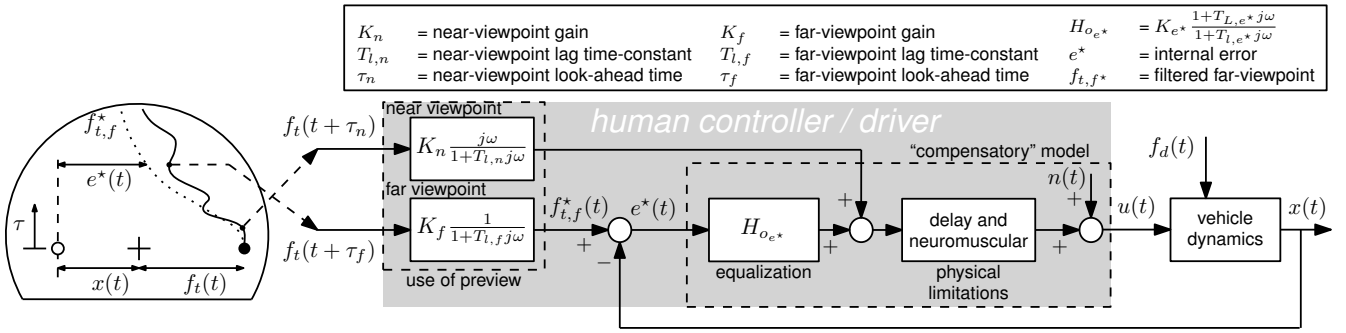
K_n = near-viewpoint gain	K_f = far-viewpoint gain	$H_{o_{e^\star}}$ = $K_{e^\star}\frac{1+T_{L,e^\star}j\omega}{1+T_{l,e^\star}j\omega}$
$T_{l,n}$ = near-viewpoint lag time-constant	$T_{l,f}$ = far-viewpoint lag time-constant	$e^\star$ = internal error
τ_n = near-viewpoint look-ahead time	τ_f = far-viewpoint look-ahead time	$f_{t,f^\star}$ = filtered far-viewpoint

Figure 6: Control diagram for preview tracking tasks, derived using multiloop system identification in [El16b].

which were repeated with gain, single- and double-integrator vehicle dynamics. The desired trajectory and disturbance signals had a bandwidth of 1.5 rad/s and a highest frequency components of 16 rad/s. Multiloop identification results for a single subject are reproduced in Fig. 5. The observed dynamics in each response block were first modeled separately [El16b], after which common elements were regrouped and the block diagram was rearranged to obtain a novel model that reflects human controllers' most likely control organization (see Fig. 6).

This new model for preview tracking tasks extends McRuer *et al.*'s model for compensatory tracking tasks with two responses to the previewed trajectory ahead. A far viewpoint, located τ_f s ahead (typically 0.6-2 s), provides a preshaped, smoothed trajectory input to a "compensatory" error response. The "error" $e^\star$ responded to by the human is thus not the true error, but a time advanced, cognitively determined internal error signal. Humans use the far-viewpoint response mechanism only to track the low frequencies (i.e., slow changes) in the desired trajectory, so the model includes a low-pass smoothing filter, characterized by time constant $T_{l,f}$ (typically 0-1 s). Gain K_f (typically 0.5-1.2) reflects the human's priority to track the previewed trajectory; when $K_f=0$ the human completely ignores the desired trajectory and focuses only on stabilizing the vehicle, while high values of K_f indicate a high priority for trajectory-tracking. The near viewpoint, located τ_n s ahead (typically 0.1-0.9 s), is the input to an open-loop feedforward response. Humans can use this near-viewpoint response to better track the higher frequencies (quick changes) in the desired trajectory [El17], which are not followed well with the far-viewpoint response mechanism. However, not all

subjects were found to apply a near-viewpoint response, and the near-viewpoint response is less pronounced when less preview is available, or when the order of the vehicle dynamics increases [El17].

Following the development of this new preview model, we performed a second preview tracking experiment to investigate how humans adapt their control behavior to the preview time τ_p [El16a]. This experiment was preformed only with integrator vehicle dynamics, and with six preview times between 0 and 1 s (of which four are reproduced here, see Tab. 1). Fig. 7 shows the multiloop system identification results for $H_{o_t}(j\omega)$ and $H_{o_x}(j\omega)$, together with the least-squares fit of the model to the measurement data. Higher preview times clearly evoke more phase lead in the human's response to the desired trajectory, which is captured in the model mainly by the far-viewpoint look-ahead time τ_f. Tab. 1 shows that the estimated value of τ_f indeed increases when more preview becomes available. The human subject kept the far viewpoint approximately at the end-point of the previewed trajectory, regardless of the amount of preview available. Note that the estimated far viewpoint position is occasionally slightly beyond the available preview limit, because the estimated values are affected by the noise in the system (i.e., human remnant).
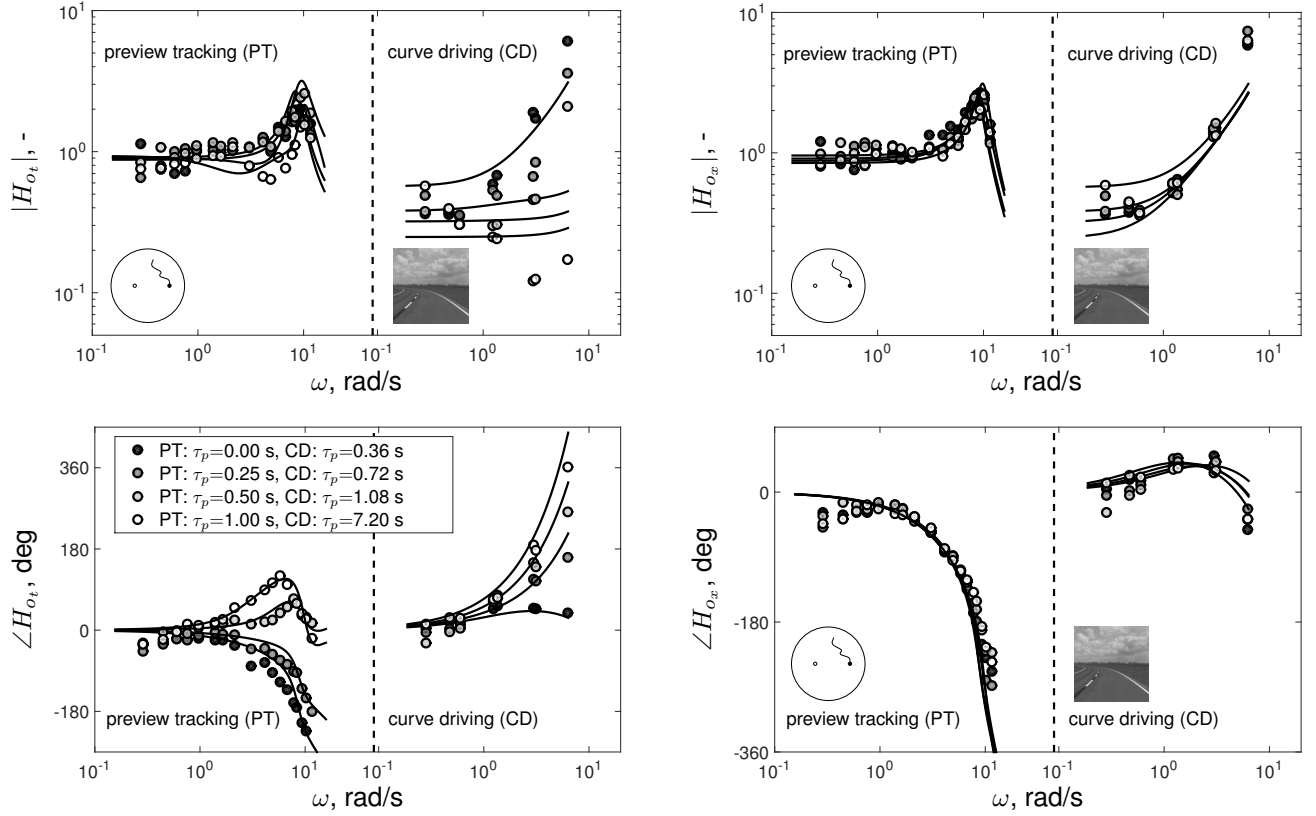
Curve Driving (Step 4)

As a start to Step 4, we recently performed a first curve driving experiment, also with various preview times [Ste11]. The driving task was performed at a constant forward velocity of 50 km/h, in a fixed-base simulator with a 180 deg field-of-view visual screen. Moreover, opposed to the preview tracking task from Step 1, the task involved perspective viewing, visual yaw rotational cues (i.e., path and heading), "bicycle model" vehicle dynamics, and two lane edges (boundary avoidance); control inputs were given with a steering wheel, and the highest frequency component in the desired trajectory and disturbance signals was 6.5 rad/s. Fig. 2, Step 4 shows the presented visuals.

Because, at this point, we lack understanding of human adaptation to the discussed differences between our curve driving and preview tracking task, we fit exactly the same preview tracking model to the curve driving data. Note that the bicycle model vehicle dynamics used in [Ste11], which approximate a double integrator from steering wheel inputs to lateral position, required substantial lead equalization in

Table 1: Experimental preview times τ_p and the human's estimated far-viewpoint look-ahead times τ_f.

preview tracking [El16a]		curve driving [Ste11]	
τ_p, s	τ_f, s	τ_p, s	τ_f, s
0.00	0.05	0.36	0.03
0.25	0.18	0.72	0.82
0.50	0.38	1.08	1.14
1.00	1.01	7.20	1.50

Figure 7: Estimated multiloop human control dynamics for a single subject, together with fits of the preview model, for a preview tracking (PT) [El16b] and a curve driving (CD) task [Ste11].

the human's internal error response $H_{o_{e^*}}(j\omega)$ to obtain integrator open-loop dynamics around crossover [McR67, El16b]. The near-viewpoint response was excluded from the model, as the desired-trajectory forcing function did not contain the high-frequency components at which the near-viewpoint response is active in preview tracking tasks [El16b].

The estimated $H_{o_t}(j\omega)$ and $H_{o_x}(j\omega)$ dynamics in the driving task are shown in Fig. 7, together with the model fits. Longer preview times evoke a highly similar adaptation of the $H_{o_t}(j\omega)$ response dynamics as seen in preview tracking tasks; namely, more phase lead and a lower response magnitude at the higher input frequencies. More phase lead shows that the subject better anticipates the desired trajectory, while a lower response magnitude indicates that more of the trajectory's high frequencies are ignored (i.e., trajectory smoothing or corner cutting). Tab. 1 shows that the estimated value of τ_f increases with increasing preview time (similar as for preview tracking), and stabilizes around 1.5 s when abundant preview is available. This suggests that drivers do not use preview information beyond 1.5 s ahead (about 20 m at 50 km/h), which is consistent with the control theoretical optimum [Mil76], empirical findings that use occlusion [McL73, Lan95] and eye-tracking data [Kon68, Lan94].

Fig. 7 also shows that the preview model does not perfectly capture the shape of the estimated driver dynamics. The estimated $H_{o_t}(j\omega)$ and $H_{o_x}(j\omega)$ dynamics in the driving task are likely a lumped combination of multiple driver responses. While the mul-

tiloop system identification results do show exactly how curve driving behavior differs from preview tracking behavior, separate experiments are needed to attribute these adaptations to the viewing perspective (Step 2), additional feedback cues (Step 3), the lane width (Step 4), or even other, more subtle differences between the two tasks. Nonetheless, the effect of preview time on driver behavior is already captured quite well by the preview tracking model. The model's τ_f parameter, which reflects the human's look-ahead time, allows for unique quantitative insight into driver adaptation, as well as a direct comparison to tracking data. We expect that extending the preview model to curve driving tasks will further add to this insight.

Conclusions

In this paper, we presented an approach to bring the applicability of the crossover model for human compensatory tracking behavior to curve driving tasks. Differences between compensatory tracking and curve driving were divided into four main categories: 1) pursuit and preview, 2) viewing perspective, 3) multiple feedback cues, and 4) boundary avoidance. Multiloop system identification was shown to be a valid method to separately measure multiple, simultaneously present human responses, which recently led to the extension of the crossover model to pursuit and preview tracking tasks. The preview tracking model provides new insight into driver adaptation to the preview time in curve driving tasks, but, in its current form, does not fully capture driver steering dynamics. We aim to extend the preview model to curve

driving in future work, by studying human adaption to the viewing perspective, multiple feedback cues, and boundary avoidance. This new model's physically interpretable parameters can yield unmatched insights into between-driver steering variations, and facilitate the systematic design of novel individualized driver support systems.

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